Essays on the determinants of firm productivity and openness, evidence from Tunisia

JIEUN CHOI

OXFORD DEPARTMENT OF INTERNATIONAL DEVELOPMENT

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

ST. ANTONY COLLEGE, UNIVERSITY OF OXFORD

TRINITY 2016/17

Abstract

Economic growth per capita is ultimately driven by private sector growth; specifically, by productivity growth of existing firms and by improvements in allocative efficiency. Therefore, how to make firms more productive is an essential concern in the study of growth and development. This thesis consists of three essays that explore the determinants of firms' productivity using Tunisian firm surveys from 1997 to 2007. First, I evaluate the role of technology distance and exports in explaining productivity growth of manufacturing firms. I find strong evidence of convergence in productivity at the firm-level, both unconditionally and conditionally, whereas there is little evidence of such at the macro-level. While exporters' productivity premium is explained by self-selection, the further a firm lies behind the frontier, the greater the potential for technologies to be transferred through exporting. Second, I test whether internal (create) and external (buy) sources of innovation have different effects on productivity, and whether firms benefit from using both. I find that buying has a positive effect on productivity, whereas creating does not. There is no synergy from using both simultaneously. I consider the possibility that "creating" and "buying" substitute for each other when the effect of innovation requires a minimum investment. The estimation result using the Tobit model supports this assumption. Finally, I investigate how to measure service performance and whether the variation in service firm performance can be explained by foreign ownership. Using two related measures, total factor productivity (TFP) and markup, I demonstrate Tunisian service firm performance across subsectors and over time. I show that foreign-owned firms have higher TFP but lower markups than local firms, as foreign ownership serves as a channel of knowledge transfer and brings more competition into the market, but with large sectoral variations. All chapters are closely linked to each other as they conclude that economic openness, obtained through exporting, outsourcing innovation, and acquiring foreign ownership, is a major driver of productivity and support the predictions of endogenous growth theory.

Table of Contents

Abstract 1

List of tables 4

List of figures 6

Abbreviations and Acronyms 7

Acknowledgement 8

I. Introduction 9

References 21

II. Chapter 1. Productivity Convergence and Learning by Exporting 27

1. Introduction 27

2. Literature review 31

3. Data and variables 40

4. Empirical strategy 50

5. Concerns and solutions 56

6. Results 65

7. Conclusions 86

References 89

Appendix A. Empirical evidence on productivity convergence 96

Appendix B. TFP estimation and variables 100

Appendix C. Different measures of technology frontier/distance 107

Appendix D. Additional result tables 113

III. Chapter 2. “Create” or “Buy”?, Internal vs. External Innovation and Firm Productivity 119

1. Introduction 119

2. Literature Review 122

3. Data 128

4. Empirical Strategy 136

5. Results 150

6. Conclusion 173

References 178

Appendix A. Summary Statistics 186

Appendix B. Additional Results 189

IV. Chapter 3. Measurement and Performance of Service Firms, and Foreign Ownership 194
1. Introduction 194
2. Literature Review 198
3. Data and Descriptive Information 211
4. Estimating Service Firm Performance 215
5. Results 229
6. Conclusion 252
References 259
Appendix A. Services Sector in Tunisia and Descriptive Information from the INS Data 269
Appendix B. Additional Methods 273
Appendix C. Service Firm Performance 274
V. Conclusions 280

List of tables

Chapter 1. Productivity Convergence and Learning by Exporting

Table 1. List of variables 42
Table 2. TFP, TFP growth, and frontier firm by industry 49
Table 3. Relations between international demand (IV) and export status 59
Table 4. Comparison of different technology frontiers and distances 62
Table 5. International and domestic frontiers/distance, using labour productivity 65
Table 6. Evidence of unconditional convergence 66
Table 7. Results with firm FE effect, with export Dummy 67
Table 7-1. Average TFP level between exporters and non-exporters 70
Table 7-2. Regression result of export dummy (value) on TFP level 70
Table 7-3. Regression result of export dummy (value) on labour productivity level 70
Table 8. Three-way interaction (tech dist. × export × FDI vs. tech dist. × export × innov.) 74
Table 9. Regression results with firm fixed effects, with export value 76
Table 10. Regression results firm fixed effects, with current-year export dummy 77
Table 11. Fixed effects, with export dummy, plus different time and industry dummies 78
Table 12. Different econometric techniques – IV 2SLS with export dummy 79
Table 13. Different econometric techniques – GMM 82
Table 14. Comparisons of different technology distance - FE, Lag export dummy 83
Table A.1. Summary of some of the empirical evidence on convergence 96
Table B.1. Average TFP growth 105
Table B.2. Standard deviation of TFP growth within industry, over time 105
Table B.3. Standard deviation of (domestic) technology distance variable 106
Table D.1. Manufacturing Firms' export participation in INS data 113
Table D.2. Frontier firms' export participation 113
Table D.3. FDI firms among all manufacturing firms in INS data 113
Table D.4. FDI firms among frontier firms 113
Table D.5. IV2 export volume first stage 114
Table D.6. RE Domestic GAP export Dummy 114
Table D.7. Hausman tests results 115
Table D.8. Different econometric techniques – IV 2SLS with export volume 116
Table D.9. Comparisons of different distance – OLS, lag export dummy 117
Table D.10. GMM with Lag Export Dummy 118

Chapter 2. "Create" or "Buy"?, Internal vs. External Innovation and Firm Productivity

Table 1. Innovation Variables, 1997 to 2007 132
Table 2. Summary Statistics of the Variables 135
Table 3. Determinants of Innovation Decision, Panel Firm Fixed Effects 150

Table 4. Determinants of Innovation Intensity, Panel Firm Fixed Effects 152
Table 5. Innovate Internally or Externally? Using GMM 157
Table 6. Innovation Impact on Output, OLS, FE, and LP 164
Table 7. Determinants of Innovation Using Tobit Methods 168
Table 8. Innovation Impact on Output, GMM, and Predicted Value 170
Table 9. Using TFP as a Dependent Variable, GMM 172
Table A.1 Top 15 Industries with the Most Innovating Firms 186
Table A.2 Innovator's Ratio by Exporting Status 187
Table A.3 Innovator's Ratio by FDI status (Full/Partial/None) 188
Table B.1 Determinants of Innovation Decision Using Probit Model 189
Table B.2 Determinants of Innovation: Random Effects 192
Table B.3 Hausman Test Results 193

Chapter 3. Measurement and Performance of Service Firms, and Foreign Ownership

Table 1. Observations by Subservice Sectors 213
Table 2. Ownership Variables 213
Table 3. Comparison of Key Firm Characteristics between FDIs and Non-FDIs 215
Table 4 Production Function Estimation by Subservice Sectors 229
Table 5. Log TFP Estimations by Subservice Sectors 230
Table 6. Markups by Subservice Sector 233
Table 7. Different FDI Variables and TFP 243
Table 8. Different FDI Variables and Markups 244
Table 9. FDI Effect on TFP and Markups 246
Table 10. First-Stage Logit Model 250
Table 11. Propensity Score Matching Results 251
Table A.1. Tunisian Economic Structure Over Time 270
Table C.1. ACF-CD Markup by Subservice Sector 274
Table C.2. Different Markup Estimation 275
Table C.3. Unlogged Markup by Subservice Sector—the CD Production Function, ACF 277
Table C.4. Unlogged Markup by Subservice Sector—the Translog Production Function, ACF 277
Table C.5. FDI and SOE's Market Power by Sector 279

List of figures

Chapter 1. Productivity Convergence and Learning by Exporting

Graph 1. TFP level over time 46
Graph 2. TFP growth, industry average over time 46
Graph 3. Technology distance (TFP gap) over time, by industry 48
Graph 4. Standard Deviation of technology distance, by industry-level 48
Graph C.1. Top1% distance over time 107
Graph C.2. S.D of top 1% distance 107
Graph C.3. Labour productivity level over time 108
Graph C.4. Distance to domestic frontier, using lalor productivity 109
Graph C.5. Standard deviation of distance to domestic frontier, using log labor productivity 110
Graph C.6. Labor productivity level over time, comparing to international frontier 111
Graph C.7. International distance, using labour productivity, by 2-digit industry level 112
Graph C.8. S.D of international distance, using labor productivity 112

Chapter 3. Measurement and Performance of Service Firms, and Foreign Ownership

Graph 1. TFP Distribution, All Firms 232
Graph 2. TFP Distribution by Subsectors 232
Graph 3. TFP Distribution, excluding Constant Term 232
Graph 4. Markup Distribution for All Firms 235
Graph 5. Markup by Subsectors 235
Graph.6. Labor Input Elasticities(θ_{ijt}^{L} 236
Graph 7. Labor Cost Share in the Revenue 236
Graph 8. Log TFP Mean by Subsectors 239
Graph 9. Log Markups Mean by Subsectors 239
Graph A.1. Composition of Service Exports 271
Graph A. 2. Graph A.7 Ownership Structure by Subservice Sectors 271
Graphs C.1 and C.2 Unlogged Markups Distribution for All Firms and by Subsectors 278
Graphs C.3. and C.4. Box Plot—Workers and Average Wage 279

Abbreviations and Acronyms

ACF	Ackerberg, Caves, and Frazer
API	Agence de Promotion de l'Industrie (Investment Promotion Agency)
AR	Autoregressive Model
ATT	Average Effect of Treatment on the Treated
CD	Cobb-Douglas
CIS	Community Innovation Survey
DID	Difference-in-Differences
ENAE	Enquete Nationale Sur Les Activites Economiques (Enterprise Survey)
FDI	Foreign Direct Investment
FE	Fixed Effects
GATS	General Agreement on Trade in Services
GDP	Gross Domestic Product
GFCF	The Gross Fixed Capital Formation
GMM	General Method of Moments
INS	L'Institut National de la Statistique (Institute of National Statistics)
IV	Instrumental Variables
LBE	Learning by Exporting
LHS	Left-Hand Side
LP	Levinsohn and Petrin's
NACE	Nomenclature Statistique des Activités Economiques dans la Communauté Européenne
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
OP	Olley and Pakes
R&D	Research and Development
SOE	State-owned enterprise
TD	Tunisian Dinar
TFP	Total Factor Productivity
TFPR	Revenue-Based TFP
TFPQ	Quantity-Based TFP
WTO	World Trade Organization

Acknowledgement

First and foremost, I would like to express my sincere gratitude to my advisors, Professor Xiaolan Fu and Professor Christopher Adam, for their supervision, patience, and immense knowledge. Without their precious guidance, it would not be possible to complete this dissertation. Also, I gratefully acknowledge the ESRC for the funding that made my DPhil work possible. I would like to thank the Tunisian Institut National de la Statistique for allowing me to access to L'Enquête Nationale sur les Activités Économiques dataset. Special thanks goes to my friends and colleagues who encouraged me in pursuing the DPhil. Last but not the least, I wish to thank my family: my parents and my brother, for all their love and support. My gratitude to them is beyond words. Thank you.

I. Introduction

"Productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker."

Paul R. Krugman, The Age of Diminished Expectations (Cambridge: MIT Press,1994).

Economic growth per capita is ultimately driven by private sector growth; specifically, by productivity growth of existing firms and improvements in allocative efficiency (entry of more efficient firms and exit of less efficient ones). Therefore, how to make firms more productive is an essential concern in the study of economic growth and development. However, though the growing availability of firm-level data and the development of better theoretical frameworks have permitted extensive studies on firm productivity in various contexts, much about the determinants of productivity remains unknown. Moreover, the literature is dominated by studies on a few well-studied countries and mostly on the manufacturing sector.

This thesis explores the determinants of productivity in firms in developing countries, and aims to contribute to our understanding of the factors that would allow less productive firms to catch up to more productive ones, and therefore drive their countries to catch up with their more developed counterparts. I address this question from three perspectives. First, I examine whether there is evidence of firm-level productivity convergence in Tunisia and whether learning by exporting (LBE) can be a source of productivity convergence, and how the effectiveness of LBE varies depending on a firm's distance from the technology frontier. Second, I test whether internal (create) and external (buy) sources of innovation have different effects on firm productivity, and whether firms benefit from using both. Finally, I investigate how to measure the performance of service firms, and whether the variation in service firms' performance can be explained by foreign ownership. The questions above are

investigated in three empirical chapters, each of which can be read as a stand-alone paper.

In the first chapter, I analyse whether there is productivity convergence at the firm-level, unconditionally and conditionally, and whether LBE varies depending on a firm's distance from the technology frontier, and can therefore be a source of productivity convergence. Growth theories often consider distance from the technology frontier a source of productivity convergence, yet, evidence from macro data is mixed and does not appear consistent with theoretical predictions. Also, existing literature on convergence mostly consists of macro-level analyses that use country-level or industry-level data, and does not clarify the causes of technology transfer, or why convergence exists only in some industries. Moreover, existing studies mostly test for the presence or absence of convergence, but do not typically reveal factors that drive convergence. In this chapter, I evaluate the role of technology distance and exports in explaining the productivity growth of manufacturing firms in Tunisia, a developing country, from 1997 to 2007. I link the convergence literature to export and productivity literature and provide firm-level evidence of convergence and LBE while controlling for self-selection into exporting.

In the second chapter, "Create" or "Buy"?: Internal vs. External Innovation and Productivity", I answer the following questions: are there any differences in the determinants of a firm's decision to create versus to buy? Does creating have a different effect on productivity than buying? If so, which source of innovation is more effective in increasing final output via productivity? The role of innovation in improving productivity might vary according to a country's relative position in technology advancement. Specifically, countries close to the technology frontier will grow faster by investing in innovation, while the follower group of countries will benefit more from adopting existing technology (Aghion 2004; Aghion, et al. 2013). This suggests that innovation policy should vary according to the level of a country's technological advancement. However, there is little systematic research and analysis

of the effects of innovation outsourcing, and research on representative firms in developing countries is particularly rare, despite rapidly growing innovation outsourcing.

In the final chapter, I measure the performance of service firms, which is an under-researched area in productivity analysis due to the conceptual and methodological challenges involved. I provide a survey of the literature on performance measurement in the service sector, review the existing measures and their limitations, and suggest two possible indicators of the performance of service firms – total factor productivity (TFP) and markups. Using these performance measures, I analyse service firm performance in Tunisia, where the service sector accounts for 60% of GDP but faces high protection and complex entry barriers. Lastly, I investigate whether variations in these performance measures can be explained by firm foreign ownership. Previous literature suggests that foreign ownership, obtained by Foreign Direct Investment (FDI), serves as a channel of knowledge transfer from foreign investors. Additionally, foreign participation results in a more competitive market, therefore lowering firm markups in the sectors with a greater FDI presence.

While each chapter can be read as a stand-alone paper, they are closely linked in a number of ways. First, the empirical findings of the three chapters support endogenous growth theory and economic openness, in that the further away from the technology frontier firms are, the faster firms grow by learning from the more advanced firms through economic openness (as shown with exports in chapter 1, and innovation outsourcing in chapter 2). Chapter 3, while different, as it is a methodological exercise in measuring the performance of service firms, nevertheless provides further evidence on the determinants of productivity, as it investigates foreign ownership as a channel of knowledge transfer from abroad, which also connects it to the theme of economic openness.

Furthermore, each chapter considers questions related to the determinants of firm productivity in Tunisia. These questions are identified by selecting external factors (export and distance to technology frontier) and internal factors (innovation and ownership) of productivity determinants in Tunisian firms, both of which are topics that have received much attention but still feature many unknowns in terms of their relation to productivity convergence as well as their heterogeneous effect on productivity as they depend on firms' distance from the technology frontier, especially in developing country contexts. These questions are motivated by existing empirical evidence on the drivers of firm productivity, are introduced using existing theoretical frameworks that create the basis for my hypotheses, and are tested on Tunisian firms via the latest econometric techniques.

In the remainder of this introduction, I will provide a short summary of the literature on 1) the empirical evidence on the determinants of productivity, and 2) the theoretical frameworks which underpin my hypotheses (firm heterogeneity in trade and endogenous growth theories). Then I explain why Tunisia is an appropriate source of empirical evidence for these questions.

The drivers of firm productivity: empirical evidence

Given the extensive efforts made to understand this issue in multiple fields, this section is by no means a comprehensive summary of all existing work, and provides only some of the recent research. More comprehensive literature reviews are, for instance, Syverson 2010, Wagner 2007, Hall 2011, Harrison and Rodriguez-Clare 2010.

Following Syverson, 2010, I divide the determinants of productivity into two categories, internal and external. However, some forces belong in both of these categories and interact with other factors in other categories, as the distinction between internal and external determinants is blurred and they can be closely linked to each other. For instance, firms that conduct innovation, which is considered as an

internal determinant of productivity, can outsource it. Also, firms could be acquired by foreign investors and be influenced by entry regulations and competition at the same time.

The first category, determinants of productivity within firms, includes firms' efforts to enhance production via innovation, their ownership, their size, the heterogeneous quality of inputs, managerial capacity, and experiences. The positive relationship between innovation and productivity has been long discussed. Recent evidence provides specific channels through which this positive relationship occurs. For instance, investment in R&D and IT equipment, such as computers, provides product innovation in high-technology industries and enhances firm performance. In addition, the interaction between R&D and exports could further influence productivity. For instance, firm's decision to export is often accompanied by large R&D investment. Also, firms' investment in R&D, as well as process and product innovation tend to increase export market entry (Brynjolfsson and Hitt, 2003, Inklaar et al., 2008, Griffith et al., 2004, Aw et al., 2011, Bernard et al., 2011)

The effect of firm ownership on productivity has been widely investigated, but the empirical evidence remains mixed. State-owned enterprises (SOEs) might be less efficient or less profitable than private enterprises due to political and agency cost (Shleifer 1998, Shleifer and Vishny, 1997, Boycko et al., 1996, Krueger, 1990, Dewenter and Malatesta, 2001). Therefore, privatization and liberalization (allowing foreign ownership) may have a positive effect on firm performance (Javorcik and Spatareanu, 2011, Markusen et al., 2005)

Firm size has been also recognized as a determinant of productivity. Larger firms are more likely to be productive. Specifically, large firms invest more in process R&D, while small firms invest more in product R&D (Acs and Audretsch 1991; Cohen and Klepper 1996).

Firm age (and experience) have mixed effects on productivity. Accumulated know-how and experience could positively affect firm productivity through learning-by-doing; in other words, productivity increases over time without any changes in inputs or the production process. Recent evidence shows that gaining experience reduces required labour inputs and defect rates, without any other changes. Experience working with a single supplier also increases productivity (Kellogg, 2009, Hendel and Spiegel, 2014). Meanwhile, other literature finds that younger firms are more likely to innovate, and are therefore more productive (Huergo and Jaumandreu 2004; Balasubramanian and Lee 2008).

This category also includes heterogeneous inputs, such as labour, and the processes by which those inputs are handled. Human capital contributes to some part of productivity differences. For instance, it has been shown that firm productivity is influenced by the workers' quality and human resources practices, such as incentive pay. In addition, productivity is affected by the way those inputs are managed. In recent years, a growing body of evidence has clarified the effect of management on productivity. The characteristics of managers and managerial skill, as well as firms' organizational structure, influence how easily new technologies are adopted, and thereby increase firms' productivity, profitability, and survival rates. (Bertrand and Schoar, 2003, Bandiera, et al., 2007). Consulting and training on management practices as well as enhancing management structure and incentive schemes have a positive effect on TFP (Abowd et al., 2005, Fuand and Hoyes, 2003, Bloom and Van Reenen, 2007 and 2010, Bloom et al., 2013).

The second category includes external drivers of productivity, such as firms' openness to international markets through trade, foreign direct investment, market environment and competition, geographic locations, and other spill-over effects.

Extensive literature documents the positive relations between trade and productivity, and evidence of learning-by-exporting. After being exposure to consumers and

competitors abroad, firms tend to adopt advanced technology and improve management practices. In addition, the larger and more competitive markets incentivize firms to invest in technology, thereby increase productivity but lower markups. Meanwhile, liberalizing trade increases demand for more developed technology and skilled labour, thus improving innovation and productivity. Also, liberalizing trade reduces tariffs on imported intermediate inputs, thus enhancing product quality and productivity (Caliendo and Hansberg, 2012, Yeaple, 2005, Melitz and Ottaviano, 2008, Eaton et al., 2011, Goldberg et al., 2008, Lileeva and Trefler, 2010, Javorcik and Spatareanu, 2011, Bustos, 2011, and Eslava et al., 2013).

A firm's technology advancement relative to other firms (technology distance) could determine its productivity growth rates. Technology distance is regarded as a source of productivity in growth theories (Ramsey, 1928, Solow, 1956, Koopmans, 1965, Aghion and Howitt, 2006, Acemoglu, 2009, and Mc Morrow et al., 2010).

Foreign Direct Investment (FDI) has been widely recognized as a source of productivity, since via management skill and know-how, foreign knowledge is transferred to domestic partners, competitors, suppliers, and customers. However, the spill-over effects of FDI may depend on absorptive capacity and innovation-complementary assets in the host region, as well as other institutional features, such as origin of FDI, firm ownership structure, and tariff benefit and subsidy (Javorcik, 2004, Fu et al., 2012, Fu, 2011, and Du et al., 2011).

Competition is closely related to firms' openness to international markets. Depending on the firm's technology level, competition has both negative and positive effects on productivity via innovation and growth. Firm entry increases innovation in technologically advanced sectors, while decreases it in less technologically advanced sectors (Aghion et al., 2013, Aghion and Griffith, 2008). However, most empirical studies are limited to U.S. and the effect of competition on productivity is not well understood in other economies. Competition's effect on productivity and might be

very different in developing countries since most firms are likely to be far from the frontier.

Meanwhile, macroeconomists are decomposing macro-level growth, such as per capita income, into various micro-components, such as firm productivity and firm dynamics, in order to understand the sources of such growth and issues related to income convergence, resource allocation, and technology spill-over. In the field of industrial organization, productivity is linked to technology, demand, and market structure. Studies in this field investigate the relations between productivity and competition, sunk costs of firm entry, knowledge spill-over, and firms' organizational structure.

Lastly, spill-overs from other firms can contribute to a firm's productivity level. Firms' interaction with other firms nearby (agglomeration) catalyses knowledge exchanges among firms. Also, where a firm conduct its R&D matters. For instance, U.K. firms with large R&D activities in the U.S. have faster growth than those with R&D in the U.K. In addition, distance from the technology leader facilitates the firms' learning speed, thus, those that are further behind to catch up. This productivity convergence is faster towards the productivity level of the domestic leader than the global leader (Griffith, et al., 2007, Bartelsman et al., 2008).

Firm heterogeneity in trade and endogenous growth theories

Throughout the abovementioned three empirical chapters, I provide a survey of some recent literature on the determinants of firm productivity and summarize the channels through which the identified determinants affect productivity. While an in-depth literature review is provided for the selected topic in each empirical chapter, here I describe some background information about how firm-level analysis has emerged and explain the theoretical framework that provides the basis for the subsequent empirical chapters.

The discovery of large productivity differences between firms has motivated researchers in a number of fields and inspired a new theoretical framework to explain such differentials, such as firm heterogeneity in trade theory and endogenous growth theories.

International trade literature provides much insights of micro-level productivity. Theoretical frameworks using heterogeneous firms, like Melitz (2003), are now the dominant conceptual lenses through which researchers view trade impacts and firm-level productivity analysis, providing ample empirical evidence to accompany these theories. In addition, productivity related to openness, such as export and FDI, has been studied from various perspectives.

In contrast to traditional trade theory, which predicted that trade should involve the exchange of different goods and should be greater the more countries differed in their relative production possibilities[1], most trade after World War II was in the form of relatively similar goods (manufactures) between relatively similar countries (developed ones). Dixit and Stiglitz (1977) introduced individual preferences on differentiated products into the utility function, and Krugman developed the theoretical framework of intra-industry trade by introducing monopolistic competition with increasing returns into the general equilibrium framework (1979), and later on embedded his findings in Hecksher-Ohlin (1981). The "new" models, consisting of economies of scale and preferences for variety, lead otherwise identical firms to "specialize" in a product, and explain intra-industry trade (Neary 2009).

More recently, as firm-level data becomes more available, many studies have documented heterogeneity across firms. They find that exporting is a rare activity and there is considerable variation in export market participation across industries within manufacturing (for instance, Bernard and Jensen 2004), which contrasts to traditional

[1] For instance, comparative advantage implies that when trade is free, countries will specialize in the production of goods that they produce more efficiently (Ricardo, 1817), with differences in factor endowments their main source of comparative advantage.

trade theory[2]. Exporting firms tend to be more productive and larger, use more skill- and capital-intensive inputs, and pay higher salaries than non-exporters. This is the case not only for developed countries but also for developing countries, which are plausibly unskilled labour-abundant, which is difficult to be explained within the traditional theory of comparative advantage (see chapter II for the list of literature that document "exporter's premium").

When empirical findings started to demonstrate the contradictions of old trade theory, Melitz (2003) developed a framework with firm heterogeneity in a general equilibrium model of trade, in which the exposure to trade will induce only the more productive firms to enter the export market (self-selection) and will simultaneously force the least productive firms to exit. This provides a theoretical explanation to the empirical findings of firm heterogeneity (new trade theory).

Meanwhile, micro-level productivity studies have been linked to traditional growth theory. Specifically, the Schumpeterian growth model, wherein growth is primarily driven by entrepreneurial innovations, has developed into an integrated framework for understanding many microeconomic issues when linked with industrial organization, which explains the relationship between growth, competition, and firm dynamics. This theoretical framework has been tested using micro- data, such as firm-level data, and these empirical results further motivated the development of theoretical framework.

In the Schumpeterian growth model, firms innovate to get rewarded with rents if the innovation is successful. However, these (monopoly) rents reduce when other firms imitate that innovation and even disappear when new innovations drive the old one out of the market (creative destruction) (Aghion et al., 2005). Moreover, competition and productivity (via innovation) display "an inverted-U shape relationship". Firm entry positively affects innovation in firms near the technology frontier or in firms that

[2] While old trade theory can explain why a country trade in some industries, it cannot explain why some firms export and other produce only for the domestic market, or how the firm-level decision to export interacts with comparative advantage.

compete with their rivals, but less so in firms below the frontier (Aghion and Griffith, 2008).

Such firm entry and exit dynamics reallocate resources from less productive to more productive firms and industries, and thereby enhance aggregate productivity. How efficient this allocative process could explain the large differences in productivity across countries. Economic openness, such as international trade, facilitates this allocative process, and thus increases aggregate productivity (Bernard et al., 2011, Foster et al., 2005, Bartelsman et al., 2013, Hsieh and Klenow, 2009).

Analysing productivity: the case for Tunisia

Tunisia is an interesting country case to study productivity and innovation issues for a number of reasons. Its liberal trade policies, such as export-promotion policies and accessions to multiple trade agreements in the early stages, have resulted in a relatively large manufacturing sector compared to neighbouring countries, economic growth, a large share of export to GDP, and a large share of firms investing in innovation. For instance, from 1997 to 2009, Tunisian GDP growth averaged 4.6%, exports of goods and services to GDP was more than 40%, and 62% of Tunisian manufacturing firms invested in innovation[3].

However, despite Tunisia's impressive economic performance, productivity in the country has not increased as much as its GDP in recent decades. This thesis documents that only a small portion of top-performing firms have increased their productivity, whilst most firms' productivity levels have remained stagnant. This finding might imply that Tunisia's recent GDP growth might be a one-off event rather than a sustainable trend, since the growth has been fuelled by increases in factor inputs

[3] GDP and export data is from the World Development indicator, and innovation data is from the INS. This ratio of Tunisian firms that engage in innovation is relatively large and similar to the ratios in developed economies (average is 51 percent of manufacturing firms in the period 1994–96; 62 percent of Belgium firms engage in innovation, Cassiman and Veugelers 2006).

rather than increases in productivity. Therefore, increasing productivity is a key economic priority in Tunisia.

Meanwhile, economic growth in Tunisia has coincided with economic openness following its WTO accession. A key question arising from this situation is how important economic openness, such as participating export activities and attracting foreign investment, have been for productivity increases and bringing Tunisian firms closer to the technology frontier.

At the same time, the government's industrial policies had an emphasis on the manufacturing sector, while neglecting services. Services were excluded from government support programs for firms and from the rules in the major trade agreements, such as the Association Agreement with the European Union (EU). With complex entry barriers for foreign investors, FDI is limited in the Tunisian service sector, which is dominated by SOEs.

In this context, previous studies and policy recommendations to the government argue that Tunisian firms in both manufacturing and service sectors could become more productive by participating in exports and innovation, and acquiring foreign investment (Nellis 1999, Konan and Markus 2006, and World Bank, 2010); however, systematic evidence of productivity increases from such efforts is rare.

References

Abowd, J. M., J. Haltiwanger, R. Jarmin, J. Lane, P. Lengermann, K. McCue, and K. Sandusky. 2005. "The Relation among Human Capital, Productivity, and Market Value: Building Up from Micro Evidence." In *Measuring Capital in the New Economy* 153-204. Chicago: University of Chicago Press.

Acs, Z. J., and D. B. Audretsch. 1991. "Firm Size and Innovative Activity. Innovation and Technological Change: An International Comparison," Ann Arbor, MI: University of Michigan Press.

Aghion, P. 2004. "Growth and Development: A Schumpeterian Approach." *Annals of Economics and Finance* 5: 1-25 (2004).

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and P. Howitt. 2005 "Competition and Innovation: an Inverted-U Relationship", *The Quarterly Journal of Economics*, 120(2), 701–728,

Aghion, P., and P. Howitt. 2006. "Joseph Schumpeter Lecture. Appropriate Growth Policy: A unifying framework." *Journal of the European Economic Association*, 4(2-3), 269-314.

Aghion, P., U. Akcigit, and P., Howitt. 2013. "What Do We Learn from Schumpeterian Growth Theory?" *National Bureau of Economic Research (NBER)* Working Paper Series, Working Paper 18824, Cambridge, MA.

Aghion, P., and R, Griffith. 2008. "Competition and growth: reconciling theory and evidence." Zeuthen Lectures. *MIT Press*: Cambridge, US.

Aw, B., Roberts, M., and D., Xu. 2011. "Rand Investment, Exporting, and Productivity Dynamics." *American Economic Review*, 101(4): 1312-44.

Balasubramanian, N., and J. Lee. 2008. "Firm Age and Innovation." *Industrial and Corporate Change.* 17 (5): 1019-47.

Bandiera, O., Barankay, I., & I., Rasul. 2007. "Incentives for managers and inequality among workers: evidence from a firm-level experiment." *The Quarterly Journal of Economics*, *122*(2), 729-773.

Bartelsman, E. J., Haskel, J. and R., Martin. 2008. "Distance to which Frontier? Evidence on Productivity Convergence from International Firm-level Data." *Centre for Economic Policy Research.*

Bartelsman, E., Haltiwanger, J. and S., Scarpetta. 2013. "Cross-country differences in productivity: The role of allocation and selection." *The American Economic Review*, *103*(1), 305-334.

Bertrand, M. and A., Schoar. 2003. "Managing with style: The effect of managers on firm policies." *The Quarterly Journal of Economics*, *118*(4), 1169-1208.

Bernard, A. B., & J. B. Jensen. 1999. "Exceptional exporter performance: cause, effect, or both?" *Journal of international economics*, *47*(1), 1-25.

Bernard, A. B., and, J. B., Jensen. 2004. "Why some firms export." *Review of Economics and Statistics*, *86*(2), 561-569.

Bernard, A. B., Jensen, J. B., Redding, S. J., and P. K., Schott. 2011. "The empirics of firm heterogeneity and international trade." *National Bureau of Economic Research* w17627.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and J., Roberts. 2013. "Does management matter? Evidence from India." *The Quarterly Journal of Economics*, *128*(1), 1-51.

Bloom, N., and J., Van Reenen. 2007. "Measuring and Explaining Management Practices Across Firms and Countries." *Quarterly Journal of Economics*, 122(4): 1351-1408.

Bloom, N. and J., Van Reenen. 2010. "Why Do Management Practices Differ across Firms and Countries?" *Journal of Economic Perspectives*, 24(1)

Boycko, M., A. Shleifer, and R. W. Vishny. 1996. "A Theory of Privatisation." *The Economic Journal* 106 (435): 309-19.

Brynjolfsson, E. and L, Hitt. 2003. "Computing Productivity: Firm-Level Evidence." *Review of Economics and Statistics*, Vol. 85, No. 4, Pages 793-808

Bustos, P. 2011. "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms." *American Economic Review* 101(1): 304-340.

Caliendo, L. and E. Rossi-Hansberg. 2012. "The Impact of Trade on Organization and Productivity." *The Quarterly Journal of Economics* 127(3): 1393-1467.

Cohen, W. M., and S. Klepper. 1996. "Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D." *The Review of Economics and Statistics* 232-43.

Dewenter, K. L., and P. H. Malatesta. 2001. "State-Owned and Privately Owned Firms: An Empirical Analysis of Profitability, Leverage, and Labor Intensity." *American Economic Review* 320-34.

Dixit, A. K., and J. E., Stiglitz. 1977. "Monopolistic competition and optimum product diversity." *The American Economic Review*, *67*(3), 297-308.

Du, L., Harrison, A. and G., Jefferson. 2011. "Do institutions matter for FDI spillovers? The implications of China's 'Special Characteristics.'" *National Bureau of Economic Research Working Paper* 16767

Eaton, J. and S., Kortum. 2002. "Technology, Geography, and Trade." Econometrica, 70(5): 1741-79.

Eaton, J., Kortum, S., and F., Kramarz. 2011. "An anatomy of international trade: Evidence from French firms." *Econometrica*, *79*(5), 1453-1498.

Eslava, M., Haltiwanger, J., Kugler, A., and M.,Kugler. 2013. "Trade and market selection: Evidence from manufacturing plants in Colombia." *Review of Economic Dynamics*, *16*(1), 135-158.

Foster, L., Haltiwanger, J., and C., Syverson. 2008. "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?" *The American economic review*, *98*(1), 394-425.

Fu, X. 2012, "How does openness affect the importance of incentives for innovation?" *Research Policy*, 41, 512-523.

Fu, X. 2011. "Processing Trade, FDI and the Exports of Indigenous Firms: Firm-Level Evidence from Technology-Intensive Industries in China."" *Oxford Bulletin of Economics and Statistics*, 73(6), 792-817.

Fu, X., Helmers, B. and C., Zhang. 2012. "The two faces of foreign management capabilities - fdi and productive efficiency in the uk retail sector (1)." *International Business Review* 21 71-88.

Fu, X. and R., Hoyes. 2003. "The role of management practices in closing the productivity gap: a literature review," University of Cambridge, *Centre for Business Research*, Memo.

Goldberg, P.K., Khandelwal, A., Pavcnik, N. and P., Topalova. 2008 "Multi-product firms and product turnover in the developing world: evidence from India," *National Bureau of Economic Research Working Paper* 14127.

Griffith, R., Redding, S. and Simpson. 2004, "Foreign Ownership and Productivity: New Evidence from the Service Sector and the R&D Lab", *Oxford Review of Economic Policy*, 20(3): 440-456.

Griffith, R., Redding, S. and J., Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *The Review of Economics and Statistics,* 86(4): 883-895.

Griffith, R., Harrison, R. and J., Van Reenen. 2007. "How Special is the Special Relationship? Using the Impact of U.S. R&D Spillovers on U.K. Firms as a Test of Technology Sourcing." *American Economic Review*, 96(5): 1859-75.

Hall, B. 2011, "Innovation and productivity." *National Bureau of Economic Research Working Paper* 17178.

Harrison, A. and A., Rodriguez-Clare. 2010. "Trade, FDI and Industrial Policy for Developing Countries." *Handbook of Development Economics*, Vol. 5, North-Holland.

Helpman, E. 1981. "International trade in the presence of product differentiation, economies of scale and monopolistic competition: A Chamberlin-Heckscher-Ohlin approach." *Journal of international economics*, *11*(3), 305-340.

Hendel, I., and Y., Spiegel. 2014. "Small steps for workers, a giant leap for productivity." *American Economic Journal: Applied Economics, 6*(1), 73-90.

Hsieh, C and P., Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics,* 124(4): 1403-48.

Huergo, E., and J., Jaumandreu. 2004. "Firms' age, process innovation and productivity growth." *International Journal of Industrial Organization*, *22*(4), 541-559.

Inklaar, R., M. P. Timmer, and B. Van Ark. 2008. "Market Services Productivity across Europe and the US." *Economic Policy* 23 (53): 140-94.

Javorcik, B. S. 2004. “Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages.” *The American Economic Review* 94(3): 605-627.

Javorcik, B. S. and M. Spatareanu 2011. “Does it matter where you come from? Vertical spillovers from foreign direct investment and the origin of investors.” *Journal of Development Economics* 96(1): 126-138.

Kellogg, R. 2009. “Learning by drilling: Inter-firm learning and relationship persistence in the Texas oil patch.” *National Bureau of Economic Research Working Paper* 15060

Konan, D. E. and K. E. Kim 2004. “Beyond Border Barriers: The Liberalization of Services Trade in Tunisia and Egypt.” *World Economy* 27(9): 1429-1447.

Krueger, A. O. 1990. “Government failures in development.” *National Bureau of Economic Research Working Paper* 3340

Krugman, P. R. 1979. “Increasing returns, monopolistic competition, and international trade.” *Journal of international Economics*, *9*(4), 469-479.

Krugman, P. R. 1981. “Intraindustry specialization and the gains from trade.” *Journal of political Economy*, *89*(5), 959-973.

Krugman, P. 1991. “Geography and Trade.” *MIT Press.* Cambridge, MA.

Lileeva, A. and D. Trefler. 2010. “Improved Access to Foreign Markets Raises Plant-level Productivity.” *The Quarterly Journal of Economics* 125(3): 1051-1099.

Markusen, J., T. F. Rutherford, and D. Tarr. 2005. “Trade and Direct Investment in Producer Services and the Domestic Market for Expertise.” *Canadian Journal of Economics/Revue Canadienne d'Économique* 38 (3): 758-77.

McMorrow, K., Röger, W. and A., Turrini. 2009. “The EU-US total factor productivity gap: An industry-level perspective.” *CEPR Discussion Papers* 7237

Melitz, M. J. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica* 71(6): 1695-1725.

Melitz, M. J. and G. I. P. Ottaviano. 2008. “Market Size, Trade, and Productivity.” *The Review of Economic Studies* 75(1): 295-316.

Nellis, J. R. 1999. “Time to Rethink Privatization in Transition Economies?” Vol. 38. Washington, DC: *World Bank Publications*

Neary, J. P. 2009. “Putting the “new” into new trade theory: Paul Krugman's Nobel Memorial Prize in economics.” *The Scandinavian Journal of Economics*, *111*(2), 217-250.

Ramsey, F. P. 1928. “A mathematical theory of saving.” *The economic journal*, *38*(152), 543-559.

Shleifer, A. 1998. “State versus Private Ownership.” *National Bureau of Economic Research Working Paper* 6665, Cambridge, MA.

Shleifer, A. and R. W. Vishny. 1997. “A Survey of Corporate Governance.” *The Journal of Finance* 52 (2): 737-83.

Solow, R. M. 1956. “A contribution to the theory of economic growth.” *The quarterly journal of economics*, *70*(1), pp.65-94.

Syverson C. 2010. “What determines productivity?” *National Bureau of Economic Research Working Paper* 15712

Wagner. J. 2007. “Exports and Productivity: A Survey of the Evidence from Firm-level Data.” *The World Economy*, 30-1, 60-82

World Bank. 2010. “Tunisia Development Policy Review: Towards Innovation-Driven Growth.” *The World Bank Group. Report No. 50847*

Yeaple, S. R. 2005. “A simple model of firm heterogeneity, international trade, and wages.” *Journal of international Economics*, 65(1), 1-20.

II. Chapter 1. Productivity Convergence and Learning by Exporting

1. Introduction

Despite impressive economic growth, productivity in Tunisia has not increased as much as its GDP in recent decades. This paper documents that only a small portion of top-performing firms have increased their productivity, however; most manufacturing firms' productivity levels have been stagnant. This finding might imply that Tunisia's recent GDP growth might be a one-off event rather than a sustainable trend since the growth has been fuelled by an increase in factor inputs, rather than a productivity increase. Therefore, increasing productivity is a key priority in economic and development policies in Tunisia. Meanwhile, economic growth in Tunisia has coincided with economic openness, following its WTO accession. A key question arising from this phenomenon is how important participating export activities have been for productivity increases, thus bringing exporters closer to the technology frontier.

This paper evaluates the role of technology distance and exports in explaining the productivity growth of manufacturing firms in Tunisia from 1997 to 2007. The purpose of this study is twofold.

First, I test whether less productive firms grow faster than more productive firms (whether there is convergence), both conditionally and unconditionally. The previous convergence literature is mostly cross-country analysis using industry-level data, and firm-level evidence is rare even in developed countries and much rarer in developing countries, although a country's growth is ultimately driven by individual firms' growth. In addition, there has been almost no evidence of unconditional convergence despite the prediction of existing theories.

Inspecting the firm-level evidence of unconditional convergence is useful for several reasons. First, micro-level convergence is a necessary, although not a sufficient, condition for macro-level convergence. If there is no evidence of unconditional

convergence at the firm-level, there is unlikely to be evidence at the industry or country level, despite the prediction of exiting growth theories. Also, if observed convergence is only conditional, those conditions might be ultimately factors of firms' productivity growth and unconditional convergence might not exit. However, if an unconditional convergence pattern is observed at the firm level, despite its rare evidence at industry- and country-level, similar to the previous explanation of the unconditional convergence pattern at the industry-level (Rodrik 2012), our focus should be understanding the constraints that prevent firm-level convergence aggregating up to industry- and country-level convergence, unconditionally. Therefore, I fill the gaps in the literature by examining micro-level convergence evidence, conditionally and unconditionally.

Second, I examine whether exporting has a direct effect on productivity growth and whether the impact of exporting on productivity growth depends on the distance from the technology frontier. Whether more-productive firms "self-select" into export markets, or whether exporting causes productivity growth through some form of "learning by exporting (LBE)" is an on-going debate in the trade and development economics literature. I link the LBE literature to the convergence literature by examining the importance of the interaction between exporting and the technology distance in driving productivity growth, in addition to examining their separate effects. While export's role in technology transfer and productivity gains is well-studied, its direct relation with convergence has been rare and, to my knowledge, this is the first (or one of a few) papers to examine the role of exporting as a driver of convergence.

I present an empirical framework in which technology distance and exports provide two sources of productivity growth. Following the convergence literature, I consider productivity growth as a function of technology distance that is measured as the difference in TFP levels between a given firm and frontier firms with the highest productivity level within an industry. In addition, following the literature on exports and productivity, I consider productivity growth as a function of firms' participation in exporting but, going beyond the existing literature, I question exports' effect on productivity in relation to technology distance. This framework allows me to test

exports' effect on productivity while controlling for firms' initial productivity levels relative to the technology frontier, which indirectly controls the potential selection issue of faster growing firms becoming exporters.

The use of a large amount of firm-level data for a relatively long period (around 11,400 observations for total factor productivity (TFP) growth over the 11-year time period, maximum) enables me to produce statistically convincing results and to examine the disaggregated forces, underlying firm-level productivity, such as technology distance and exports, while controlling for unobserved heterogeneity in the sources of productivity growth.

My main results are as follows:

First, there is strong evidence of unconditional convergence at the firm level, implying that firms far away from the technology frontier grow faster than those firms close to the technology frontier, regardless of firm-specific characteristics, such as managers' capabilities and labour skills, which are often unobservable factors that influence on firms' productivity growth. The estimated coefficient is approximately 6.7%, which implies that it takes less than 8 years to eliminate 50% of the initial technology gap.

Second, the evidence of convergence remains even stronger when I test the abovementioned empirical framework with firm-fixed effects and other control variables (conditional convergence). The estimated technology distance coefficients, which are the elasticity of technology distance relative to productivity growth rate, are in the range of 12% to 14.5%. This means that being 1% further away from the technology frontier is associated with 12% higher growth from the initial growth rate (for instance, if initial growth rate was 2% per annum, a firm that is 1% further away from the technology frontier would have 2.24% growth rate (2×1.12%=2.24%)), which is much larger than the previous findings from industry- and country-level studies.

Third, the fact that exporters exhibit higher productivity levels than non-exporters is explained by self-selection, but not because of LBE. While exporters show higher TFP level than non-exporters, exports' role in determining TFP growth rates is insignificant, and becomes negative when controlling for the previous year's technology distance.

Fourth, the further a firm lies behind the frontier, the greater the potential for technologies to be transferred through exporting and the higher the rate of productivity growth. My results show that an interaction term between exports and technology distance has a positive and significant effect on productivity growth. While exporters in general do not show faster productivity growth, probably because they are closer to the technology frontier, those far behind the frontier grow even faster when they are exporting.

Last, FDI further facilitates technology spill-overs, especially for exporters that are far behind the technology frontier, but innovation does not. Within the empirical framework, I explore the three-way interactions between previous-year FDI status (or innovation), exports status, and technology distance. I find a positive and significant effect of three-way interactions with FDI status on productivity growth. Meanwhile, the three-way interactions with innovation provide a small but negative effect on productivity growth.

The results are robust to different specifications and econometric techniques applied in order to avoid potential measurement error in export variables, collinearity between industry-invariant unobservable and firm-specific characteristics, and simultaneity between export and productivity. The results are also robust to the different definitions of the technology frontier between the domestic and international frontier.

The paper is structured as follows. Section II.2 introduces the theoretical framework from which my main econometric equation is derived and convergence and LBE literature. Section II.3 describes the data and provides a summary of stylized factors on firm productivity trends in Tunisia, using estimated TFP. Sections II.4 and II.5 present

the empirical strategy, with associated concerns and solution. Section II.6 shows the econometric results and robustness checks. Section II.7 concludes.

2. Literature review

Technology distance and convergence – standing on the shoulders of giants[4]

Previous literature on convergence is mostly based on the neoclassical and endogenous growth theories and consider technology distance as a source of convergence.

In neoclassical growth theory, diminishing rate of returns of factors are assumed, therefore, countries that are poorer (and have less capital) have higher marginal productivity of capital. Therefore, if countries are similar in respect to preferences and technology, then poor countries grow their income and productivity faster than rich countries. In an open economy, factors, such as capital, can move from richer countries to poorer countries where the return on factors is higher. Therefore, poorer countries grow their income and productivity even faster (Ramsey, 1928, Solow, 1956, Cass, 1965, and Koopmans, 1965)[5].

In a growth model with endogenous technological change, such as a Schumpeterian growth model, growth depends on technology, and the ability to adopt existing technology.[6] While frontier countries will benefit from creating new technologies, follower countries gain more by adopting existing technologies, which is cheaper and faster than creating. Therefore, distance from the technology frontier influences the technology transfer from more advanced countries (or firms) to less advanced countries

[4] This metaphor of dwarfs standing on the shoulders of giants was, first used in a letter by Isaac Newton in 1676, expresses discovering truth by building on previous discoveries.
[5] In the neoclassical growth model, TFP is exogenous and corresponds to the Solow residual.
[6] In the Schumpeterian model, firms create innovation with the expectation of being rewarded with "monopoly rents" if their innovation is successful. However, these rents decrease when other firms imitate those innovations and eventually disappear when new innovation competes with the existing technologies and drives them out of the market (creative destruction). (Aghion et al., 2013)

(or firms). Therefore, countries further away from the frontier grow their productivity and income faster (Aghion et al., 2013, Acemoglu, 2009, and Mc Morrow et al., 2010).

Whether convergence is driven by higher return on factors or adapting existing technology rather than creating a new one, growth theories predict that there is a force that promotes unconditional convergence in levels of income and productivity. Like dwarfs standing on the shoulders of giants can see further, poorer countries grow faster.

Despite predictions of these theories, empirical findings tend to be inconsistent and vary depending on the data used, although the evidence of convergence seems to be more obvious when using micro-level data. Here I review the literature that has tested whether there is productivity convergence across countries, industries, and firms. The summary of literature reviewed is provided in Appendix A.

At the country level, there seems to be no systematic evidence of convergence across countries. The existing evidence is regional, meaning the productivity level becomes similar among narrowly selected developed economies, such as OECD countries or among the U.S. states. The convergence evidence in a wider group of countries is found only when controlling for other factors, such as human capital, institutions, and other country-specific circumstances (see, for instance, Barro and Martin, 1990, Vandenbussche et al., 2006, Inkaar and Timmer, 2009).

At the industry level, there is more evidence of convergence, as most convergence analysis has used industry-level data, but the convergence pattern is inconsistent depending on which data is used. Most literature has found that there is large heterogeneity in convergence across industries, resulting in some industries managing to converge while the others do not. However, which industry actually shows convergence varies depending on the time and country coverage of data used. For instance, several studies on OECD countries have shown stronger convergence patterns across service sectors but not in manufacturing industries (Bernard and Jones, 1996), while more recent industry-level studies with wider country-coverage, including

developing nations, found that manufacturing industries, but not services, exhibit strong unconditional convergence (Rodrik, 2012). The mixed results might be caused by countries' level of income or development, which influence the major growth sector. Similarly, the different pattern of both country-level and industry-level results might be related to the relative position in the technology distance of the applied data.

At the firm level, convergence evidence is rare, probably because of the difficulty in obtaining firm-level data. However, a few existing literatures on analysing firm-level convergence confirms the findings of country- and industry-level studies in that there is large heterogeneity across industries in convergence speed. For instance, high-tech industries, such as IT industries, show higher convergence rates (Nishimura et al., 2005 for Japanese firms). Also, there is systematic variation of productivity growth by the level of firms' distances to the technology frontier (Aghion, et al., 2006 on UK firms). In addition, firms' relative position in technology advancement influences their relationship between exports, FDI, innovation, and firm productivity. Specifically, being far from the frontier reduce innovators' rents, the incentives to innovate (Aghion, 2004, Howitt and Prantl, 2006 for U.K. firms). The effect of government policy on productivity (or final outputs) varies depending on the firm's distance to the technology frontier (Aghion and Howitt, 2006). Exports and FDI improve firm productivity once the productivity convergence effect is controlled for (Kimura and Kiyota, 2006 for Japanese firms).

In addition, above listed firm-level convergence analysis tends to find that convergence rates are faster among firms than among industries or countries, which might be because firm-level analysis sometimes uses different measures of convergence from the industry- and country-level analysis. For instance, with firm-level data, the technology distance could be measured not only to the international technology frontier, but also to the domestic frontier (the firm with the highest productivity level), unlike country- and industry-level data. It has been found that the national frontier exerts a stronger pull on local firms than does the international frontier, which might explain why follower firms

might not be able to learn from the global frontier, but would still benefit from domestic knowledge (Bartelsman, et al. 2013).

Another reason might be that certain mechanisms, such as allocating resources from less-productive firms to more-productive firms, are required in order for faster firm-level convergence rate to be transferred to industry-level convergence rate. Industry productivity growth consists of existing firm productivity growth and the set of firm changes (productive firms enter and less productive firm exits) that reallocate resources across firms and industries, and, thereby, enhance aggregated productivity. Empirical studies found that the set of firm changes contributes to a significant portion of industry growth. For instance, convergence rate is higher when controlling for these "entry and exit dynamics" (Nishimura et al., 2005 for Japanese firms) and the productivity differential between entering and exiting firms accounts for as much as one-half of growth in some industries (Chen et al., 2001 for Taiwanese manufacturing sector).

This finding of faster convergence patterns at the micro-level data rather than macro-level data, driven by the inefficiency of allocative process, is also documented in industry- and country-level convergence evidence. For instance, lack of structural transformation, which implies the production resources used from less-productive industry move to more-productive industry, is the reason why there is greater evidence of industry-level convergence, but relatively less obvious results in cross-country convergence (Rodrik, 2012). Also, this efficiency of allocative process is one of the key sources of the large differences in productivity across countries, and facilitating allocative efficiency increases aggregate productivity (Bernard et al., 2007, Foster et al., 2008, Hsieh and Klenow, 2009).

However, existing firm-level convergence evidence is mostly from OECD countries, and evidence from developing countries is scarce or, to my knowledge, does not exist. Examining firm-level evidence of unconditional convergence in developing countries is particularly important for a number of reasons.

First, as seen in country- and industry-level studies, convergence patterns may vary by income level; therefore, firm-level convergence in developing countries, like Tunisia, might be different from those in OECD countries.

Second, as mentioned above, micro-level convergence is a necessary, although not a sufficient, condition for macro-level convergence. Countries' growth consists of different factors, such as public spending and private sector growth. But the larger and more developed countries, then the role of public spending is more limited, and countries' growth is essentially driven by private sector growth, which consists of individual firms' growth. Therefore, if there is no evidence of convergence at the firm-level, there is unlikely to be evidence at the industry or country level.

Lastly, inspecting the firm-level evidence of unconditional convergence could help clarify the rare evidence of macro-level convergence. Similar to the concept of unconditional convergence at the country level[7], unconditional convergence exists at the firm level if those firms far away from the technology frontier grow faster than those one close to technology frontier, regardless of firms' specific characteristics, such as what kind of product they produce, how big they are, and how skilled their employees are.

Similar to Rodrik's explanation about industry-level convergence, if an unconditional convergence pattern is observed at the firm level, despite scant evidence of unconditional convergence at the industry and country level, research should focus on understanding the factors that prevents firm-level unconditional convergence aggregating up to industry-level or country-level convergence unconditionally. However, if convergence is only conditional at the firm level, the existence of convergence is not convincing because those conditions are ultimately factors of firms' productivity growth.

[7] At the country level, unconditional convergence refers to the income gap between two countries decreasing irrespective of these countries' characteristics. If growth rates are characterized only by conditional convergence, economies will tend towards different levels of income in the long-run (Rodrik, 2012).

Therefore, finding evidence of unconditional convergence at the firm level can provide insightful micro-level evidence of growth theory and empirical literature; however, there are gaps in the literature as to examining the unconditional convergence pattern at the firm-level.

Exports, knowledge transfer, and convergence

While the abovementioned studies mostly examine whether there is convergence or not, they typically do not reveal what drives the convergence, and, specifically, what causes the technology spill-over from more advanced countries to less advanced countries, and why convergence exists only in some industries.

For instance, if there is unconditional convergence in manufacturing, as documented in Rodrik (2012), it is not clear what aspects of manufacturing drive convergence. One possible hypothesis involves the tradability of manufacturing products. If they are exported, there will be learning from the international markets, which in turn generates knowledge spill-over to non-exporters. In this case, tradable services should also demonstrate a similar pattern to manufacturing, and unconditional convergence would be associated with the tradable aspect and not be limited to manufacturing. While previous firm-level studies have mostly focused on innovation and FDI as sources of technology transfer, exporting is another important source of technology transfers from foreign knowledge.

In fact, there are multiple channels that could generate "learning by exporting", which describes the pattern of firms' productivity growth after entering a foreign market.

First, after gaining exposure to the international buyers and partners, firms improve management practice and adopt advanced technology. This can be caused by foreign buyers providing technical assistance to exporters to improve production efficiency. Also, this could be led by partners in foreign-invested firms which are willing to transfer

technology. Those exposures to international buyers and partners improve exporting firms' access to knowledge about more advanced technologies (Yeaple, 2005).

Second, exporters are exposed to more intense competition in international markets, which leads to incentives to improve productivity. The increased market size also increases the expected benefits, therefore providing more incentive for firms to invest in technology. Indeed, the most productive firms adopt the most advanced technology, implying that the benefit of adopting new technology is proportional to revenue, while its cost is fixed. Also, the increased competition lead firms to invest in technology and increase productivity, but with lower mark-ups (Aghion et al., 2013, Melitz and Ottaviano, 2008, Bustos, 2011).

Third, exporting may lead to faster learning about market opportunities for new products or for specific needs of buyers. International markets would require higher-quality standards compared to domestic markets, thus, participating in exporting could incentivize firms to upgrade production technologies (Verhoogen, 2007, Fafchamps et al., 2008). Participating in exports could increase the demand for skilled labour and technology, thus enhancing innovation and productivity (Goldberg et al., 2008, Lileeva and Trefler, 2010).

Lastly, exports improve the economies of scale in production, and improve capacity utilization, by expanding sales. This reduces firms' vulnerability to occasional downturns in the domestic market, and results in productivity gains in new export entrants.

In fact, much of the literature has documented that exporters are systematically more productive than non-exporters. There is an export premium, meaning that exporters have higher productivity levels, employment, sales, wages and capital intensity, than non-exporters (for instance, Bernard and Jensen, 1999 among U.S. firms and Cherides et al., 1998 for developing countries, among many others).

Some literature has also documented the positive correlation between exports and productivity growth, instead of productivity level. Cross-country studies document a positive relationship between trade and growth performance (Frankel and Romer, 1999). The lower the average export unit values (export price per product) of a country's manufacturing exports, the faster the country's subsequent growth, unconditionally (Hwang 2007).

However, the causal impact of exporting on productivity growth is controversial, since increases in productivity could cause exports, or increases in productivity and exports could be caused by other factors. In addition, if there is "self-selection" into exporting – in other words, only those firms which know they will have higher growth will participate in exporting since more-productive firms can afford the sunk cost of export entry – the correlation of exporting and productivity growth can't necessarily be interpreted as a causal relation.

The empirical evidence on LBE is somewhat mixed, while self-selection is strongly supported theoretically and empirically[8]. Some works do not find any evidence of post-entry productivity changes, and those that do find that changes differ in the time span and extent of the productivity changes[9]. Whether more-productive firms "self-select" into export markets, or whether exporting causes productivity growth through some form of "learning by exporting", is an on-going debate in the trade and development economics literatures.

One drawback of the previous studies on learning by exporting is that they cannot distinguish clearly the effects of exporting from the unobservable differences between exporters and non-exporters. Since the decisions to export and how much to export are endogenous choices of the firm, these empirical specifications fail to convincingly isolate

[8] Melitz, 2003, Bernard and Jensen, 1999, etc.

[9] Wagner, 2007, Arnold and Hussinger, 2005, Greenaway and Kneller, 2004, 2007, 2008; Girma et al., 2005; Biesebroeck, 2005; Damijan and Kostevc, 2006; De Loecker, 2007. Also, the literature is well summarized in Fatou and Choi (2013).

the causal effect of exporting on productivity growth. To understand the causal effect between exporting and productivity growth, several techniques have been applied to control the simultaneous effect between productivity growth and exporting; but causal effect continues to require a careful interpretation[10]. Export status might be correlated with unobserved firm characteristics that directly influence both the level and growth rate of firm productivity.

Literature on Tunisia and neighboring countries

Only a few studies have analysed productivity convergence in Tunisia or in its neighbouring countries. Chaffai, Plane and Guermazi (2009), using industry-level data, shows that there has been TFP convergence and catch-up to OECD member countries in six manufacturing sectors from 1983 to 2002. However, the convergence rate varies across sectors. The technology gap with other OECD countries has been slightly reduced in textiles and leather, building and ceramics, and chemical industries, while the gap has been increased in electronics, and metallic products, food processing.

Guetat and Serranito (2007), using country-level data of per capita income, shows that there has been convergence among 11 countries in the Middle East and North Africa (MENA), including Tunisia, from 1960 to 2000. They find that both absolute and conditional convergence is not rejected for the majority of the group. In other words, countries in MENA converge to their regional frontier or come to have similar productivity to their neighbouring countries. However, they find that Tunisia is the only country that showed divergence from neighbouring countries' productivity levels, probably because of the relatively different economic structure and the better economic growth performance of Tunisia compared to other neighbouring countries. This might

[10] One way to control for selection bias is the use of matching estimators (see De Locker 2007) although it cannot address bias associated with unobservable firm characteristics. Another way is the use of structural approach with an additional maximum likelihood estimation for export entry. However, it does not solve the fundamental identification problem, may be sensitive to a functional form assumption about the joint error distribution, and does not consider the endogenous between exporting and productivity (Bigsten et al., 2004, De Locker, 2013).

imply that Tunisia showed convergence to the international frontier, rather than the regional frontier.

These studies have tested the convergence pattern until early 2000, but not afterwards, and have used industry- and country-level data, but not firm-level data. Therefore, I can't directly compare my results with these studies; however, these studies provide valuable information related to productivity convergence in Tunisia.

3. Data and variables

The data used in this study come from the annual enterprise survey, Enquete Nationale Sur Les Activites Economiques (ENAE), which is conducted by the Tunisian Institute of National Statistics (INS).

The data have been collected with around 2,300 firms surveyed each year since 1997. The survey coverage is extensive, as firms accounting for about 30 percent of firms with 6 or more employees in each sector, excluding agriculture, are included in the sample. In each year, a sampling method was applied, taking into account stratifications by industry and company size in terms of actual employees. I have confirmed that the sample includes representative Tunisian firms by comparing the key firm characteristics of the INS data with the aggregated information of firms listed by the Investment Promotion Agency (API).

The big drawback of the INS data is that the survey generates a repeated cross section, which represents the Tunisian economy well, but makes it difficult to apply econometric techniques for panel data. However, since many firms appeared for at least 2 years, I construct a weakly balanced panel by linking firms through time. Therefore, econometric techniques for the panel data could be applied to the whole set of data.

One of the benefits of the INS data is that the selection bias of data, caused by firm entry and exit dynamics, is less of a concern compared to a balanced panel, since the INS data

includes representative samples, instead of having a panel of firms that survive for consecutive years. In a balanced panel, there might be reasons why some firms have been repeated in selected consecutive years in the surveys; they also would not include firms that have newly entered the market or that have closed down their business.

Another benefit of the INS data is that it provides rich information on firm characteristics (industry, ownership), balance sheets (revenue, labour, tangible assets, expenditure on intermediate goods, expenditure on R&D), and production (export and production value), as well as other information that standard firm-level surveys would include, which permits an investigation of the research questions of this paper.

Using INS data, I estimated TFP using information of sales revenue, labour, intermediate input, and capital. I also estimated TFP growth, technology frontier, and distance to technology frontier (technology distance). How I estimated these variables is explained in the next section. To understand export's effect on productivity, I use the export amount variable to capture the information about export intensity and a dummy variable for export participation. To understand additional factors that might influence the relationship between export and productivity, I generate a dummy variable which is 1 when firms has any foreign ownership (FDI) and an innovation variable, by using the sum of investment in innovative activities, which are R&D investment, paying for royalty, and receiving technical consulting service.

Table 1 provides the list of key variables used for this paper.

Table 1. List of variables

	Variables	Description	Obs.	Mean	S.D.	Min	Max
Variables used to estimate TFP	ln_revenue_d	Log amount of sales revenue, deflated with the Producer price index (PPI)	16,464	13.91	1.65	6.17	21.5
	ln_labor	Log number of employees	16,472	3.98	1.23	0	8.48
	ln_interme~d	Log amount of material input, deflated with the PPI	16,168	12.73	2.23	1.6	20.19
	ln_capital_d	Log amount of tangible capital asset beginning of year, deflated with capital price index	16,031	13.42	1.83	4.61	20.57
Key variables	TFP_GMM	TFP, as residual of production function using GMM	15,749	0.01	0.68	-4.83	6.38
	tfp_delta	TFP growth	11,428	-0.01	0.42	-5.62	5.04
	GAP1	technology distance	15,749	2.36	1.15	0	9.32
	exp	dummy variable of export participation (exp=1 if exporting)	16,473	0.51	0.5	0	1
	expv	log amount of export value, deflated	16,473	7.75	7.68	0	21.5
	FDI	dummy variable of having foreign ownership (FDI=1 if foreign ownership	16,473	0.27	0.44	0	1
	ln_n_innov	log amount of investment in innovative activities, deflated	16,473	6.03	4.67	0	21.5
Previous year	LGAP1	previous year technology distance	11,552	2.3	1.11	0	9.32
	lexp	previous year export status	11,996	0.52	0.5	0	1
	lexpv	previous year export amount	11,996	7.87	7.72	0	22.4
	LFDI	previous year FDI status	16,473	0.18	0.38	0	1

Note: S.D. is standard deviation.

TFP level and growth variables

Using INS data, I measure TFP for Tunisian manufacturing firms as described below, as the residual in a Cobb-Douglas production function, which is an output as a function of the inputs the firm employs and its productivity[11].

[11] It is worth mentioning that there are also other ways of measuring productivity that have been used in the previous convergence literature, such as index number, Bernard and Jones (1996). However, I have used TFP instead of index

Denote firms by i = 1,…, N, industries by j=1,…, J, and years by t=1,…, T. Output measured by sales revenue (Y) in each sector j, at time (t) is produced with labour (L), capital (K) and intermediary input (M). The empirical specification can be written as follows:

$$\ln Y_{ijt} = A_{ijt} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \delta_t + \delta_i + \xi_{ijt} \quad \text{(a)}$$

- Y_{ijt} : The real output of firm i operating in sector j at time t, which is calculated by the sales revenue deflated by sub-industry level deflators from the Producer Price Index
- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by capital price index, from the National Account
- L_{ijt} : Number of employees
- M_{ijt} : The value of material inputs adjusted for changes in material inventories, deflated by the Producer Price Index
- A_{ijt}: The Hicks neutral efficiency level of firm (TFP of firm) measured as the residual of the model/stochastic error term
- δ_t : time dummies for 1997-2007
- δ_i : firm fixed effect
- ξ_{ijt}: Idiosyncratic error which varies across individual firms

TFP estimated from the equation (a) in OLS or FE might provide biased results if inputs are correlated with error term, A_{ijt} (simultaneous input selection bias). For instance, when there is an exogenous price shock, if material is considered more easily adjustable than labour and capital, then material is more strongly correlated with the error term. Therefore, material is upward-biased and others are downward-biased. One way to deal with this simultaneous selection issue is estimating TFP using General Method of Moments (GMM), which treats factor input endogenously and uses its own lagged and differenced variable of outputs and inputs as instruments to provide a consistent estimate.

number because index numbers require an assumption on the input share or use the industry average input share across all firms and, therefore, do not reflect firm-specific information.

The INS dataset has a relatively short time dimension (T=11 at most, after dropping the information after 2008, but most observations have less than 11 years) and a larger firm dimension (>16,000 firm observations, although many of them repeated several times), which is a recommendable characteristic for using GMM.

I use GMM to estimate the above specification; specifically, a non-dynamic system GMM with lag (2 3) for instruments. In other words, I treat all current-year factor inputs, which are labour, capital, and material, as endogenous, and previous two- and three-year information are used as instruments for all of the endogenous inputs. A dynamic model, which has lag dependent variable and lag factor inputs as additional regressors, requires one additional lag in instruments, which significantly reduces the number of observations with the weakly balanced INS data. Therefore, I use the non-dynamic equation. Likewise, further lags in instruments reduce the number of observations significantly; therefore, I use 2 and 3 lags in instruments.

Also, I measure TFP separately at the 2-digit industry level in manufacturing, which is from NACE 15-36, to allow the factor input shares to vary across industries. While some industries, such as automobile, are more capital intensive, some others, such as textile, are more labour intensive. Therefore, assuming the same factor input across different industries could cause bias in TFP estimation. More detail on TFP estimation is provided in Appendix B.

In 2008, the INS questionnaire changed and dropped questions about exports. Therefore, I use the data from 1997 to 2007. Also, since the focus of this paper is on the manufacturing sector, I limit my data to manufacturing firms, which belong to NACE 15-36. After dropping those observations with missing values in key variables, such as revenue and employment, I obtain approximately 15,800 TFP out of 16,471 firm observations.

The number of observations further drops when I calculate TFP growth, since it requires two consecutive years of TFP information in the data. To increase the number of

observations, I utilize additional information in the INS survey, which also asked firms for their previous-year revenue, employment, capital, and material cost. This effort generated additional previous-year TFP information for around 400 firms.

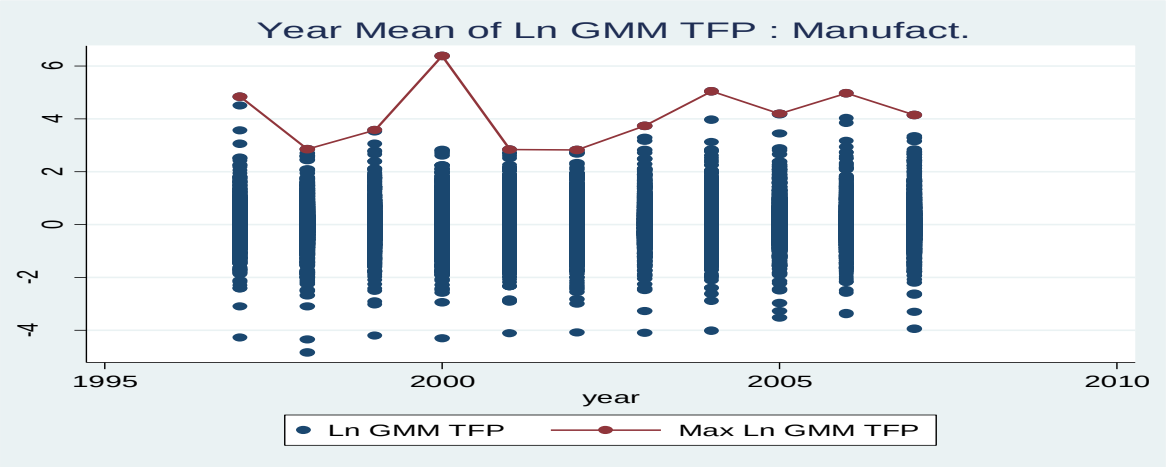
In addition, I measure TFP growth with the current year TFP and with available previous years, but closest to the current year in case there were several previous-year observations, which helped me to generate previous-year TFP information for an additional 1,200 firms. Measuring TFP growth this way allows me to use the information of all the firms that are showing in the data set at least twice during the period, which is true of the majority of observations. With these efforts of increasing the observation, I have obtained around 11,400 observations for TFP growth, which is around 70% of observations.

Using close to 70% of the firms in the data might reduce a concern of potential selection bias if there is a reason why those firms appear in the data at least twice. Moreover, the number of observations is large enough to produce statistically convincing results for both beta (β) and sigma (σ) convergence. Graph 1 and 2 provide the TFP level and growth for manufacturing firms in the INS data.

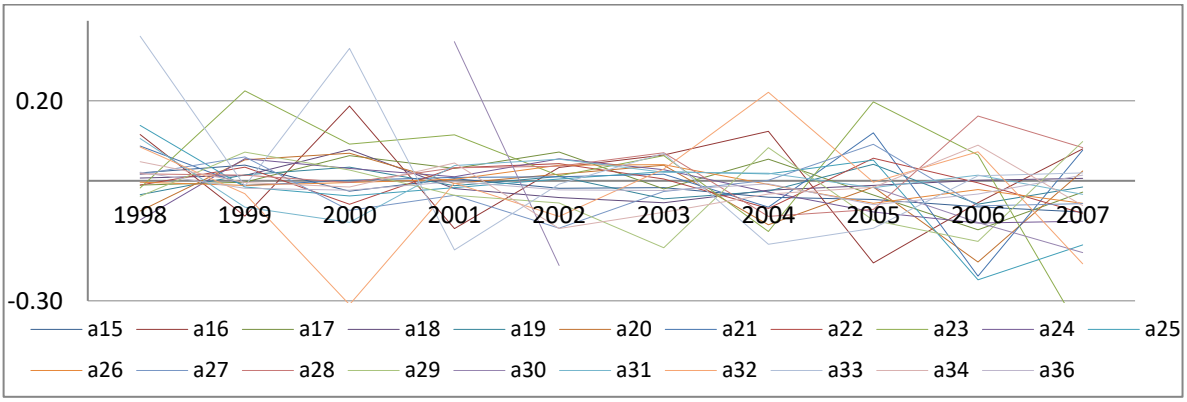
Graph 1 shows the TFP level for Tunisian manufacturing firms from 1997 to 2007. Most firms have a TFP level between -log 2 and log 2. While the exact pattern is unclear from this chart, the differences in TFP among firms are slightly reduced over time.

Graph 2 shows average TFP growth rates over time by 2-digit level industry. While growth rate varies greatly by year and by industry, the average TFP growth rate is in the range between -0.2 and 0.2 for most industries and most years, except for a17 in 1999 and 2007, a18 in 2001, a32 in 2000, and a33 in 1998 and 2000. Table B.2 and B.3 in appendix B provide the average growth rates and their standard deviation by industry and by year. The average TFP growth is close to zero and standard deviation of TFP growth is very small for most of industries.

Graph 1. TFP level over time



Graph 2. TFP growth, industry average over time



Note: The TFP growth is measured as $\log(\text{TFP}_{ijt}) - \log(\text{TFP}_{ijt-1})$. I have dropped a35 to make the graph to easier to read since its TFP growth rate was below -0.3 in that industry. The index of each industry is provided in table 2 below.

Technology frontier and technology distance variables

Using the estimated TFP, I identify a technology frontier firm (TFP_{Fjt}), which is defined as a firm that has the highest TFP level within the industry j and year t, followed by Bartelsman et al., (2008). I estimate the distance to technology frontier (technology distance) as a difference of log technology frontier firm (TFP_{Fjt}) and a firm's TFP (TFP_{ijt}).

- Technology frontier (TFP_{Fjt}): a firm that has the highest TFP level in sector j, at time t
- Technology Distance: $\log(\text{TFP}_{Fjt}) - \log(\text{TFP}_{ijt})$, which is equal to $\log(\text{TFP}_{Fjt}/\text{TFP}_{ijt})$

It is worth mentioning that there are also other ways to measure technology frontier, such as stochastic production frontiers (Aigner 1977). In the stochastic frontier analysis, frontier is identified as firms' profit maximization (or cost minimization), and technology efficiency is the ratio of observed output to maximum feasible output. While the frontier in the stochastic frontier analysis uses a 'half-normal' distributional assumption as the basis for measuring distance from the frontier, the technology frontier that I use is a fitted full-normal distribution of firms behind the frontier. Under this distributional assumption, my technology frontier is mostly within the 99th percentile, but depending on the number of observations within the industry i and year t, the median firm will be three standard deviations below that level. For instance, in the textile industry in year 1997, the technology frontier firm is the firm which has a TFP level of log 2.24 while the median TFP level of all other firms is close to zero (-0.02).

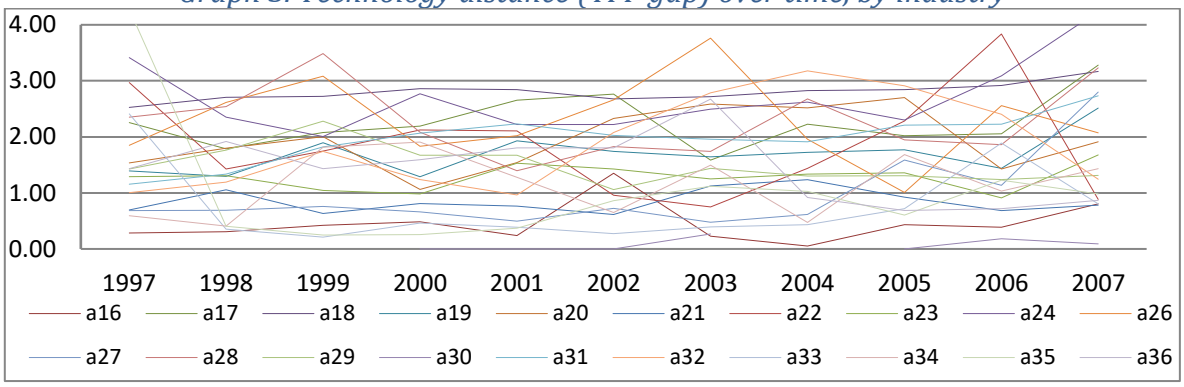
Graphs 3 and 4 provide technology distance and its standard deviation over time.

Graph 3 shows that there is large heterogeneity in technology distance across industries. The technology distance is in the range of 0 and 3 for most industries. This implies that a firm's TFP can be almost similar to the technology frontier (if $TFP_{Fjt} = TFP_{ijt}$, technology distance is log1, which is 0) but also can be more than 20 times smaller than the technology frontier (ln20 is almost 3), which is quite large. Also, the technology distance has increased in some industries, while not in others.

Graph 4 shows the standard deviation of the TFP gap in each industry by year, which is the widely used measurement of sigma (σ) convergence in previous literature. While in most industries the standard deviation seems to be slightly increased, in some industries, such as a16, a26, and a29, it has been much reduced. However, in most industries, the standard deviation of technology distance has been sustained in the range of 0.03 and 0.15. This implies that firms' distances to the technology frontier remain at a similar level. Again, there is large heterogeneity in sigma convergence patterns across

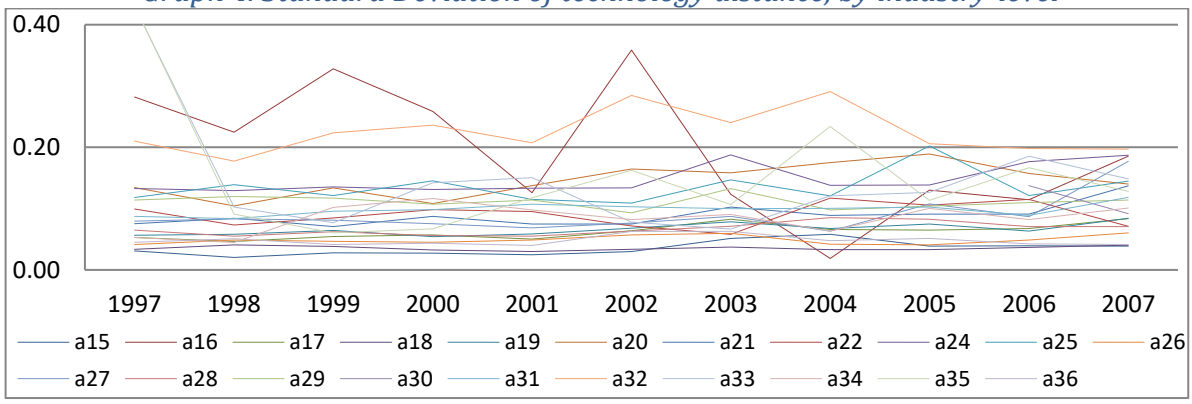
industries. The table B.4 in appendix B shows the actual standard deviation of the technology gap variable by industry and year.

Graph 3. Technology distance (TFP gap) over time, by industry



Note: I deleted the line for a15 and a25 industries to make the graph to easier to read since the technology gap in both industries were over 4. The index of each industry is provided in table 2.

Graph 4. Standard Deviation of technology distance, by industry-level



Note: I deleted a23 since its S.D. is higher than 0.6 in some years, which seems to be an outlier.

The important thing to note is that the frontier firm of one year is not necessarily the frontier firm in another year. As mentioned above, the INS data set is a survey of a representative sample of around 30% of all Tunisian firms; therefore, the firms that are selected in the survey are different each year (a weakly balanced panel). Also, firms can move up or down in their productivity level, or even exit from the market, while new firms that entered the market could also be included in the data set. Therefore, the above graphs show the overall trend of the subsectors, not a group of specific firms.

Table 2 shows average TFP level, TFP growth rate, and number of frontier firms by industry, which shows the weakly balanced characteristic of the INS data. For instance, in food industries, the number of observations is 2,030 but the number of firms are 597, meaning firms have been repeated on average less than 4 times for the 11-year period. Average TFP level from 1997-2007 is close to zero, but growth rate is around -2%. 8 firms have been frontier firms in 11 years, meaning the same firms repeatedly become frontier only for 3 years, or two firms are at the frontier for two years and all the rest are at the frontier only once.

Table 2. TFP, TFP growth, and frontier firm by industry

NACE code	Description	# of obs.	# of firm	Mean TFP	Mean TFP growth	# of frontier firm
15	Food Industries	2030	597	0.00	-0.02	8
16	Tobacco Industry	46	7	0.26	0.01	3
17	Textile Industry	1246	354	0.01	0.00	11
18	Clothing and Furs	4947	1263	0.03	-0.01	4
19	Leather and Footwear	965	257	-0.03	-0.01	8
20	Woodworking, Wood Manufacturing	275	98	-0.22	-0.01	5
21	Paper and Carton	254	62	0.27	0.01	7
22	Editing, Printing, Reproduction	430	133	0.05	0.00	7
23	Coke, Refining, Nuclear Industries	44	7	-0.42	0.02	5
24	Chemical Industry	787	180	0.03	-0.02	8
25	Industrial Rubber and Plastics	637	172	-0.16	-0.02	9
26	Non-Metallic Mineral	1256	328	-0.01	-0.01	8
27	Metallurgy	235	52	-0.05	-0.02	6
28	Metalworking	871	275	0.04	0.02	10
29	Machinery and Equipment	382	100	0.05	-0.02	6
30	Office Machinery; Computer Equipment	11	5	0.82	-0.06	2
31	Manufacturing of Machinery and Electrical Appliances	598	161	-0.07	0.00	7
32	Manufacturing of Radio, TV and Communication Equipment	167	50	0.46	-0.02	7
33	Medical, Optical, and Watch Devices	101	30	-0.05	0.01	9
34	Automotive	253	69	-0.08	-0.01	8
35	Other Transport Equipment	131	43	-0.09	-0.06	8
36	Furniture; Various Industries	791	224	0.02	-0.01	6

4. Empirical strategy

Previous literature has typically measured convergence by two methods. First, they compared the growth rates between the poor and the rich (so called, β-convergence). Convergence occurs if a poor country grow faster than a rich one, as the poor country will catch up with the rich. Second, they measured cross-sectional dispersion of income or productivity level (σ-convergence). Convergence occurs if the dispersion, which is measured by the standard deviation of the income or productivity across a group of countries or industries, declines over time. As mentioned above, there is no clear pattern of σ-convergence in Tunisian manufacturing firms (see details in table C.4 appendix C)[12].

The empirical model that I present aims to test for the presence of a β-convergence pattern, which is measured in the previous studies by regressing productivity growth on two explanatory variables. The first is an estimate of productivity growth at the frontier, which captures the link to productivity growth in the "catching- up" country. The second is a measure of technology distance, which is the productivity of the poor relative to the productivity of the technologically-advanced. This technology distance variable captures the extent to which productivity growth in a specific country can be explained by the adoption of more efficient existing technologies as explained in a Schumpeterian framework. Both empirical models capture the link between productivity growth of the poor and the extent of knowledge spill-over from the most technologically advanced. (Bernard and Jones, 1996, Nishmura et al, 2005, Griffith et al., 2008, Mc Morrow et al., 2010, Barro and Martin, 1990[13]).

Following the previous studies, I test the existence of β-convergence by regressing a firm's productivity growth on its relative technology distance, which is its previous year TFP relative to the above-identified technology frontier firm's TFP, as seen in equation

[12] β-convergence works toward σ-type convergence; however, it does not guarantee σ-convergence if growth rates are driven not only by the forces of convergence but also by external shocks, such as an economic crisis, which are new disturbances that increase dispersion (Barro and Sala-i-Martin, 1990).

[13] Convergence exists if the coefficient gap variable (β) is greater than 0.

(1). I estimate equation (1) with OLS without any control variables. Therefore, the coefficient, η_1, describes the existence of unconditional convergence: the further away from the technological frontier, the higher the potential to adopt more efficient and available technologies, and, consequently, the faster productivity growth, regardless of firms' specific characteristics.

$$\Delta \ln A_{ijt} = \eta_1 \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \varepsilon_{ijt} \qquad (1)$$

Then, I measure productivity growth as a function of previous-year export status, as seen in equation (2) following previous empirical literature on exports and productivity that assumes that current exporting participation influences future productivity (for instance, Castellani, 2002, Baldwin and Gu, 2004, De Loecker, 2013).

$$\Delta \ln A_{ijt} = \eta_2 \, Export_{ijt-1} + \gamma \, X_{ijt-1} + U_{ijt} \qquad (2^{14})$$

- η_2 is the export effect on productivity growth
- $Export_{ijt-1}$ is a dummy variable of previous-year export status
- X_{ijt-1} is a vector of control variables, which includes innovation and FDI
- U_{ijt} is a stochastic error

I control for unobserved heterogeneity that is correlated with the explanatory variables by allowing the error term (U_{ijt}) to include a firm-specific fixed effect (α_i). I allow the error term (U_{ijt}) to include a full set of year dummies (α_t) and a full set of industry dummies (α_j). Since I have already controlled firm, industry, and time effects in computing the dependent variables, I expect that the coefficient of α_t and α_j would not be significant, however, I included them because there may be also a specific trend by common macroeconomic shocks and by industry that affects the relation between export and TFP growth. Because some firms have changed their industry over time,

[14] Previous empirical literature on productivity convergence typically used either output/income growth or productivity growth as a dependent variable. Given that output growth consists of factor input growth and productivity growth, using output growth as a dependent variable while controlling factor inputs as independent variables is essentially the same as using productivity as a dependent variable.

industry dummies and firm fixed effects are not perfectly correlated, which allows me to use both firm fixed effects and industry dummies. ε_{ijt} is a serially uncorrelated error.

$$U_{ijt} = \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt}$$

I link above equations (1) and (2), and augment them by adding an interaction term between the previous export status and technology distance, based on the assumption that learning by exporting effect depends on the level of technology distance, and export status plays a role in technology transfer.

$$\Delta \ln A_{ijt} = \beta_a \text{ Export}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (3)$$

- TFP_{Fjt}: the most productive firm (technology frontier=F) in sector j, at time t

In equation (3), β_a is to measure whether exporting has a positive effect on productivity growth. β_b is to measure the role of technology transfer in productivity growth. If a firm behind the technology frontier grows faster than those firms close to the technology frontier, $\beta_b > 0$ (β_b is also the elasticity of productivity increase with respect to distance from technology frontier). Lastly, β_c is to capture the variation of learning effects from exporting on a firm's relative productivity level and whether export plays a role in the relationship between technology distance and productivity growth. I expect that the further away a firm is from the technology frontier, the higher the learning might be, therefore $\beta_c > 0$.

Therefore, this specification in equation (3) is related to both convergence[15] and learning by exporting literature. Specifically, this specification has implications for standard measures of β–convergence – whether poor economies tend to grow faster than rich ones.[16] Moreover, this specification allows me to test exports' effects on productivity

[15] Taking a simple version of equation (3), writing TFP as A throughout and dropping extraneous terms, including export status and interaction terms, and equation (3) now becomes $\Delta \ln A_{ijt} = \beta \ln\left(\frac{A^F}{A_{ij}}\right)_{t-1} + \varepsilon_{ijt}$, which is a typical convergence model in the previous literature, where evidence of convergence is typically tested by productivity (or output) growth as a function of initial productivity level or relative productivity (technology distance).

[16] Also, this specification has implications for σ–convergence, which is measured as the dispersion of productivity of a group of firms, since the intra-industry sample standard deviation of relative TFP may change over time, depending

increases while controlling for firms' initial productivity level, relative to the technology frontier, which indirectly controls the potential self-selection issue of more productive firm become exporters, in testing learning by exporting effect.

This specification is similar to previous convergence literature, such as Griffith, Redding and Van Reenen (2004), in a sense that it is testing for the effect of relative productivity level and other factors on productivity growth. However, while their focus was the relationship between R&D and productivity growth, my interest is in understanding export's effect on productivity growth. Also, while they have used industry-level data to test the existence of convergence cross countries; I test firm-level convergence within industries in Tunisia.

Moderating effects of FDI and innovation

There might be additional factors that influence export's effect on productivity, such as having foreign ownership (FDI) and innovation. Those factors might affect TFP growth directly, but also via their interaction with the explanatory factors in the baseline specification. For instance, if foreign ownership and innovation would facilitate learning from abroad, export's effect on productivity growth would be also affected by those variables. Therefore, in the baseline specification of Regression 3, I include those factors as control variables. In addition, I test the additional interaction effects of these factors with export and technology gap.

FDI has been widely recognized as a productivity source, since foreign investors' knowledge is transferred and/or spills-over to domestic partners, competitors, suppliers, and customers, via management skill and know-how. Multinationals tend to be technologically advanced, spend larger amounts on R&D and have better managerial practices. Therefore, FDI as a bundle of technological and managerial knowledge has

on the correlation between the initial and steady-state distributions of relative TFP (a group of firms are converging if $\sigma_t > \sigma_{t+T}$, where σ_t is the time t standard deviation of log $Y_{i,t}$).

been regarded as a major vehicle for the transfer of advanced foreign technology to developing countries (Fu, et al., 2011). Additionally, spill-over from FDI firms was observed in upstream sectors in Lithuania and in China (Javorcik, 2004, Liu, 2008, Du et al, 2011), in downstream sectors (Javorcik et al., 2011, Du et al, 2011), and horizontally (Damijan et al. 2012, Du et al, 2011). Also, having foreign ownership can influence a firm's export participation. FDI firms are more likely to be exporters than local firms, which suggests that FDI is an important vehicle for trade, and additional productivity gains can be reaped through trade (Javorcik, 2011).

Therefore, my hypothesis is that firms (and particularly exporters) are more likely to benefit from associations with their international investors that are most likely to have higher technology.

Equation (4) is to test this hypothesis using the additional interaction of FDI with the interaction term of export and technology gap. I construct a dummy variable of FDI with firms' ownership information from the data. I expect that FDI would have a positive effect on the relation between export and convergence, since it might further facilitate technology spill-over, especially in developing countries where technology is far behind the frontier.

$$\Delta \ln A_{ijt} = \beta_a \, \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c FDI_{ijt-1} + \beta_d \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_e \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} \times FDI_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (4)$$

FDI_{ijt} = 1 if there is any foreign ownership, and 0 if otherwise.

However, the above hypothesis is based on the assumption that Tunisian manufacturing firms have absorptive capacity to benefit from FDI. The previous literature argues that the magnitude and direction of the benefit from FDI depend on local firm's absorptive capacity. There is also a minimum absorptive capacity level below which productivity spill overs from FDI are negligible or even negative (Smeets, 2008, Fu, et al., 2012, Fu, 2011, Du, et al., 2011).

Innovation is a widely-used proxy for firms' absorptive capacity[17], which influences convergence. Firms need a certain level of internal innovation and technology before they can benefit from new technologies discovered by others. Innovation input, measured by R&D investment, facilitate the assimilation of external technologies, thus boosting productivity (Girma, 2005, and Fu, 2008). In this regard, those firms far from the technology frontier without a certain level of internal innovation might not be able to converge to the frontier. In fact, the role of innovation varies depending on the country's relative position in technology advancement (Aghion et al., 2005).

Innovation's effect on productivity is often related to exporting. For instance, the decisions to export and to expand the export market often accompany R&D investment and productivity improvement (Aw et al., 2011). Innovation is correlated with a share of exporters within an industry (Bernard et al., 2010). Investment in R&D and IT brings process innovations for exporters (Brynjolfsson and Hitt, 2003, Van Ark, et al., 2008).

The INS data provides detailed information about expenses on innovation activities, such as conducting R&D, receiving consulting services, and purchasing royalties. These expenses related to innovation activities have been widely used as proxies for innovation in the previous literature (Cohen and Levinthal, 1990, Quinn 1999, Griffith et al., 2004, Lokshin et al., 2008, Bloom and Van Reenen, 2010).

Following previous literature, I construct innovation variable using cost items that are directly related to technical innovation. Specifically, innovation variable is constructed as the sum of investment amount in the activities which are directly related to innovation, which are payment to R&D, external royalties and receiving consulting services. Innovation variable is deflated with output deflator.

[17] There are different proxies for measuring absorptive capacity, such as R&D intensities and human capital embodied in local firms. While growth theories consider distance from the frontier as a measure of this absorptive capacity (because the further away from the frontier, more technologies there are to be transferred), literature on innovation consider absorptive capacity as an firm's internal level of innovation and technology. Cohen and Levinthal (1989) defined absorptive capacity as firms' ability to identify, imitate, and exploit knowledge from the environment.

Regression (5) is to test the potential interaction effect between innovation and the interaction term of exporting and technology gap. While the interaction between innovation and exports could show a positive influence on productivity, given that Tunisian firms are relatively far away from the technology frontier, the expected direction and magnitude of these interaction effects are not clear.

$$\Delta \ln A_{ijt} = \beta_a \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \ln \text{innovation}_{ijt-1} + \beta_d \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_e \text{Export}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} \times \ln \text{innovation}_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (5)$$

ln Innovation = log (cost of conducting R&D + cost of receiving technical consulting service + cost of purchasing royalties).

5. Concerns and solutions

There might be several issues related to the above econometric strategy, namely, potential measurement error in export variables, collinearity between industry-invariant unobservable and firm-specific characteristics, endogenous export decisions, and the definitions of the frontier. For a robustness check, I use different specifications and econometric techniques to deal with the abovementioned issues, and test whether the regression results are consistent across them.

Using different export measures in case any measurement errors exist in export variables

Although most of the existing literature has used the previous year export status to analyse its effect on productivity, there might be other variables to better show a firm's participation in export. For instance, export volume could provide additional information on export intensity. Also, if there is no time required to transmit the exporter's learning to productivity increase, using current export status is more appropriate.

Export Volume: Some researchers have used export intensity, such as export volume, instead of an export dummy, to understand exports' effect on productivity. They have found a significantly positive effect of export intensity on productivity growth (Castellani, 2002, Girma et al., 2005), but others have found no larger or statistically significant relationship (Aw et al., 2011, Cherides et al., 1998). The benefit of using that value term would be that it captures the information of export intensity. Since the export amount is a continuous variable, the coefficient of export value shows how much a given increase in previous export amount drives TFP growth.

$$\Delta \ln A_{ijt} = \beta_a \, ln \, \text{ExportVolume}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \ln \text{Export Volume}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (6)$$

Current year exporting status: The reason I have initially used the previous export status is, as explained in the empirical strategy section, that I assume the export would take time, perhaps at least one year, to influence productivity. Therefore, firms' participation in exporting would influence TFP level in the following year, thus affecting productivity growth. But if my assumption on required time for transmitting learning from exporting to productivity does not hold, the export status would influence same-year productivity level and growth. Therefore, I use current-year export status.

$$\Delta \ln A_{ijt} = \beta_a \, \text{Export}_{ijt} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (7)$$

Using different fixed effects to deal with the potential collinearity between industry-invariant unobservables and firm-specific characteristics

As explained in section 5, Empirical Strategy, I control for unobserved heterogeneity that is correlated with the explanatory variables by allowing the error term (U_{ijt}) to include a firm-specific fixed effect (α_i), a full set of year dummies (α_t) and industry dummies (α_j), to control for firm and industry specific characteristics and common macroeconomic shocks that affect rates TFP growth.

Because some firms have changed their industry over time, in several industries, industry dummies and firm fixed effects are not perfectly correlated. However, in some industries, industry dummies are highly correlated with firm fixed effects.

Therefore, I test the baseline specification, without industry fixed effects, and test whether the results are consistent with and without the alternate specification. In addition, in order to capture unobservable potential macroeconomic shocks and industry heterogeneity while keeping firm fixed effects, I use an interaction term of time and industry dummies, to avoid high collinearity of some of the industry and firm fixed effects, and to examine whether the test results are consistent across specifications.

Using IVs and GMM to address potential endogeneity in exporting decisions

In equation (3), if those firms which know they will have higher growth participate in exporting, the coefficient of exports might be biased. Export status might be correlated with unobserved firm characteristics, other than the initial productivity level, that would directly influence future productivity level, thus productivity growth. Therefore, the specification in Regression (3) might fail to convincingly isolate the causal effect of exporting on firm productivity growth.

Instrumental variable (IV): To understand the causal effect between exporting and productivity, I first use external instrumental variables for exports to deal with the potential bias caused by endogenous export status.

The suggested instrument is "international market demand", which is measured as a sum of import values of France, Italy, and Germany, which are Tunisia's major export destinations (IV1). The import values are those countries' imports from the rest of the world by 2-digit industry. Since Tunisia is a small economy, it is unlikely that Tunisian firms would influence the international market, while it is likely that the export volume of Tunisian firms would be correlated with the international market demand. Also, the timing and pattern of international market demand for each industry were unforeseen.

Therefore, this instrument plausibly satisfies the requirement that the instrument be uncorrelated with the ultimate outcomes of interest except via the channel of interest (the change in export status).

However, the international market demand is industry-level information and does not provide firm-specific information. Therefore, I deduct firms' sales revenue from the international market demand (IV2). So now the intuitive interpretation for the IV2 is the potential world market of firm A that firm A can export to, in addition to their current sales volume, and it provides a firm-level instrument. By using this IV, I expect that the coefficient of 2SLS would be reduced, by removing the global market demand change.

I run the following regression to see whether suggested IV (IV2) is a strong instrument.

$$\text{Export status}_{ijt-1} = \delta + \beta_a IV2_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (9)$$

Here, δ is a constant term and ε_{ijt} is a serially uncorrelated error. Because the impact of an individual firm's international market demand (IV2) on the firm's export status may vary by year and industry, I included year and industry dummies, α_j and α_t, respectively. Also, this impact may vary by individual firm characteristics, so I also run another regression with firm fixed effects.

Table 3 shows that the suggested IV explains significant variations of instrumented variable, export status.

Table 3. Relations between international demand (IV) and export status

Dep. var export status	(1) IV2_OLS	(2) IV2_FE
IV2	0.233***	0.092**
	(0.000)	(0.002)
Constant	-5.584***	-2.172**
	(0.000)	(0.003)
Observations	11987	11987
R^2	0.365	0.258*

Note: Year and industry dummies were included but not reported. Standard errors are corrected and robust (white correction for heteroskedasticity), *p*-values in parentheses, Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, * Reported R^2 for fixed effect is between group.

Table 3 finds that the suggested IV (IV2) has a positive and statistically significant effect on export status, and, therefore, is relevant. To test the strength of the instrument, I also conducted F-statics of OLS regression of suggested IV on the endogenous variable, which is essentially the same as the column (1) in table 3 but without year and industry dummies, α_j and α_t. The F test results also confirm the strength of the instrument (F (1, 11985) = 16.73 and Prob. > F = 0.00)[18].

Given that LHS variable, export status, is a dummy variable, the predicted export status can now be below 0 or 1, which is beyond the range that export status can have[19]. Therefore, I also use export volume as an instrumented variable as a robustness check. Table D.8 in Appendix D shows that the IV2 explains significant variations of export volume as well.

Since equation (3) includes an endogenous variable (export status) and its interaction term with technology distance, using stata commands such as ivreg2 or xtivreg2 treat them as if there are two endogenous variables and requires more than one instrument, which is unnecessary. Therefore, I conduct 2 stage regression manually by estimating the predicted value of previous export status as seen in equation (9). Also, I generate an interaction term of $Predicted$ Export status_{ijt-1} and a previous year technology distance variable. Then, I plug these predicted variables, which are $Predicted$ Export status_{ijt-1} and $Predicted$ Export $\text{Statuse}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1}$ into equation (3). Since the OLS standard errors

[18] A common rule of thumb for models with one endogenous regressor is that the F-statistic against the null, which is the excluded instruments that are irrelevant in the first-stage regression, should be larger than 10 (Angrist and Pischke (2009), based on Staiger and Stock (1997)'s rule of thumb about instruments). Also, my F test result (16.73) is larger than Stock and Yogo (2005)'s weak ID test critical values (16.38) at 10% maximal IV size, with 1 instrument and 1 endogenous regressor, therefore, I reject the null hypothesis that the maximum relative bias due to weak instruments is at least 10%. (Stock and Yogo (2005)'s table 2, provides 16.38 when k=1, n=1, at a significance level is 5%, using the F-statistic form of the Cragg-Donald statistic (a 5% Wald test of β = β0)).

[19] However, my first stage regression is still linear (linear probability model) and it is different from the so-called "forbidden regression" mentioned by Hausmann (1975), which describes having a non-linear model, such as probit, in the first stage. Unlike the residual of OLS, a non-linear model residual can be correlated with the fitted value and regressors, therefore, plugging in the predicted value of it in the second stage is prohibited.

from the manual second stage will not be correct (Angrist and Pischke (2009))[20], I correct for standard error with a method provided by Kit Baum (2010)[21].

The second stage regression is now:

$$\Delta \ln A_{ijt} = \beta_a Predicted \text{ Export stat}_{ijt-1} + \beta_b \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + \beta_c Predicted \text{ Export Stat}_{ijt-1} \times \ln\left(\frac{TFP_F}{TFP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (10)$$

Generalized methods of moments (GMM): In addition to that, as a robustness check, I apply GMM in measuring equation (3), in order to deal with potential endogeneity in the export decision. In case the decision to participate in exporting is correlated with productivity level (endogeneity), GMM gets rid of this endogeneity issue by using the dependent variable and export status as its own instrument, by removing them from the regression equation (using the differenced equation with lagged levels as instruments), or by removing them from the instruments (using differences as instrument in a levels regression). However, in my view, IV could be a preferred estimation over GMM because INS data is a weakly balanced panel, therefore, I lose significant firm observation when using GMM, which requires previous years of information.

Different measures of technology frontier and technology distance

There might be a concern if the above-identified technology frontier is an outlier for a certain year or if technology is transferred from the international frontier, rather than the domestic frontier. Here, I suggest new measures of the technology frontiers for the robustness check that allow me to compare the current frontier with a set of high-productivity firms (top 1% frontier) and to compare the differences in domestic frontier and international frontier, using available information (labor productivity).

[20] The OLS standard errors from the manually conducted second stage will be larger than the actual one since it includes not only the variance of the second stage but also the variance generated by the difference between actual value and predicted value (Angrist and Pischke, 2009).
[21] This is done by using actual value, instead of predicted value, in measuring the residual of second stage regression and using that in estimating the standard errors of coefficients.

Appendix C provides additional information on these new measures of technology frontier and Tunisian firms' technology distance to these new frontiers. The similar level and pattern between the initial frontier/distance and the top 1% frontier/distance, as well as the international and the domestic frontier/distance, using labor productivity, ensure that the initially identified technology distance measure is a good measure for the technology transfer from more technologically advanced domestic firms to less advanced firms, and a good, although indirect, proxy for technology transfer from foreign firms to domestic firms.

Top 1% frontier: To avoid identifying an outlier as a technology frontier, I generate another frontier measure by taking the average TFP of firms that have top 1% of TFP level in industry j and year t (Frontier–top 1%). Now the technology distance is a log difference of the Frontier–top 1% and TFP level of an individual firm that belongs to bottom 99% of TFP in industry j and time t (Distance-top1%).

Table 4 compares these new frontier and distance measures and the previous frontier (Frontier–the highest) and the previous distance (Distance–the highest). As expected, the Frontier–top 1% has smaller value than Frontier–the highest, therefore the Distance-top1% is also smaller than the Distance–the highest. Graphs C.1 and C.2 in appendix C provide the average and standard deviation of this new measure of technology distance (Distance-top 1%), which shows a very similar pattern with graph 3-4 in the data section that provides the initial distance variable (Distance-the highest).

Table 4. Comparison of different technology frontiers and distances

Variables	Description	Obs.	Mean	S.D.	Min.	Max.
Frontier – the highest	Highest TFP in industry j and time t in Tunisia	244	2.37	0.93	-0.34	6.38
Distance – the highest	Distance from Frontier –the highest	15,749	2.36	1.15	0.00	9.33
Frontier – top 1%	Average top 1% TFP in industry j and time t in Tunisia	244	2.10	0.75	-0.34	6.38
Distance-top1%	Distance from Frontier –top 1%	15,434	2.13	0.97	0.00	9.32

International vs. domestic frontier, using labor productivity: As mentioned before, domestic distance might be a more relevant measure than international distance for examining firm-level convergence in developing countries, where firms are more likely to learn from other firms in the country, rather than from foreign firms (Bartelsman, et al. 2008).

Meanwhile, domestic distance might not be a good measure to test export's role in technology transfer since one could argue that participating in exporting activities could bring technology transfer from technologically advanced foreign firms (international frontier) to domestic exporters. However, because there is no available TFP information of international frontier firms, I use domestic technology distance to test export's role in technology transfer, which might be a concern.

To understand whether domestic technology distance can be a good measure to test export's role in technology transfer, I first check whether domestic frontier firms are more exposed to the international market than other firms. However, I find that domestic technology frontier firms (244 firms from 22 industries for 11 years) do not participate in exporting activities more than the rest of firms, although they have greater exposure to foreign investment than other firms, which could also lead to their learning from the internationally advanced firms. Specifically, among domestic technology frontier firms, around 50% are exporters and around 40% received FDI. Meanwhile, among the rest of the firms, around 50% have participated in exporting but only 27% receive FDI (the detail is in D.1-D.4 in appendix D). Therefore, domestic technology distance is only an indirect proxy of the technology transfer channel from abroad.

As a robustness check, I measure productivity in a different way which allows me to obtain international technology distance, which is typically the hypothesized source of knowledge spill-overs in the previous literature. Specifically, I measure the international technology distance as the productivity difference between Tunisia and France. I consider France as a benchmark country for Tunisia since France is the largest export

destination and both countries have had close cultural and economic ties[22]. While I can't obtain firm-level TFP information of France, industry average labor productivity is available at the 2-digit industry-level in France, provided by EU KLEMS[23]. Therefore, I consider industry-level labor productivity of France as the international benchmark of Tunisian firms (international frontier, $L_{\boldsymbol{FF}\,jt}$).

For the comparison, I measure an additional domestic technology distance using labour productivity of Tunisian firms. This additional frontier is measured by log labour productivity of the firm that has the highest labour productivity in industry i, time t (Domestic frontier, $L_{\boldsymbol{DF}\,jt}$). Now the distance is the distance between this additional technology frontier and the individual firm's log labour productivity of firm in industry i and time t.

- International frontier, using labour productivity ($L_{\boldsymbol{FF}\,jt}$): French industry-level labour productivity in sector j, at time t
- Domestic frontier, using labour productivity ($L_{\boldsymbol{DF}\,jt}$): a Tunisian firm that has the highest labour productivity in sector j, at time t

Table 5 compares the international and the domestic frontier/distance, using labour productivity. The technology distance between domestic and international frontier is not large. International distance has some negative value because some Tunisian firms have higher labour productivity levels than the French industry average labour productivity level. I delete the negative values when I run the following regressions.

[22] Tunisia was a French protectorate from 1881 until its independence in 1956. Its legal system and institutions were heavily influenced by France. French is an official language. France is Tunisia's largest foreign investor and trade partner.

[23] 2011 EU KLEMS data in ISIC Rev.3 provides a limited set of variables for 72 industries up to 2007. I use the output data at current basic prices (in millions of Euros), deflated by the price indices, provided by the EU KLEMS. I convert year 2000 as a base year of price indices to be consistent with INS data and convert it to Tunisian dinars, using exchange rates provided by IMF. Then I divide this deflated output by number of workers, provided in EU KLEMS.

Table 5. International and domestic frontiers/distance, using labour productivity

Variables	Description	Obs.	Mean	S.D.	Min	Max
Domestic LP frontier, $L_{\boldsymbol{DF}\,jt}$	Labour productivity (LP)of the Tunisian firm that has the highest LP in sector j, at time t	244	13.3	1.3	9.3	16.1
Domestic LP distance	Distance from the domestic frontier	16,464	3.4	1.8	0.0	12.5
Int. LP frontier, $L_{\boldsymbol{FF}\,jt}$	French industry-level labour productivity in sector j, at time t	244	11.8	0.5	10.9	13.0
Int. LP distance	Distance from the international frontier	16,464	1.8	1.1	-4.4	8.2

I test the main equation (3), using this international distance and domestic distance and labour productivity, as seen in equation (11) and (12).

$$\Delta \ln A_{ijt} = \beta_a \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{LP_{FF}}{LP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt-1} \times \ln\left(\frac{LP_{FF}}{LP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (11)$$

$$\Delta \ln A_{ijt} = \beta_a \text{Export}_{ijt-1} + \beta_b \ln\left(\frac{LP_{DF}}{LP_i}\right)_{jt-1} + \beta_c \text{Export}_{ijt-1} \times \ln\left(\frac{LP_{DF}}{LP_i}\right)_{jt-1} + X_{ijt-1} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (12)$$

An additional benefit of using labour productivity-based technology distance in the above specification is that it might avoid collinearity in the regression, because using TFP-based technology distance results in having the TFP variable in both the RHS and LHS. However, compared to the TFP, labour productivity is a less preferable measure since it can't capture other input factors such as capital, which might affect the process of technology transfer.

6. Results

Evidence of unconditional convergence

Table 6 provides evidence of unconditional convergence among Tunisian manufacturing firms. Column (1) provides the results of equation (1) which tests the relationship between technology distance and productivity growth, without firm fixed effects as well as any other control variables (unconditional convergence).

Table 6. Evidence of unconditional convergence

Dep Var=TFP growth	OLS Without time and industry dummies			OLS With time and industry dummies		
	(1)	(2)	(3)	(4)	(5)	(6)
Exporter		-0.007	-0.046*		-0.007	-0.062**
		(0.242)	(0.034)		(0.369)	(0.006)
Lag Ln tech distance	0.067***	0.067***	0.058***	0.095***	0.095***	0.085***
(lag ln TFP_Fj/ln TFP_ij)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exporter*GMM TFP GAP			0.017			0.025**
			(0.054)			(0.008)
Constant	-0.161***	-0.157***	-0.138***	-0.288***	-0.290***	-0.260***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11428	11428	11428	11428	11428	11428
R^2	0.031	0.031	0.032	0.047	0.047	0.048

Note: Standard errors are clustered, and robust (white correction for heteroskedasticity), p-values in parentheses, Significance level: * p < 0.05, ** p < 0.01, *** p < 0.001

The coefficient of technology transfer is 0.067, which means that 1 percent increase in the technology gap corresponds to 6.7% increase in productivity growth rate. For instance, if productivity growth was 2% per annum, this would increase to 2.134% per annum (2 × 1.067=2.134). This also means that it takes less than 8 years to eliminate 50% of the initial gap, regardless their firm specific characteristics, such as manager's capabilities and worker's skills, which are often unobservable factor which could influence on firm's productivity growth. This finding is remarkable and contrast to the previous findings that does not find unconditional convergence in country- and industry- level.

I add additional columns (2) -(6) to show how convergence pattern is changed based on the conditions it included in each column. In column (2) and (3), I have added export variable and the interaction between export and technology distance, which are key variables of this paper. Column (2) and (3), therefore, showing convergence pattern controlling firms' participating in export. The coefficients remain the same in column (2) when including export and slightly decreased in column (3).

Column (4) -(6) are duplication of column (1) -(3) but with including time and industry dummies, but without firm fixed effects. Coefficients of tech distance are increased than those in column (1) -(3), implying that convergence pattern are stronger when controlling industry specific characteristics and time shocks. This pattern of larger coefficients with additional control of industry/time dummies are consistent with the previous cross countries study, which finds that the estimated convergence coefficients decreased when country dummies were excluded (Rodrik, 2012).

Table 7 provides the results for equation 3. The dependent variable is TFP growth. The regressors are previous export status, the log of initial productivity level relative to technology frontier, interaction term of the previous export status and relative productivity. Each regression is run with 2-digit level industry and year dummies, as well as firm fixed effects. Hausman test results are provided in appendix D and show that fixed effect is better estimate than random effect.

Table 7. Results with firm FE effect, with export Dummy

Dep Var=TFP growth	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Lag Exporter	-0.023		-0.043**	-0.203***	-0.202***
	(0.104)		(0.002)	(0.000)	(0.000)
Tech Distance		0.145***	0.145***	0.120***	0.120***
(Lag Ln TFP_Fj/TFP_ij)		(0.000)	(0.000)	(0.000)	(0.000)
Lag Exporter*Tech Distance				0.071***	0.071***
				(0.000)	(0.000)
Lag Innovation Investment					-0.001
					(0.249)
Lag FDI status					-0.014
					(0.572)
Constant	0.150	-0.335	-0.336	-0.253	-0.235
	(0.586)	(0.254)	(0.260)	(0.412)	(0.446)
Observations	11428	11428	11428	11428	11428
R^2	0.013	0.081	0.082	0.088	0.088

Note: With firm fixed effects. Year dummy and industry dummy were included but not reported. Standard errors are clustered at the firm level, and robust (white correction for heteroskedasticity), p-values in parentheses, Significance level: * p < 0.05, ** p < 0.01, *** p < 0.001

Now the coefficients of technology distance in table 7 become larger than those in table 6. Including firm fixed effects would result in upward bias in coefficient, if firm-specific conditions that are correlated with initial productivity, such as managers' characteristics, workers' skill and firms' location, play a role in determining the speed of convergence.

This result is in line with Rodrik (2012) who shows that coefficients of technology transfer increased when country fixed effects were included, and Barro (2012) who explained that growth regressions with country fixed effects could yield upwardly biased estimates of the convergence rate when the time horizon is short, due to the "Nickell bias"[24]. Therefore, the estimated coefficient in the table 7 can be upper bounds of gauging the magnitude of the unconditional convergence rates.

Column (1) shows the role played by exports in determining rates of TFP growth, excluding other terms. The coefficient is statistically insignificant, but becomes negative in other columns when I add technology transfer and other terms. The magnitude of coefficient gets larger when an interaction term between export and technology gap is added. This might be explained by the fact that more productive firms are more likely to be exporters (self-selection into exporting), thereby increasing their productivity slower than those firms that are further behind of the technology frontier.

In fact, exporters have a higher productivity level than non-exporters, which could support the possibility of self-selection into exporting activities.

Table 7-1 shows that exporters have higher TFP level than non-exporter, in average.

Table 7-2 provides regression results of export status (dummy) and export value (intensity) on TFP level, with and without time and industry dummies. Column (1)-(4) are the results using OLS, which show that both export status and export value have

[24] Nickell (1981) shows that the estimate of the coefficient on the lagged dependent variable is biased downwards in the presence of a fixed effect. If there is persistence in the level of the dependent variable, which is underestimated, the estimated convergence rate tends to be overestimated.

significant and positive coefficients on TFP level. Column (5)-(8) show the results using firm fixed effect. The coefficients of export dummy variables become statistically insignificant, however, the coefficients of export value are still statistically significant and positive, although the magnitude become smaller than those with OLS estimation.

The table 7-3 provides the estimation results that duplicated the estimation of table 7-2, but using labour productivity as a dependent variable, instead of using TFP. The magnitude of coefficients for both export dummy and export value become much larger than those with TFP as dependent variable, in column (1)-(4). With firm fixed effect, the coefficients get smaller but still are positive and significant, as seen in column (5) -(8). These results are quite similar to other studies on different countries. For instance, Bernard and Jones (1996) found that exporters show higher productivity level in US manufacturing (3 percent for TFP and 11 percent for value-added per worker). Here I use labour productivity, instead of value added per worker, which has a higher value on the dependent variable and could explain the larger export premium in table 7-3.

Table 7-1. Average TFP level between exporters and non-exporters

	Exporters	Non-exporters
Mean	0.0366	-.0206
(S.D)	(0.702)	(0.665)
Observations	8080	7669

Table 7-2. Regression result of export dummy (value) on TFP level

	OLS				FE			
	(1) without industry and time dummy	(2) with industry and time dummy	(3) without industry and time dummy	(4) with industry and time dummy	(5) without industry and time dummy	(6) with industry and time dummy	(7) without industry and time dummy	(8) with industry and time dummy
Export dummy	0.054*	0.057*			0.009	0.014		
	(0.013)	(0.021)			(0.366)	(0.226)		
Export value			0.006***	0.007***			0.002***	0.003***
			(0.000)	(0.000)			(0.001)	(0.000)
Constant	-0.019	-0.007	-0.042**	0.010	0.004	-0.346***	-0.009	-0.346
	(0.203)	(0.663)	(0.006)	(0.608)	(0.473)	(0.200)	(0.107)	(0.204)
# of obs.	15749	15749	15749	15749	15749	15749	15749	15749
R^2	0.017	0.017	0.020	0.029	0.000	0.015	0.001	0.017
Rho	N/A	N/A	N/A	N/A	0.8034	0.830	0.804	0.829

Note: Standard errors are clustered, and robust (white correction for heteroskedasticity), p-values in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001, overall R2 are reported fixed effects estimation, Rho reports fraction of variance due to u_i. for fixed effect estimates.

Table 7-3. Regression result of export dummy (value) on labour productivity level

	OLS				FE			
	(1) without industry and time dummy	(2) with industry and time dummy	(3) without industry and time dummy	(4) with industry and time dummy	(5) without industry and time dummy	(6) with industry and time dummy	(7) without industry and time dummy	(8) with industry and time dummy
Export dummy	0.308***	0.276***			0.070***	0.055**		
	(0.000)	(0.000)			(0.000)	(0.001)		
Export Value			0.029***	0.028***			0.008***	0.009***
			(0.000)	(0.000)			(0.000)	(0.000)
Constant	9.775***	9.746***	9.710***	9.741***	9.897***	9.862***	9.867***	9.863***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of bs.	16464	16464	16464	16464	16464	16464	16464	16464
R^2	0.332	0.336	0.345	0.349	0.002	0.012	0.007	0.017
Rho	N/A	N/A	N/A	N/A	0.862	0.868	0.862	0.869

Note: Standard errors are clustered, and robust (white correction for heteroskedasticity), p-values in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001, , overall R2 are reported for fixed effects estimation, Rho reports fraction of variance due to u_i for fixed effect estimates

In table 7, the coefficient of technology gap variable is positive and statistically significant, across different specifications from column (1) to (5), indicating that the further away firms are from the technology frontier, the faster they grow.

The estimated technology transfer coefficients are the elasticity of technology gap changes with related to productivity growth rate and are in the range of 12% to 14.5%. This means that 1 percent increase in the technology gap corresponds to 12-14.5% increase in productivity growth. Therefore, the productivity growth was for instance 2% per annum, 1% further away from the technology distance would increase to 2.24-2.29%per annum (2 × 1.145%=2.29%).

This coefficient is almost twice larger than Griffth, Redding and Van Reenen (2004) who provided industry level convergence evidence cross OECD countries. Their coefficient of log technology transfer term on log TFP growth, which is directly comparable with my coefficient of technology transfer, are in the range between 6.7% and 8%. This coefficient is much larger than Rodrik (2012) who provided industry level convergence cross wider group of countries, including developing countries. His coefficient of log initial labour productivity on log labour productivity growth are in the range between 5.4% to 6.0%, which is not directly comparable with my estimated coefficient of technology transfer but still provide a valuable information for the cross check.

The faster convergence pattern in my results comparing to others might be explained by the fact that firms in developing countries like Tunisia are in a lower level of productivity to be start with, therefore, have faster productivity growth than firms in OECD countries in Griffith et al (2004).

Another explanation of the faster convergence pattern in my results comparing to others could be that a lack of firm entry and exit dynamics prevents firm level convergence adding up to aggregated convergence of industry. Industry productivity growth consists of existing firm productivity growth and the set of firm changes (productive firms enter and less productive firm exits), that reallocate resources across firms and industries, and

thereby, enhance aggregated productivity. If firm entry and exit dynamics are below the optimal level, caused by the complex regulatory environment for establishing and closing firms (for instance, difficulties in access to finance or lack of entrepreneurship and complex regulations for closing their business or bankruptcy procedures), the firm level convergence does not add up to aggregated convergence of industry level.

In fact, Chaffai, Plane and Guermazi (2009) compare Tunisian industry level TFP and OECD member countries' TFP, for 6 manufacturing industries for the earlier period than my data analysis. Their results show that the TFP distance between Tunisian TFP and OECD countries have been slightly reduced only in some industries, which also suggest that the convergence rate might not be very high in industry level in Tunisia[25]. This might also support that the firm level convergence often does not add up to of the industry level convergence.

This is similar to Rodrik's explanation on the reason why industry level convergence does not add up to aggregated convergence of a whole economy. Specifically, there is a lack of structural transformation, which implies the production resources used from less productive industry move to more productive industry. His coefficient also gets larger when the level of disaggregation gets larger (from 2 digits to 4 digits), which might strengthen my explanation for higher micro level convergence, but lower aggregated convergence of manufacturing.

The interaction term between exports and technology transfer is to test export's role in technology transfer. As expected, the coefficients of this interaction term are positive and statistically significant at 0.1% level in column (4) and (5). This implies that the

[25] Chaffai, Plane and Guermazi (2009) provide Tunisian industry-level convergence pattern to OECD member countries in six manufacturing sectors from 1983 to 2002, therefore, I can't directly compare the technology transfer coefficients rates with them. In fact, they have not used an empirical model similar to mine nor provide the convergence rates. But they have provided the TFP trends over time for 6 manufacturing industries, together with other countries' industry level TFP level, which demonstrate the trend of the industry level distance to international technology. As mentioned before, the technology gap with other OECD countries has been slightly reduced in the textiles and leather, building and ceramics, and, chemical industries, while the gap has been increased in electronics and metal, and food processing.

further a non-frontier firm lies behind the frontier (the larger gap variable), the greater the potential for technologies to be transferred through exporting and the higher the rates of productivity growth. In addition, while the coefficient of linear export term is negative, as explained above, the linear term of the gap variable remains positive and significant. This supports my explanation on the negative coefficient of exports. While exporters in general do not show faster productivity growth, since they are closer to the technology frontier, those far behind the technology frontier grow even faster when they exporting.

Column (5) reports the results with control variables, lagged innovation input investment amount and lagged FDI status. The result for the exports, gap and interaction terms remains the same.

In sum, the regression results from table 6 and 7 show that there are strong convergence patterns among Tunisian firms. Those firms that have lower TFP levels grow faster. While exporting's effect on productivity growth is negative, the further a non-frontier firm lies behind the frontier (the larger gap variable), the greater the potential for technologies to be transferred through exporting, thus, the higher the rates of productivity growth. This finding also suggests that without considering the convergence and its interaction effect with exports, only looking into exports' effect on productivity would underestimate the learning by exporting effect.

Moderating effects of FDI and innovation

Table 8 provides the baseline specification, regression (3) with the additional interaction terms of FDI and innovation, which might be additional factors that influence export's effect on productivity.

Table 8. Three-way interaction (tech dist. × export × FDI vs. tech dist. × export × innov.)

Dep Var=TFP growth	(1) FE	(2) FE-interaction with FDI	(3) FE-interaction with innov.	(4) FE-both
Lag Exporter	-0.202***	-0.201***	-0.211***	-0.210***
	(0.000)	(0.000)	(0.000)	(0.000)
Tech Distance	0.120***	0.119***	0.120***	0.118***
(Lag Ln TFP_Fj/TFP_ij)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Exporter	0.071***	0.062***	0.091***	0.084***
×Tech Distance	(0.000)	(0.000)	(0.000)	(0.000)
Lag Innovation	-0.001	-0.001	0.002	0.003
	(0.249)	(0.286)	(0.296)	(0.157)
Lag FDI status	-0.014	-0.089*	-0.010	-0.094*
	(0.572)	(0.025)	(0.693)	(0.018)
Lgap exp fdi		0.040**		0.045**
		(0.007)		(0.003)
Lgap exp inno			-0.003**	-0.003**
			(0.006)	(0.002)
Constant	-0.235	-0.178	-0.259	-0.200
	(0.446)	(0.570)	(0.399)	(0.523)
Observations	11428	11428	11428	11428
R^2	0.088	0.090	0.089	0.092
F_f	0.991	0.997	0.991	0.999
rho	0.582	0.598	0.579	0.596

Note: With firm fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), p-values in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i

Column (1) is the baseline specification for the comparison. Column (2) includes the three-way interactions among previous-year FDI status, previous-year export status and previous-year technology gap. As expected, FDI has a positive and significant effect on the relation between export and convergence, which implies that it further facilitates technology spill-over, especially for exporters that are far behind the frontier. Specifically, in column (2), the estimated technology transfer coefficients are 11.9%, implies that 1 percent increase in the technology gap corresponds to 11.9% increase in

productivity growth (If mean productivity growth was, say 2% per annum, this would increase to 2.29%per annum, since 2 × 1.119%=2.24%). But this convergence rate will be 6.2% higher for exporters and it will be additionally 4% higher if the firms also have foreign ownership (FDI). Therefore, those firms that are participating exports and at the same time having foreign ownership will have convergence rate of 22.1% (22.1=11.9+6.2+4), which is almost twice faster than the firms that are non-exporters and non FDI firms.

Column (3) shows the results with a three-way interaction term with innovation. The coefficient of innovation is negative and significant, although the magnitude of coefficient is very small. This might be explained by Aghion (2004) that innovation effect varies depending on the distance from the technology frontier, and the relationship between innovation and productivity shows an inverted U-shape. The negative coefficient of innovation might be caused by the fact that Tunisian firms are behind the technology frontier, and therefore form the left side tail of inverted U-shape.

Robustness checks

Different export variables

The results in Table 7 are consistent when I use different export measures, as shown in Table 9 and Table 10.

Table 9 shows the results when I use previous-year export value, deflated by the output deflator, instead of using a previous-year export status. The results are consistent with the Table 2 where I use previous-year export status. The coefficient of export value shows the association between percentage increase in previous export amount and TFP growth generated. While the absolute magnitude of the coefficient of export and interaction terms is slightly smaller than in the previous table, the direction and statistical significance of coefficients remain the same between both tables.

Table 9. Regression results with firm fixed effects, with export value

Dep Var=TFP growth	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Lag Export Value	-0.002*		-0.004***	-0.014***	-0.014***
	(0.011)		(0.000)	(0.000)	(0.000)
Tech Distance (Lag Ln TFP_Fj/TFP_ij)		0.145***	0.145***	0.121***	0.121***
		(0.000)	(0.000)	(0.000)	(0.000)
Lag Exporter Value ×Tech Distance				0.005***	0.005***
				(0.000)	(0.000)
Lag Innovation					-0.001
					(0.275)
Lag FDI status					-0.012
					(0.611)
Constant	0.139	-0.339	-0.347	-0.277	-0.260
	(0.616)	(0.249)	(0.247)	(0.367)	(0.397)
Observations	11422	11422	11422	11422	11422
R^2	0.013	0.081	0.083	0.089	0.089
F_f	0.853	0.969	0.974	0.996	0.993
rho	0.563	0.567	0.574	0.584	0.584

Note: With firm fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), *p*-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i

Table 10 shows the results when I use current-year export status rather than previous export status. The results are consistent with table 2 with previous-year export status where I assumed that exporting would take time, and therefore, export status would influence TFP during the following year. But if export affects productivity immediately, the current-year export status should be used to assess current-year productivity level and growth. Therefore, I used current-year export status but obtained results consistent with when I used previous-year export status.

Table 10. Regression results firm fixed effects, with current-year export dummy

Dep Var=TFP growth	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Exporter	0.002		-0.003	-0.128***	-0.127***
	(0.891)		(0.847)	(0.000)	(0.001)
Tech Distance (Lag Ln TFP_Fj/TFP_ij)		0.145*** (0.000)	0.145*** (0.000)	0.121*** (0.000)	0.122*** (0.000)
Exporter×Tech Distance				0.054*** (0.000)	0.054*** (0.000)
Lag Innovation Investment					-0.002 (0.189)
Lag FDI status					-0.014 (0.569)
Constant	0.142 (0.604)	-0.339 (0.249)	-0.338 (0.250)	-0.287 (0.340)	-0.267 (0.374)
Observations	11422	11422	11422	11422	11422
R2	0.012	0.081	0.081	0.085	0.085
F_f	0.851	0.969	0.969	0.979	0.977
rho	0.559	0.567	0.567	0.573	0.573

Note: With firm fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), *p*-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, F_f reports F test that all u_i=0 and rho reports that fraction of variance due to u_i

Using different fixed effects to deal with potential collinearity between industry-invariant unobservables and firm-specific characteristics

The results in Table 7 are consistent when I add different fixed effects as below. In Columns (1) and (2), I test the baseline specification, without industry dummies, and find that test results are consistent. In Columns (3) and (4), I provide the baseline specification, wherein both time and industry dummies are included, as well as firm fixed effects (this is the same result as in Table 6). In Columns (5) and (6), in order to capture unobservable potential macroeconomic shocks and industry heterogeneity while keeping firm fixed effects, I use interaction terms of time dummies and industry dummies to prevent collinearity of some of the industry and firm fixed effects. As expected, when I have additional fixed effects, the coefficient of technology gap variable

becomes much larger, at 41.7% and statistically significant. Meanwhile, the coefficients of the exporter and interaction terms are diminished. Overall, the test results are consistent when different fixed effects are used.

Table 11. Fixed effects, with export dummy, plus different time and industry dummies

Dep Var=TFP growth	(1) FE-time dummy	(2) FE-time dummy	(3) FE-time and industry	(4) FE-time and industry	(5) FE-time × industry	(6) FE-time × industry
Lag Exporter	-0.204***	-0.202***	-0.203***	-0.202***	-0.101**	-0.100**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Tech Distance	0.120***	0.120***	0.120***	0.120***	0.417***	0.417***
Lag Ln (TFP_Fj/ TFP_ij)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag Exporter	0.071***	0.072***	0.071***	0.071***	0.037**	0.037**
×Tech Distance	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)
Lag Innovation Investment		-0.002		-0.001		-0.001
		(0.208)		(0.249)		(0.243)
Lag FDI status		-0.015		-0.014		0.004
		(0.531)		(0.572)		(0.864)
Constant	-0.275***	-0.262***	-0.253	-0.235	-1.845***	-1.842***
	(0.000)	(0.000)	(0.412)	(0.446)	(0.000)	(0.000)
Year dummies	Yes	Yes	Yes	Yes	No	No
Industry dummies (2 digit)	No	No	Yes	Yes	No	No
Time * industry dummies	No	No	No	No	Yes	Yes
Observations	11428	11428	11428	11428	11428	11428
R^2	0.080	0.080	0.088	0.088	0.249	0.250
F_f	1.004	1.004	0.994	0.991	1.572	1.566
rho	1.004	1.004	0.994	0.991	1.572	1.566

Note: With firm fixed effects. Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), *p*-values in parentheses, Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, F_f reports F test that all u_i=0. rho reports that fraction of variance due to u_i

Econometric techniques to deal with endogenous export decision –IV and GMM

Table 12 and 13 report the results of estimating the baseline specification with IV and GMM approach, in order to remove to potential endogeneity in the decision to participate in exports and understand the causal effect between exporting and productivity growth.

Since my specification includes the previous productivity level relative to the technology frontier, unobservable related to the firms' previous productivity level are largely removed. However, if export status variable is correlated with unobserved firm characteristics, other than the initial productivity level, that would directly influence future productivity level, thus productivity growth. Therefore, the empirical results using OLS and FE might not provide the casual effect of exporting on firm productivity.

I use external instrumental variables for export variable to deal with simultaneity issue in export variable. Table 12 provides the estimation results using instrument variable, specifically, the second stage regression results using predicted value of export status.

Table 12. Different econometric techniques – IV 2SLS with export dummy

Dep Var=TFP growth	(1) IV2 OLS	(2) IV2 OLS	(3) IV2 Panel	(4) IV2 Panel
Lag Exporter	0.076 (0.196)	0.065 (0.208)	-0.344 (0.535)	-0.272 (0.666)
Tech Distance (Lag Ln TFP_Fj/TFP_ij)	0.051*** (0.000)	0.051*** (0.000)	0.049*** (0.001)	0.049*** (0.001)
Lag Exporter×Tech Distance	0.106*** (0.001)	0.109*** (0.002)	0.299** (0.009)	0.300** (0.010)
Lag Innovation Investment		-0.001 (0.222)		-0.002 (0.053)
Lag FDI status		0.032** (0.001)		-0.017 (0.470)
Constant	-0.323*** (0.000)	-0.318*** (0.000)	-0.348 (0.248)	-0.342 (0.255)
Observations	11422	11422	11422	11422
R^2	0.053	0.054	0.116	0.116
Rho	N/A	N/A	0.598	0.600
Test regression – Coeff. of IV on the second stage residual (equ.10)	-0.008*** (0.000)	-0.008*** (0.000)	0.150*** (0.000)	0.149*** (0.000)
R^2 of the test regression	0.003	0.003	0.064	0.064

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity) and corrected. P-values in parentheses, Significance level: * p < 0.05, ** p < 0.01, *** p < 0.001, R2 is reported but it is not important in 2SLS. * Rho is fraction of variance due to u_i. ** R2 of the test regression is from the OLS of IV on the residual of second stage regression.

Columns (1) -(2) provide the estimation results using OLS and column (3)-(4) provide the results using firm fixed effect. As mentioned before, the instrument used is "the potential world market of firm i that firm i can export to, in addition to their current sales volume (global market demand).

Instrumenting initial export status reduces the estimated coefficient of technology transfer to between 4.9% and 5.1% in Columns (1)-(4). The interaction term between previous export status and technology gap increased significantly for all the specifications using instrument variables, and even more so when I used firm fixed effects, as shown in Columns (3) and (4). Meanwhile, the estimated coefficient of export status become insignificant, by getting rid of the global market demand change factor. The coefficients of FDI remain positive and significant while the coefficients of innovation remain insignificant.

As mentioned above, I conduct two stage (2SLS) model manually with the predicted value of export status and its interaction term with the technology distance. In the empirical strategy section, I provide the first stage regression result and show that the instrument is relevant since it is strongly correlated with export variables - both export status and volume.

In addition, I conduct additional tests to show whether the suggested instrument is valid, in other words, the instrument effects on productivity growth only through export, by showing whether IV2 is correlated with the residual of the second stage regression. I obtain the residual of the primary regression, which is equation (3) and test whether IV has any correlation with this residual. The coefficient of IV on the residual, using OLS with and without innovation and FDI variables, are provided for each columns. In column (1) and (2), the coefficient is statistically significant but almost close to zero and R2 of test regression are close to zero, which ensure that the suggested instrument is not correlated with the residual of the primary instrument (instrument is valid).

I correct standard error with a method provide by Kit Baum (2010), which is using actual value, instead of predicted value, in measuring the residual of second stage regression and using that in estimating the standard errors of coefficients. The corrected standard error is much smaller in OLS regression, in column (1) and (2), which is expected.

However, the results using firm fixed effects, in column (3) and (4), requires careful interpretation. Unlike OLS, standard errors become even larger when they are corrected. Also, the coefficient of instrument and R2 of test regression get larger in test regressions, which might suggest that the suggested instrument could influence the dependent variable, not only through the endogenous variable but also through other channels, when firm specific characteristics are controlled.

Table D.5 in Appendix D provides the second stage regression results with predicted value of export volume using instrument. The results are very similar to table 12.

Additionally, I apply GMM to remove the simultaneity of export decision. Table 13 provide the estimation results using GMM in measuring regression (3).

Specifically, I use dependent variable and export status as their own instruments, by removing them from the regression equation (using the differenced equation with lagged levels as instruments) or by removing them from the instruments (using differences as instrument in a levels regression). I use non-dynamic system GMM with lag 2 and 3. The instrument set for the differenced equation consists of the log of TFP growth, lagged export status, in levels, in periods t−2 and t−3 (among which missing values are treated as 0 and the instruments for each period are collapsed), the gap variable, interaction between the gap and previous-year exports, and year and industries dummies, differenced. The instrument set for the levels equation consists of the log of TFP growth, lagged export status, the gap variable, interaction between the gap and previous-year export, a constant, and year and industry dummies.

Table 13. Different econometric techniques – GMM

Dep Var=TFP growth	(1) GMM	(2) GMM
Lag Exporter	-0.266*	-0.276*
	(0.047)	(0.045)
Tech Distance	0.081***	0.080***
(Lag Ln TFP_Fj/TFP_ij)	(0.000)	(0.000)
Lag Exporter×Tech Transfer	0.094*	0.096*
	(0.033)	(0.031)
Lag Innovation Investment		-0.001
		(0.207)
Lag FDI status		0.029
		(0.116)
Constant	-0.259***	-0.268***
	(0.000)	(0.000)
Observations	11428	11428
R^2	N/A	N/A
AR2 (p-value)	0.034	0.036
Sargan, overid. P-value	0.000	0.000
Diff-in-Hansen P-value	0.965	0.965

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), *p*-values in parentheses, Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, the regression results are consistent with the previous results. The coefficient of lagged exports is negative and significant at the 5% level. The convergence coefficient becomes lower, from to 8.0 to 8.1 percent, but is statistically significant. The coefficients of the interaction terms between export and convergence become marginally larger.

However, the test results require a careful interpretation of GMM result. Test results for the AR2 are somewhat small, rejecting the null hypothesis that the differenced residuals in period t and t-2 are uncorrelated –therefore, autocorrelation in levels might be a concern in this GMM measurement. The Sargan/Hansen test of the over-identifying restrictions for the GMM estimators also rejects the null that instruments are exogenous. This might have been caused by the fact that instrument is exactly identified. A difference-in-Hansen test fails to reject the similar results that these additional instruments are valid.

Different measurement of technology distance

I compare convergence patterns between the highest vs. the top 1% distance, using TFP, and between the domestic vs. the international distance, using labour productivity. Table 14 provides the convergence patterns of the different measures of technology distance, using firm fixed effects.

Table 14. Comparisons of different technology distance - FE, Lag export dummy

Dep Var=TFP growth	(1) Domestic TFP- the highest	(2) Domestic TFP- the highest	(3) Domestic TFP – Top 1%	(4) Domestic TFP – Top 1%	(5) Domestic LP	(6) Domestic LP	(7) Intl LP	(8) Intl LP
Lag Exporter	-0.203***	-0.202***	-0.137***	-0.137***	-0.005	-0.006	0.028	0.028
	(0.000)	(0.000)	(0.001)	(0.001)	(0.868)	(0.822)	(0.243)	(0.250)
Tech Distance (Lag Ln TFP_Fj/TFP_ij)	0.120***	0.120***	0.150***	0.150***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Dom Distance (TUN LP_Fj/LP_ij)					0.108***	0.108***		
					(0.000)	(0.000)		
Int. Distance (FRA LP_Fj/LP_ij)							0.364***	0.364***
							(0.000)	(0.000)
Lag Exporter ×Tech Transfer	0.071***	0.071***	0.046*	0.046*				
	(0.000)	(0.000)	(0.013)	(0.013)				
Lag Exporter× TUN LP GAP					-0.007	-0.007		
					(0.290)	(0.312)		
Lag Exporte× FRA LP GAP							-0.024*	-0.024*
							(0.035)	(0.035)
Lag Innovation		-0.001		-0.001		0.001		0.000
		(0.253)		(0.270)		(0.315)		(0.683)
Lag FDI status		-0.014		-0.002		-0.018		-0.005
		(0.494)		(0.935)		(0.369)		(0.794)
Constant	-0.253	-0.235	-0.236	-0.223	-0.177	-0.179	-0.310	-0.312
	(0.398)	(0.433)	(0.685)	(0.702)	(0.565)	(0.559)	(0.288)	(0.286)
Observations	11428	11428	9564	9564	11428	11428	11428	11428
R^{2*}	0.088	0.088	0.094	0.094	0.045	0.045	0.132	0.132
rho	0.581	0.582	0.703	0.704	0.578	0.579	0.657	0.656

Note: With firm fixed effect. Year and industry dummies were included but not reported. Standard errors are clustered and robust (white correction for heteroskedasticity). p-values in parentheses * p < 0.05, ** p <0.01, *** p <0.001. R2* reports within group. rho reports that fraction of variance due to u_i

For the comparison, the estimation results from the initially identified technology distance measures are provided in column (1) and (2), which is the same as columns (4) and (5) in Table 6. The results using the new distance measure, which is used 1% TFP firm in Tunisia in column (3) and column (4).

The direction and statistical significances of coefficients are consistent between the initially identified technology distance measure (distance-the highest) and newly identified measure (top 1%). With top 1% distance, the coefficient of tech distance gets slightly larger, and the coefficient of interaction term of tech distance and exports become smaller, possibly because of the slightly lower level of frontier and/or the reduced number of observations with new measure. However, direction and statistical significance of the coefficient of export and tech distance are consistent between column (1)-(2) and column (3)-(4).

Also, the comparison between domestic and international distance, using labor productivity, are provided in columns (4)-(8). The test results are similar between when using domestic distance and international distance, except for the interaction term are in significant for domestic frontier, but become negative for international frontier.

The results of table 14 further supports that there is a strong convergence pattern, regardless which technology distance measure are used. This finding is remarkable since those new distance measures provide smaller magnitude in distance than the initially used distance term (the highest distance and domestic LP are larger than top 1% and international LP distance, in average). However, the export's effect on productivity growth and its interaction effects on technology distance varies depending on which specification are used. The exporter's synergy with technology distance seem to be generated only when the distance is larger. This might imply that when technology distance is smaller, the technology distance's effect on productivity become more important than that of export.

In my view, which frontier I choose (international vs domestic) might not really matter because it would not necessarily identify the sources of learning when firms have exposure to external markets and technology. Let's take the mobile phone industry as an example. When iPhones were first introduced into the market, Tunisian mobile phone manufacturer would learn from this new product (from technical questions such as LCD technology to less technical ones such as design), even if it was difficult for them to make an equally sophisticated product. If this Tunisian manufacturer exported some parts to Apple (global frontier) or received direct investment from Apple, they would learn more rapidly.

If a highly productive Tunisian phone manufacturer (domestic frontier) develops a Tunisian smartphone, it would be easier for other manufacturers (follower firms) to learn from the domestic frontier than the international frontier because they have a better knowledge of suppliers, workers, distributors and consumers domestically than abroad.

Meanwhile, if both the iPhone and the Tunisian smartphone are introduced into the market, the follower firms would learn from both, while the domestic frontier would learn from Apple (assuming the iPhone is more technologically advanced than the Tunisian smartphone). Therefore, which frontier I choose would not necessarily identify the sources of learning when all firms have exposure to global technology. What really matters is whether the follower firms grow faster than those close to the frontier.

Table D.9 and D.10 in appendix D provides the above results of Table 14 but using different econometric techniques, such as OLS and GMM. The results across different distance measures are consistent with the results using OLS methods and similar to the results using GMM, which ensure the estimation results of above tables.

7. Conclusions

The previous convergence literature is mostly cross-country analysis using industry-level data, and firm-level study in convergence literature is rare. A few existing firm-level convergence evidences is mostly from the OECD countries, and evidence from developing countries is particularly rare. Also, while previous convergence studies mostly examine whether there is convergence or not, they typically do not indicate what leads to the convergence, and specifically, what might potentially contribute technology spill-over from more advanced economies to less advanced countries.

In this paper, I link the learning by exporting (LBE) literature to the convergence literature by analysing its relation to technology transfer. I present an empirical framework in which technology transfer and exports provide two sources of productivity growth for a firm behind the technological frontier and test whether there is convergence among Tunisian firms. Using this framework, I evaluate the role of technology transfer and exports in explaining productivity growth at the firm level, for a large sample covering more than 11,400 firms, in Tunisia from 1997 to 2007. To my knowledge, this is one of the first papers to examine the role of exporting as a driver of productivity convergence.

My results show that there is strong evidence of beta (β) convergence at the firm-level, unconditionally and conditionally, which implies less productive firms tend to grow their productivity faster than more productive firms. The estimated technology transfers coefficients, without firm fixed effects and other controls (unconditional convergence) is around 6.7%, which implies that it takes less than 8 years for follower firms to eliminate 50% of the initial technology gap, regardless of firm-specific characteristics.

This convergence rate increases to above 12%, when including firm fixed effects and other controls (conditional convergence), which are twice larger than Griffth, Redding and Van Reenen (2004), who used similar technology transfer term to my specification

but with industry level data, and much larger than Chaffai, Plane and Guermazi (2009) who used Tunisian industries comparing to OECD countries' industries but with not directly comparable specification from mine. The faster convergence pattern in my results comparing to others could be that a lack of firm entry and exit dynamics prevents firm level convergence adding up to aggregated convergence of industry and/or Tunisian firms are further behind from technology frontier than firms in developed countries, thus, show faster convergence. Any case, my result confirms that technology distance is a significant factor explaining the productivity growth of firms.

In addition, my results reveal that exporters' higher productivity growth than non-exporters is explained by self-selection, but not because of learning by exporting. This finding contributes to the on-going debate in the trade and development economics literatures on whether "self-select" into export markets, or "learning by exporting". Moreover, the framework I suggest allows testing exports' effect on productivity growth while controlling for firms' initial productivity level, relative to the technology frontier, which indirectly controls the potential selection issue of more productive firm becoming exporters, in testing learning by exporting effects. My results reveal that without controlling initial productivity level, LBE effects will be underestimated.

Lastly, my results document that exports play a significant role in determining productivity convergence thus growth. The further away from the frontier, the greater the potential for technologies to be transferred through exporting, thus the higher the rates of productivity growth. The coefficient of interaction terms between exports and technology transfer are positive and statistically significant, implying that while exporters in general do not show faster productivity growth since they are closer to the technology frontier, those far behind the technology frontier grow even faster when they exporting. This finding of that less productivity firms will further benefit from exporting could be reflected in export promotion policies in Tunisia.

Remarkably, the results are robust to different specifications and econometric techniques applied in order to avoid potential measurement error in export variables,

collinearity between industry-invariant unobservable and firm-specific characteristics, endogenous export decisions, and the different definition of the technology frontier.

This finding has important policy implications and suggests further research agendas. If the lack of firm entry and exit dynamics prevents firm-level convergence adding up to aggregated convergence of industry, policy should tackle the specific barriers for firm entry and exit. Also, research on identifying barriers that prevent micro-level convergence from adding up to aggregated convergence would be very informative. Meanwhile, for Tunisian manufacturing firms, export promotion will facilitate the less productive firms' catching up with more productive ones over time; thus, promoting private sector growth. Promoting FDI will facilitate this catch-up process, but policies that promote innovation, such as subsidies on R&D investment, will not.

References

Acemoglu, D. 2009. *Introduction to modern economic growth*. MIT press.

Acemoglu, D., and Zilbotti, F. 1999. "Productivity differences" National Bureau of Economic Research. Working Paper No. 6879.

Aghion, P., and P. Howitt. 2006. "Joseph Schumpeter Lecture. Appropriate Growth Policy: A Unifying Framework". *Journal of the European Economic Association*, 4(2-3): 269-314.

Aghion, P., Akcigit, U. and P. Howitt. 2013. "What do we learn from Schumpeterian Growth Theory?" NBER Working Paper series. Working Paper No. 18824.

Aigner, D., Lovell, C. K., and P. Schmidt. 977. "Formulation and estimation of stochastic frontier production function models" *Journal of Econometrics*, *6*(1): 21-37.

Angrist, J. D., and Pischke, J. S. 2009. *Mostly harmless econometrics: An empiricist's companion.* Princeton University Press.

Aw, B., Roberts, M., and D. Xu. 2011. "Rand Investment, Exporting, and Productivity Dynamics." American Economic Review, 101(4): 1312-44.

Baldwin, J. R., and W. Gu, 2004. "Trade liberalization: Export-market participation, productivity growth, and innovation." *Oxford Review of Economic Policy*, 20(3): 372-392.

Barro, R. J., and X. Sala-i-Martin. 1990. "Economic growth and convergence across the United States." *National Bureau of Economic Research*. Working Paper No. 3419.

Bartelsman, E. J., Haskel, J., and R. Martin. 2008. "Distance to Which Frontier? Evidence on Productivity Convergence from International Firm-level Data." *Centre for Economic Policy Research.*

Bernard, A. B., and C. I. Jones. 1996. "Comparing apples to oranges: productivity convergence and measurement across industries and countries." *The American Economic Review*: 1216-1238.

Bernard, A. B., & J. B. Jensen, 1999. "Exceptional exporter performance: cause, effect, or both?" *Journal of international economics*." 47(1): 1-25.

Bernard, A. B., and, J. B. Jensen. 2004. “Why some firms export” *Review of Economics and Statistics*, 86(2): 561-569.

Bernard, A. B., Jensen, J. B. Redding, S. J., and P. K., Schott. 2011. “The empirics of firm heterogeneity and international trade.” *National Bureau of Economic Research* No. 17627.

Bijsterbosch, M., and, M., Kolasa. 2010. “FDI and productivity convergence in Central and Eastern Europe: an industry-level investigation.” *Review of World Economics*, 145(4): 689-712.

Bloom, N, and J. Van Reenen. 2011. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *National Bureau of Economic Research* Working Paper No. 16717.

Blundell, R.W., and S. R. Bond. 1998. “Initial conditions and moment restrictions in dynamic panel data models.” *Journal of Econometrics* 87: 115– 143.

Blundell, Richard and S. R. Bond. 2000. “GMM Estimation with Persistent Panel Data: An Application to Production Functions.” *Econometric Reviews*, 19(3): 321-40.

Brynjolfsson, E. and L Hitt. 2003. “Computing Productivity: Firm-Level Evidence.” *Review of Economics and Statistics*, 85(4): 793-808

Bustos, P. (2011). "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms." *American Economic Review* 101(1): 304-340.

Cameron, G., Proudman, J., and S., Redding. 2005. “Technological Convergence, R&D, Trade and Productivity Growth.” *European Economic Review*, 49(3): 775-807.

Castellani, D. 2002. “Export behavior and productivity growth: Evidence from Italian Manufacturing Firms.” *Review of World Economics*, 138(4): 605-628.

Clerides, S.K., Lach, S., and J.R. Tybout. 1998. “Is learning by exporting important? Micro-dynamic evidence from Colombia, Mexico, and Morocco.” *Quarterly Journal of Economics,* 113(3): 903–947.

Coe, D. T., and E. Helpman. 1995. “International R&D Spillovers.” *European Economic Review*, *39*(5): 859-887.

Cohen, W. M., and D. A., Levinthal. 1990. "Absorptive capacity: a new perspective on learning and innovation." *Administrative Science Quarterly*, 35(1) 128-152.

Damijan, J. P., Knell, M., Majcen, B., and M. Rojec. 2003. "The role of FDI, R&D accumulation and trade in transferring technology to transition countries: evidence from firm panel data for eight transition countries." *Economic Systems*, 27(2): 189-204.

J., De Loecker. 2007, "Do exports generate higher productivity? Evidence from Slovenia." *Journal of International Economics,* 73: 69-98.

J., De Loecker. 2013. "Detecting learning by exporting" *American Economic Journal: Microeconomics*, 5(3): 1-21.

Delgado, M.A., Farinas, J.C. and S. Ruano. 2002. "Firm productivity and export markets: a non-parametric approach." *Journal of International Economics* 57: 397– 422.

Du, L., Harrison, A. and G. Jefferson. 2011. "Do institutions matter for FDI spill overs? The implications of china's Special Characteristics." *NBER Working Paper* No 16767

El Arbi Chaffai, M., Plane, P., and D. T. Guermazi. 2009. "TFP in Tunisian Manufacturing Sectors: Convergence or Catch-up with OECD Members?" *Middle East Development Journal*, *1*(01): 123-144.

Fafchamps, M., El Hamine, S., and A. Zeufack. 2008. "Learning to export: Evidence from Moroccan manufacturing." *Journal of African Economies*, *17*(2): 305-355.

Fernandes, A. M. 2009. "Structure and performance of the service sector in transition economies." *Journal of International Economics* 71(1): 52-71

Foster, L., Haltiwanger, J., and C. Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability*?" American Economic Review* 98 (1): 394–425.

Frankel, J. A., and D. Romer. 1999. "Does trade cause growth?" *American Economic Review*, Jun 1: 379-399.

Fu, M., Fu, X. and T. Li .2008. "International and Intra-National Technology Spillovers and Technology Development Paths in Developing Countries: The Case of China." *UNU-WIDER Research Paper* No. 2008/96

Fu, X., Pietrobelli, C. and L. Soete 2010, "The role of foreign technology and indigenous innovation in emerging economies: technological change and catching up." *IADB, Technical Notes* No. IDB-TN-166

Fu, X. 2012. "How does openness affect the importance of incentives for innovation?" *Research Policy*, 41: 512-523

Fu, X., Helmers, B. and C. Zhang. 2012. "The two faces of foreign management capabilities – FDI and productive efficiency in the UK retail sector" *International Business Review* 21 71–88

Fu, X., Pietrobelli, C., and L. Soete. 2011. "The role of foreign technology and indigenous innovation in the emerging economies: Technological change and catching-up." *World development*, 39(7): 1204-1212.

Girma, S. 2005 "Absorptive capacity and productivity spillovers from FDI: A threshold regression analysis." *Oxford bulletin of Economics and Statistics*, 67(3): 281-306.

Girma, S., Greenaway, A., and R. Kneller. 2004. "Does exporting increase productivity? A micro econometric analysis of matched firms." *Review of International Economics*, 12(5): 855-866.

Girma, S., and R. Kneller. 2005. "Convergence in the UK service sector: firm level evidence, 1988–1998." *Scottish Journal of Political Economy*, 52(5): 736-746.

Görg, H., and D. Greenaway. 2004. "Much ado about nothing? Do domestic firms really benefit from foreign direct investment?" *The World Bank Research Observer*, 19(2): 171-197.

Goldberg, P. K., and N. Pavcnik. 2007. "Distributional effects of globalization in developing countries." *National Bureau of Economic Research,* Working Paper No. 12885.

Griffith, R., Redding, S., and J. Van Reenen. 2004. "Mapping the two faces of R&D: productivity growth in a panel of OECD industries." *Review of Economics and Statistics*, 86(4): 883-895.

Guetat, I., and F. Serranito. 2007. "Income convergence within the MENA countries: A panel unit root approach." *The Quarterly Review of Economics and Finance*, 46(5): 685-706.

Hall, R. E., and C. Jones. 1999. "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *The Quarterly Journal of Economics*, 114(1): 83-116.

Helpman, E, Melitz, M. and S. Yeaple. 2003. "Export versus FDI." *National Bureau of Economic Research,* Working Paper No. 9439.

Havik. K., Mc Morrow. K., Röger, W. and A. Turrini. 2008. "The EU-US total factor productivity gap: An industry perspective." *European Commission Directorate General Economic and Financial Affairs (DG ECFIN) Papers*. 339.

Howitt, P. 2000. "Endogenous growth and cross-country income differences." *American Economic Review* Sep 1: 829-846.

Hsieh, C. and P. Klenow 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124(4): 1403–48.

Iacovone L, Ferdinand R, and A. Winters. 2013. "Trade as an engine of creative destruction: Mexican experience with Chinese competition." *Journal of International Economics* 89(2): 379-392.

Inklaar, R. and M. Timmer. 2009. "Productivity convergence across industries and countries: the importance of theory-based measurement." *Macroeconomic Dynamics*, 13(S2): 218-240.

Javorcik, B. S. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages." *The American Economic Review* 94(3): 605-627.

Javorcik, B. S. and G. Narciso. 2008. "Differentiated products and evasion of import tariffs." *Journal of International Economics,* 76(2): 208-222.

Javorcik, B. S. and M. Spatareanu. 2011. "Does it matter where you come from? Vertical spillovers from foreign direct investment and the origin of investors." *Journal of Development Economics,* 96(1): 126-138.

Keller, W. 2004. "International technology diffusion." *Journal of Economic Literature*, 42(3), 752-782.

Kimura, F., and K. Kiyota. 2006. "Exports, FDI, and productivity: Dynamic evidence from Japanese firms." *Review of World Economics*, 142(4): 695-719.

Levinsohn, J. and A. Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies*, 70(2): 317-41.

Lileeva, A. and D. Trefler. 2010. "Improved Access to Foreign Markets Raises Plant-level Productivity." *The Quarterly Journal of Economics,* 125(3): 1051-1099.

Mankiw, N. G., Romer, D., and D. N. Weil. 1992. "A contribution to the empirics of economic growth." *National Bureau of Economic Research,* Working Paper No. 3541

Marel, E. 2010. "What Determines Services TFP Growth: Services Trade or Services-Trade Regulation?" Sciences Po Paris. Mimeo.

Mc Morrow, K., Röger, W., and A. Turrini. 2010. "Determinants of TFP growth: A close look at industries driving the EU–US TFP gap". *Structural Change and Economic Dynamics*, 21(3): 165-180.

Melitz, M. J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica,* 71(6): 1695-1725

Melitz, M. J., and G. I. Ottaviano. 2008. "Market Size, Trade, and Productivity." *The review of Economic Studies*, 75(1), 295-316.

Meyer, K. E., and E. Sinani. 2009. "When and Where Does Foreign Direct Investment Generate Positive Spill Overs and Quest; A meta-analysis." *Journal of International Business Studies,* 40(7): 1075-1094.

Nickell, S. 1981. "Biases in dynamic models with fixed effects." *Econometrica: Journal of the Econometric Society*, 49 (6), 1417-1426.

Nishimura, K. G., Nakajima, T., and K. Kiyota. 2005. "Innovation versus Diffusion: Determinants of Productivity Growth Among Japanese Firms." *CIRJE Discussion Paper Series.*

Olley, G.S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6): 1263–1297.

Park, A., Yang, D., Shi, X., and Y. Jiang. 2010. "Exporting and firm performance: Chinese exporters and the Asian financial crisis." *The Review of Economics and Statistics*, 92(4): 822-842.

Rodrik, D. 2012. "Unconditional Convergence in Manufacturing". *The Quarterly Journal of Economics*, 128 (1): 165-204.

Sabirianova, K., Svejnar, J. and K. Terrell. 2005. "Distance to the Efficiency Frontier and Foreign Direct Investment Spillovers." *Journal of the European Economic Association*, 3(2-3), 576-586.

Sala-i-Martin. 1996. "The Classical Approach to Convergence Analysis." *The Economic Journal*: 106 (437), 1019-1036.

Schott, P. K. 2004. "Across-Product Versus Within-Product Specialization in International Trade." *The Quarterly Journal of Economics,* 119(2), 647-678.

Smeets, R. 2008. "Collecting the pieces of the FDI knowledge spillovers puzzle". *The World Bank Research Observer*, 23(2): 107-138.

Staiger, D. and J. H. Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica*, 65: 557 – 586.

Stock, J. H., and M. Yogo. 2005. "Testing for weak instruments in linear IV regression. Identification and inference for econometric models: Essays in honor of Thomas Rothenberg." *National Bureau of Economic Research,* Working Paper No. 284

Van Ark, B., O'Mahony, M., and M. P. Timmer. 2008. "The productivity gap between europe and the United States: trends and causes." *The Journal of Economic Perspectives*: 22(1), 25-44.

Van Beveren. 2012. "Total Factor Productivity Estimation: A Practical Review." *Journal of Economic Surveys*, 26(1): 98–128.

Verhoogen, E. A. 2007. "Trade, quality upgrading and wage inequality in the Mexican manufacturing sector." *IZA Discussion Papers* No. 2913.

Wei, Y., and X. Liu. 2006. "Productivity spillovers from R&D, exports and FDI in China's manufacturing sector." *Journal of International Business Studies*, 37(4): 544-557.

Wooldridge, J. M. 2010. *Econometric Analysis of Cross-section and Panel Data.* MIT press, Cambridge, MA.

Yeaple, S. R. 2005. "A simple model of firm heterogeneity, international trade, and wages." *Journal of international Economics*, 65(1): 1-20.

Appendix A. Empirical evidence on productivity convergence

Table A.1. Summary of some of the empirical evidence on convergence

Convergence level	Main topic	Findings	Methods/ empirical specification	Data	Authors
Country level	Evidence of convergence	• Evidence of convergence among the US states and across countries, controlling other factors, which is in contrast to the previous findings on negative convergence rate across countries. • Their finding fits the neoclassical growth model with broadly-defined capital and a limited role for diminishing returns, and endogenous growth models with constant returns and gradual diffusion of technology across economies. • They also find that states in which income originates predominantly in sectors that do well at the national level tend to have higher per capita growth rates; i.e., the convergence effect shows up most strongly for manufacturing, but significant effects show up also for six other sectors: construction, mining, services, transportation, wholesale and retail trade, and finance—insurance—real estate. Countries that produce agriculture have a lower income/convergence rate.	Beta convergence in the neoclassical growth model	Growth of per capita income and product for the 48 U.S. states, 1840-1963 and 98 countries from 1960 to 1985 for 98 countries	Barro and Martin (1990)
	Human capital	• High-skilled human capital has a positive effect on TFP growth, an effect which is stronger the closer a country is to the technology frontier.	The growth rate of a country is a function of the log of the proximity to the frontier of the previous year, variable of interests, and previous year human capital and their interaction term	A panel of OECD countries	Vandenbussche, Aghion and Méghir (2006)
Industry level	The role of sectors in aggregate convergence How to compare productivity levels across countries	• Manufacturing shows little evidence of either labour productivity or multifactor productivity convergence, while other sectors, especially services, are driving the aggregate convergence result. • That productivity and output per capita differences have narrowed over time. However, the degree of catch-up is less for TFP, suggesting that capital accumulation is playing role in the convergence of labour productivity. • The paper introduces a new measure of multifactor productivity (TTP) to avoid problems with traditional measures of TFP (coefficient of factor inputs do not vary across industries) but their finding using TTP is similar to that with TFP.	Productivity growth is a foundation of the initial productivity level, $\Delta \ln(TFPi) = a + b \ln(TFP,i\ 1970) + e\ i$ (also, used labour productivity) $\Delta \ln(MFPi,t) = \Delta \ln Y\ it - a\ it\ \Delta\ lnLit - (1 - a\ it)\ \Delta\ \ln Ki$, where $ai,t= 0.5(ai,t + ai,t-1)$ and ait is the labour share of value-added in country-sector i.	14 OECD countries during 1970-1987.	Bernard and Jones (1996)

	Catching-up process, the interaction between productivity changes and capital intensity	• Contrary to the manufacturing sector and in spite of very low growth rates, productivity levels converge in services. Moreover, new investments in capital appear to exert an unexpected depressive effect on total factor productivity growth in service activities, while having a positive influence in manufacturing industries.		Service and manufacturing industries, 13 OECD countries, 1970–1987,	**constrast to Barro and Martin, and Rodrik
	Unconditional convergence in manufacturing industries	• The coefficient of unconditional convergence ("beta" convergence) is large, at between 2-3 percent in most specifications. • The paper also finds sigma-convergence at the 2-digit level for a smaller sample of countries. • Despite strong convergence within manufacturing, aggregate convergence fails due to the small share of manufacturing employment in low income countries and the slow pace of industrialization.	"Beta" convergence: regress the growth of labour productivity in nominal USD on the initial level of labour productivity, a set of industry * time, country FE (or dummies in another specification). A test of unconditional convergence consists of dropping these country dummies and checking whether the estimated coefficient -β remains negative and statistically significant.	More than 100 countries over recent decade, UNIDO INDSTAT 2 and T4	Rodrik (2012)
	Entry liberalisation and privatisation	• Entry liberalisation and privatisation have a positive impact on TFP. • Moreover, this impact appears to be stronger the further away are countries from the technology frontier. • (The interpretation is that entry regulation and public ownership prevents the adoption of existing up-to-date technologies, so that the impact is greater away from the frontier, where TFP growth is more strongly based on adoption rather than on innovation.)	MFP growth equation augmented to account for the impact of product market regulation. Assuming that each industry's MFP growth depends on country and industry characteristics and the state of knowledge in the technology leader country (the highest level of MFP). In particular, an MFP advance in the frontier country is assumed to produce faster MFP growth in follower countries, due to a widening of the production possibility set, with the size of this impact assumed to be increasing with each country's distance from the technological leader. Δ ln MFP =δ (Δ ln MFP Leader) −σ (Technology gap) +β Human capital, plus an error term and dummies that control for country-, industry- and time-specific factors. δ indicates the standard pace of technological transfer from the leader, σ quantifies the importance of the technological transfer that depends on the size of the technology gap, and β shows how the level of human capital affects the pace of technical progress.	TFP growth in 18 OECD economies	Nicoletti and Scarpetta, 2003) * This result contrasts with the findings in Aghion, Bloom, Blundell, Griffith and Howitt (2003)
	R&D and absorptive capacity	• R&D has both a direct impact on TFP growth and a role in facilitating the cross-country convergence of TFP levels. • The result is interpreted as providing support for the two "faces" of R&D in promoting	Δ ln Aijt = δ 1 ln(AF/Ai)j t_1 + δ2[(Ri/Yi) ln(AF/Ai)]j t_1 + ρ(Ri/Yi) j t_1 + γXi j t_1 + ψij + T t + εijt	12 OECD countries, 2-3 digit industry level on value added,	Griffith, Redding and Van Reenen (2004)

		productivity growth: on the one hand, R&D enhances a firm's innovative potential (thus increasing directly the rate of TFP growth); on the other hand, it improves the absorptive capacity of firms and industries, thus facilitating the adoption of existing technologies and spurring TFP convergence.		labour, capital stocks, and combined other sources of data for R&D expenditure, skill and trade	
	The effect of FDI inflows on productivity convergence	• A strong convergence effect in productivity, both at the country and at the industry level • FDI inflow plays an important role in accounting for productivity growth • The impact of FDI on productivity depends on the absorptive capacity of recipient countries and industries • Heterogeneity across countries, industries and time with respect to some of the main findings		Central and Eastern Europe	Bijsterbosch and Kolasa (2010)
	The determinants of the EU–US TFP growth gap, R&D, ICT and human capital	• TFP growth appears to be driven by catching-up phenomena associated with the gradual adoption of new technologies. • TFP growth is also significantly driven by developments at the "technological frontier", especially since the mid-1990s. • Industries with higher R&D expenditures and higher adoption for ICT-intensive technologies appear to exhibit higher TFP growth rates.	TFP growth is a function of TFP growth at the frontier and TFP growth at the frontier ΔTFPi,j,t = a+b 1ΔTFPL,j,t+ b 2[log(TFPi,j,t−1) − log(TFPL,j,t−1)] +M1Di + M2Dj + M3Dt + εi,j, (1) Measuring TFP is from, Δln AVjt = Δln Vjt − wKjtΔln Kjt − wLjtΔln Ljt whilst ¯ wjt is the two-period average share of the input in nominal value added)	10 countries (9 EU countries plus the US) and 28 industries over the 1980–2004 period, EU KLEMS	Mc Morrow, Röger and Turrini (2010)
	Reallocation efficiency accounts for the growth of industry-level productivity	• Industry productivity growth = existing firm productivity growth + the set of firm changes (productive firms enter and less productive firms exit). • The productivity differential between entering and exiting firms account for as much as one-half of industry improvement in some industries and time periods		Taiwanese manufacturing sector	Chen et al, (2001)
Firm-level	Technological frontier and market competition and for innovation.	• When firms are close to the national technological frontier that product market competition has a stronger positive impact for innovation. • This conclusion can be explained by the observation that being far from the frontier reduced the incentives to innovate by reducing innovators' rents more strongly.	Yij t = α + βEjt + ηi + τt + εij t	UK firms at the US patenting office, Incumbent UK manufacturing establishments, 4-digit, 1980–93	Aghion, Bloom, Blundell, Griffith and Howitt (2003), Howitt and Prantl (2006)
	Summary of different literature	• Important interaction effects between policies and state variables, such as distance to	The extended model typically has LHS as gross output or TFP growth and RHS include the distance from technological frontier and its		Aghion and Howitt (2006)

	using extended Schumpeterian framework	frontier or financial development, in growth regressions	interaction term with the variable of interest		
	Export/FDI and productivity	• In their paper which examines the relationship between exports, foreign direct investment, and firm productivity, they also found that exports and foreign direct investment appear to improve firm productivity once the productivity convergence effect is controlled for.	%Δθit = ln θit − ln θit−1 = α + βYit−1 + γChar.sit−1 + εit. In the above regression, they also added the initial TFP level (as variable of convergence) as Japanese firms control variable of convergence, and found a significant negative coefficient		Kimura and Kiyota (2006)
	Analysing convergence while considering firm entry/exit effects (selection)	• Convergence rates is much faster among firms (within a country) than cross-country • Without considering the selection, 1.5 percent point downward bias in the speed of convergence. • Productivity convergence, not only in manufacturing but also in non-manufacturing, but substantial differences among industries in the convergence speed (e.g., higher technology (IT) industries show faster convergence rate, faster convergence either in growing or slowing down industries – probably because of the leading firm's productivity collapse)	TFP is function of catch- up variable (distance to frontier, previous year) and the productivity of previous year, This is re-written as relative productivity (Tit/Tft) is a function of relative productivity of the previous year. Then, the selection equation captures the effects of exiting decisions of exiting firms (size, age, and ownership type and productivity, etc) using ML function of the sample selection model. TFP is measured as multilateral index method 26	Japan, both manufacturing industries and non-manufacturing firms	Nishimura, Nakajima and Kiyota (2005)
	Distance to which frontier?	• The national frontier exerts a stronger pull on domestic firms than does the global frontier • The pull from the global frontier falls with technological distance, while the pull from the national frontier does not => firms far behind the technology frontier might not be able to learn from the global frontier but still benefit from domestic knowledge	Labour productivity (average value added per worker in manufacturing)	UK firms (and other countries as frontiers)	Bartelsman, Haskel and Martin (2008)

[26] Multilateral index method is based on a hypothetical firm that has the arithmetic mean values of log output, log input, and therefore, whether exporting firms gain a productivity increase is an on-going debate in the trade and development economics literatures. Each firm's output and inputs are measured relative to this hypothetical firm.

Appendix B. TFP estimation and variables

At the firm-level, TFP is also typically estimated based on a Cobb-Douglas production function, which is an output as a function of the inputs the firm employs and its productivity[27]. Therefore, the measure of TFP obtained is the residual in this functional relationship.

The empirical specification can be written as follow:

$$\ln Y_{ijt} = A_{ijt} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \delta_t + \delta_i + \xi_{ijt}$$

- Y_{ijt} : The real output of firm i operating in sector j at time t, which is calculated by the sales revenue deflated by sub-industry level deflators from the Producer Price Index.
- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by capital price index, from the National Account.
- L_{ijt} : Number of employees
- M_{ijt} : The value of material inputs adjusted for changes in material inventories, deflated by deflators constructed based on input-output tables.
- A_{ijt}: The Hicks neutral efficiency level of firm (TFP of firm) measured as the residual of the model/stochastic error term.
- δ_t : Time dummies for 1997-2007
- δ_i : Firm fixed effect
- ξ_{ijt}: Idiosyncratic error which vary across individual firms.

Output is typically measured as deflated sales or value added. For the LHS, I use gross output (sales revenue) for manufacturing and service industries. I have also considered Value Added in the LHS. While it is unclear whether value added is a better LHS variable

[27] Cobb Douglas is a restrictive production function because elasticity of substitution between all factors is always 1 (can't reflect the fact that inputs are either complements or substituting each other). This can be addressed by estimating nonlinear production functions, such as the translog function.

than sales revenue[28], in my opinion, value added might be a preferred variable in this cross industry analysis, because when value added is LHS variable, intermediate inputs ($\ln M_{ijt}$) are no longer required in my RHS (the value added is the revenue minus the materials and indirect costs). Because the way intermediate inputs works might be different across sectors (e.g. between manufacturing and services), not including intermediary inputs in the RHS variables could reduce the potential bias coming from the different ways of measuring intermediate inputs across sectors. However, in the INS data set, there are many missing variables in value added variables, so the number of observations significantly diminished by using value added. Therefore, I use revenue as the dependent variable for the entire analysis, but provide comparison of the estimates measured with value added.

The methodological issues estimating firm-level TFP and solutions to overcome

The productivity estimate using ordinary least squares (OLS) could lead to multiple biases, including simultaneity, omitted prices and omitted variables. Here I summarize some of the issues.

Simultaneity bias (endogenous input selection): If firm has knowledge of their expected productivity, they would choose inputs based on this knowledge, thus there might be correlation between inputs and unobserved productivity shocks, which will result in upward bias in the estimated coefficient.

Econometric techniques, such as parametric 2SLS and GMM, can control endogenous input choice, and therefore overcome the simultaneity bias. I follow the existing literature on using a standard production function approach with different econometric techniques, such as FE and GMM, in addition to OLS. When panel data are available, using a firm fixed effect method can solve an omitted variable bias problem from time-invariant unobservable (e.g. work culture, etc.). For time-variant unobservable (e.g. time

[28] Teal and Soderbom (2005) reported that TFP measurements using value added can generate potential bias, while Brynjolfsson and Hitt (2003) reported that they have the advantage of reducing the potential endogeneity of firm's decision to purchase materials, the input most likely to undergo rapid adjustment to output shocks.

trends), time dummies can be added in the RHS. In addition, dynamic equations can be estimated, by adding lagged dependent variables in the RHS. Also, GMM can be used to avoid the simultaneity bias that can be raised in exporting decision and endogenous input choice, as well as other omitted variable bias in TFP estimation.[29]

Omitted price bias: TFP is a productivity measure, conceptually based on inputs quantity vs. output quantity. However, most firm-level data do not include information on quantity or firm-level price. If firm-level price variation is correlated with input choice, this will still result in biased input coefficients.

The INS data contain quantity or price information specific to products, but most of the observations are reported as missing value. In the absence of information on prices, the output and inputs variables are value terms, but not quantity terms. To deal with the data limitation, I use industry specific deflators for the value of the outputs (revenue) and inputs (capital and intermediary inputs) to deal with the omitted price bias. In addition, I estimate production functions for each sector, in order to allow the coefficient inputs to vary across sectors.[30]

The deflated values are used as proxies for their quantities. (e.g. industry-level price indices are usually applied to deflate firm-level sales and input expenditures in production function estimates). The output and intermediary input deflators are constructed from the INS's Producer Price Index (PPI). For the capital input, I have

[29] There are also other ways to measuring the TFP. One widely used methodology is Olley and Pakes, 1996 (henceforth OP)'s semi-parametric 2SLS estimation. However, this methodology can't be applied to the INS data since there is no information on firm entry and exit in this firm survey. Although I am not using this methodology, I check whether my TFP estimation results are similar to the ones using OP, and find that with OP (as well as Levinsohn and Petrin), the coefficient on L and M should decrease, while the coefficient on K should increase, comparing to OLS. De Loecker (2013) made additional extensions of Levinsohn and Petrin, by assuming productivity endogenous to export decisions. Also, recent studies have measured productivity in non-standard ways, using multilateral index (Arnold and Javorcik, 2005), two-stage DEA (Simar and Wilson, 2011) and Leontief product functions (Hendel and Spiegel, 2014), etc.

[30] The reason why it is important to allow for differences in technology as measured by differences in parameters is discussed in Eberhardt and Teal, 2008.

constructed the deflators from the Gross Fixed Capital Formation of the National Account.

However, if firm-level price variation is correlated with input choice, this will result in biased input coefficients since the omitted output price bias will arise if industry-level price deflators are used and if firm-level prices deviate from these deflators. Also, omitted output price bias will arise if industry-level price deflators are used and if firm-level prices deviate from these deflators (i.e. imperfect competition). To deal with this omitted output price bias, I use firm-fixed effects.

Generalized Methods of Moments (GMM)

To overcome the above-mentioned issues, I have used GMM specification to measure TFP. GMM can be used to avoid the simultaneity bias in the output related decision, such as exporting decision, endogenous input choice and other omitted variable bias in TFP estimation with data with short T and large N. The INS dataset has 11 years of time dimension (T=11, max, from 1997 to 2007, but most of observations have less than 11 years of observations) and a larger firm dimension (N=1589 for balanced, 12622 for unbalanced), which is a recommendable characteristic to use GMM.

The above-mentioned biases can be raised when input is correlated with error term (A_{ijt}). For instance, when there is exogenous price shock, if material is considered more easily adjustable than labour and capital, then material is more strongly correlated with error term. Therefore, material is upward-biased and others are downward biased. Instruments can be used to get rid of this bias, however, in general it is hard to find such instruments. Therefore, previous researchers used lagged variable of output and inputs as instruments, which they have already in the firm-level data.

Other productivity measurement - TTP

It is worth mentioning that a much of the convergence literature has used index numbers, which are similar to TTP as provided by Bernard and Jones (1996). The details on TTP are well described in their work – but in summary, the strength of this approach

is that the specification does not depend on the form of the production function and allows the factor input shares to vary across industries. Also, it is a relatively simple way of measuring productivity, thus, easier to compare the index number across countries.

Despite the advance of using index numbers, in my view, there are several advantages to using TFP, instead of index numbers, especially on firm level data. Index numbers require an assumption on the input share or uses the industry average input share across all firms, and therefore, do not reflect firm-specific information and could lead bias. Also, using index numbers would not control the simultaneous bias, which could be caused not only by input influences output but also by output influence on the input decision. Meanwhile, as with index numbers, by measuring TFP separately by 2-digit industry level, I can allow the factor input shares to vary across industries. Therefore, I use TFP by 2-digit industry level using recent econometric techniques, such as GMM, which allows the factor input shares to vary across industries while correcting potential simultaneous input selection bias.

TFP growth trend in Tunisia

Table B.1 shows the figure of average and standard division of TFP growth by industry over time. Like as shown in graph V in section 4, the average TFP growth are close to zero for most of industries and standard deviation of TFP growth are very small for most of industries. Industry a28 and a33 have relatively high productivity growth with growth rate of average around 3% during the period.

S.D of technology distance (σ-convergence)

Table B.2 shows the standard deviation of firm-level TFP, the widely-used measurement of σ-convergence, and (domestic) technology distance variable by industry. As seen in graph IV in data section, the standard deviation of the technology distance are heterogeneous across industry by year, and there is no clear pattern of this standard deviation has been decreasing (no evidence of σ-convergence). The standard deviations have been reduced in several industries, such as NACE 16, 22, 30, 33, 35 and 37, implying

that firms' distances to top performer become somewhat similar to each other, however, in most industries the standard deviation has been sustained.

Table B.1. Average TFP growth

NACE	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Average
a15	0.02	0.04	-0.03	0.01	-0.02	-0.02	-0.04	-0.05	-0.07	-0.08	-0.02
a16	0.12	-0.09	0.19	-0.12	0.03	0.06	0.12	-0.21	-0.05	0.08	0.01
a17	-0.01	0.00	0.06	0.03	0.07	-0.02	0.05	-0.04	-0.12	-0.03	0.00
a18	0.01	0.01	0.08	-0.02	-0.04	-0.05	-0.02	-0.01	0.00	0.01	0.00
a19	-0.04	0.01	0.03	-0.01	0.01	-0.05	-0.03	0.04	-0.06	-0.02	-0.01
a20	-0.08	0.05	0.07	-0.01	0.02	0.04	-0.11	-0.02	-0.20	0.02	-0.02
a21	0.09	-0.01	0.00	0.01	0.01	0.02	-0.07	0.12	-0.24	0.08	0.00
a22	-0.01	0.03	-0.06	0.03	0.04	0.00	-0.07	0.06	-0.01	-0.08	-0.01
a23	-0.02	0.22	0.09	0.11	0.01	0.06	-0.13	0.20	0.06	-0.38	0.02
a24	-0.10	0.06	0.03	0.01	0.05	0.03	-0.03	-0.08	-0.11	-0.10	-0.02
a25	0.14	-0.02	-0.04	-0.02	0.00	0.02	0.02	0.05	-0.25	-0.16	-0.02
a26	0.00	-0.01	0.00	0.00	0.04	0.04	-0.01	-0.06	-0.02	-0.06	-0.01
a27	0.02	0.06	-0.07	-0.04	-0.12	-0.03	0.00	0.09	-0.06	-0.06	-0.02
a28	0.02	0.01	0.00	0.03	0.04	0.07	-0.09	-0.07	0.16	0.08	0.03
a29	-0.04	0.07	0.03	-0.04	-0.06	-0.17	0.08	-0.10	-0.15	0.10	-0.03
a30				0.35	-0.21			-0.02	-0.10	-0.18	-0.03
a31	0.11	-0.07	-0.10	0.04	0.05	0.02	0.02	-0.02	0.01	-0.03	0.00
a32	0.08	-0.03	-0.31	-0.01	-0.09	0.03	0.22	0.00	0.07	-0.21	-0.02
a33	0.36	-0.01	0.33	-0.17	-0.01	0.07	-0.16	-0.12	0.01	0.02	0.03
a34	0.05	0.00	-0.02	0.04	-0.12	-0.08	-0.03	-0.02	0.09	-0.06	-0.01
a35	-0.55	-0.16	0.06	-0.09	0.05	0.12	-0.11	0.03	-0.09	-0.02	-0.08
a36	0.02	-0.02	-0.02	0.00	-0.02	-0.02	-0.01	-0.06	-0.03	0.01	-0.02
a37	-1.20						-0.09		-0.21	0.43	-0.27

Table B.2. Standard deviation of TFP growth within industry, over time

NACE	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Average
a15	0.02	0.02	0.02	0.02	0.02	0.04	0.05	0.04	0.03	0.05	0.03
a16	0.08	0.10	0.16	0.10	0.07	0.22	0.12	0.22	0.09	0.09	0.12
a17	0.03	0.04	0.04	0.04	0.05	0.06	0.05	0.04	0.06	0.07	0.05
a18	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
a19	0.04	0.04	0.04	0.06	0.05	0.06	0.04	0.07	0.07	0.08	0.05
a20	0.10	0.06	0.08	0.06	0.10	0.05	0.09	0.08	0.14	0.11	0.09
a21	0.08	0.05	0.05	0.03	0.06	0.04	0.05	0.09	0.04	0.07	0.06
a22	0.08	0.03	0.07	0.05	0.11	0.03	0.04	0.08	0.14	0.11	0.08
a23	0.03	0.18	0.33	0.14	0.04	0.11	0.17	0.16	0.21	0.32	0.17

a24	0.05	0.04	0.05	0.05	0.06	0.07	0.07	0.04	0.05	0.06	0.05
a25	0.06	0.04	0.04	0.11	0.07	0.05	0.08	0.15	0.16	0.06	0.08
a26	0.04	0.04	0.04	0.04	0.03	0.07	0.04	0.05	0.04	0.07	0.05
a27	0.05	0.05	0.04	0.08	0.09	0.09	0.06	0.08	0.07	0.16	0.08
a28	0.04	0.04	0.04	0.04	0.06	0.07	0.06	0.11	0.06	0.08	0.06
a29	0.08	0.07	0.06	0.07	0.06	0.07	0.09	0.09	0.13	0.08	0.08
a30										0.05	0.05
a31	0.09	0.09	0.07	0.08	0.06	0.06	0.08	0.06	0.07	0.12	0.08
a32	0.09	0.13	0.31	0.21	0.17	0.09	0.09	0.09	0.09	0.10	0.14
a33	0.17	0.09	0.13	0.13	0.15	0.10	0.16	0.08	0.10	0.03	0.11
a34	0.05	0.06	0.07	0.06	0.08	0.06	0.06	0.04	0.09	0.07	0.06
a35	0.71	0.08	0.07	0.09	0.10	0.13	0.20	0.18	0.11	0.15	0.18
a36	0.04	0.03	0.04	0.03	0.05	0.06	0.09	0.06	0.05	0.05	0.05
a37							0.88		0.15		0.52

Table B.3. Standard deviation of (domestic) technology distance variable

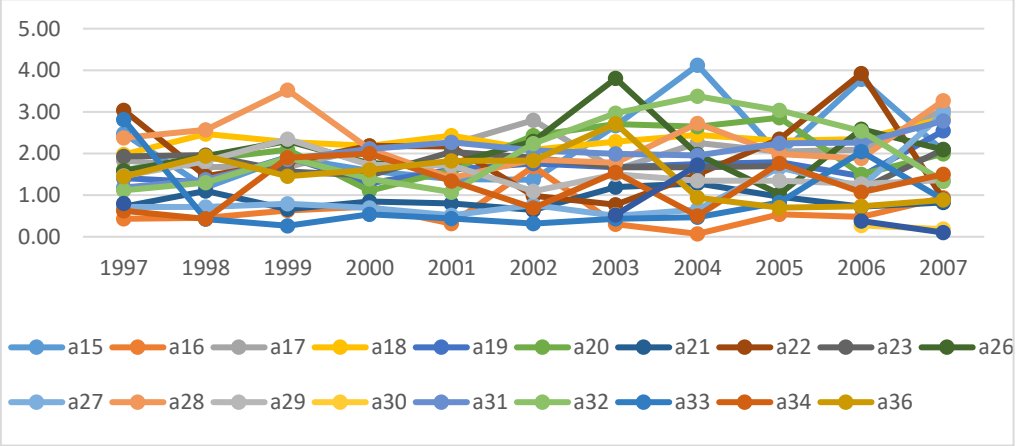
NACE	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
a15	0.03	0.02	0.03	0.03	0.02	0.03	0.05	0.06	0.04	0.04	0.04
a16	0.28	0.22	0.33	0.26	0.13	0.36	0.12	0.02	0.13	0.11	0.19
a17	0.05	0.05	0.05	0.06	0.05	0.06	0.08	0.07	0.06	0.07	0.08
a18	0.03	0.04	0.04	0.03	0.03	0.03	0.04	0.03	0.03	0.04	0.04
a19	0.06	0.06	0.06	0.05	0.06	0.07	0.08	0.07	0.07	0.06	0.08
a20	0.13	0.10	0.13	0.11	0.14	0.16	0.16	0.17	0.19	0.16	0.14
a21	0.08	0.08	0.07	0.09	0.08	0.07	0.10	0.09	0.09	0.09	0.14
a22	0.10	0.07	0.08	0.10	0.09	0.07	0.06	0.12	0.11	0.12	0.07
a23	0.65	0.66	0.56	0.71	0.75	0.71	0.60	0.56	0.58	0.61	0.67
a24	0.13	0.13	0.14	0.13	0.13	0.13	0.19	0.14	0.14	0.18	0.19
a25	0.12	0.14	0.12	0.15	0.12	0.11	0.15	0.12	0.20	0.12	0.15
a26	0.04	0.05	0.05	0.05	0.05	0.06	0.06	0.04	0.04	0.05	0.06
a27	0.08	0.08	0.08	0.08	0.07	0.08	0.09	0.06	0.11	0.09	0.18
a28	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.09	0.08	0.07	0.07
a29	0.11	0.12	0.12	0.11	0.11	0.09	0.13	0.10	0.10	0.11	0.11
a30							0.27			0.14	0.09
a31	0.09	0.08	0.10	0.10	0.11	0.10	0.10	0.10	0.10	0.09	0.12
a32	0.21	0.18	0.22	0.24	0.21	0.28	0.24	0.29	0.21	0.20	0.20
a33	0.43	0.10	0.08	0.14	0.15	0.08	0.07	0.12	0.13	0.19	0.15
a34	0.05	0.04	0.10	0.12	0.10	0.08	0.09	0.06	0.10	0.08	0.10
a35	0.43	0.09	0.06	0.07	0.12	0.16	0.11	0.23	0.11	0.17	0.13
a36	0.04	0.05	0.04	0.04	0.04	0.06	0.06	0.05	0.05	0.04	0.04
a37	0.40						0.17	0.72		0.21	0.04

Appendix C. Different measures of technology frontier/distance

- *Top 1% frontier*

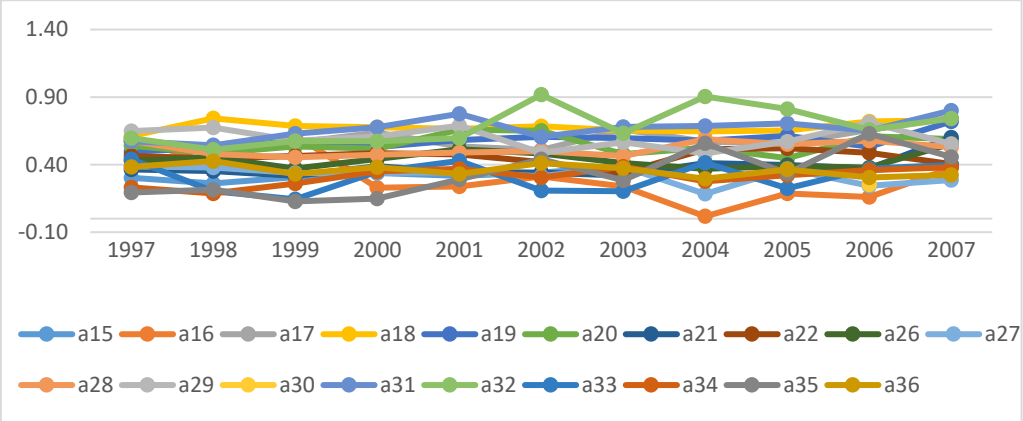
I generate another frontier measure, by taking the average TFP of firms that have top 1% of TFP level in industry j and year t (Frontier –top1%). Now the technology distance is a log difference of the frontier 2 and TFP level of an individual firm that belongs to bottom 99% of TFP in industry j and time t (Distance-top1%)

Graph C.1. Top1% distance over time



Note: a24, a25 and a35 are deleted since they are outliers.

Graph C.2. S.D of top 1% distance



Note: a23, a24 and a25 are deleted since they are outliers, with s.d. more than 1 in some years.

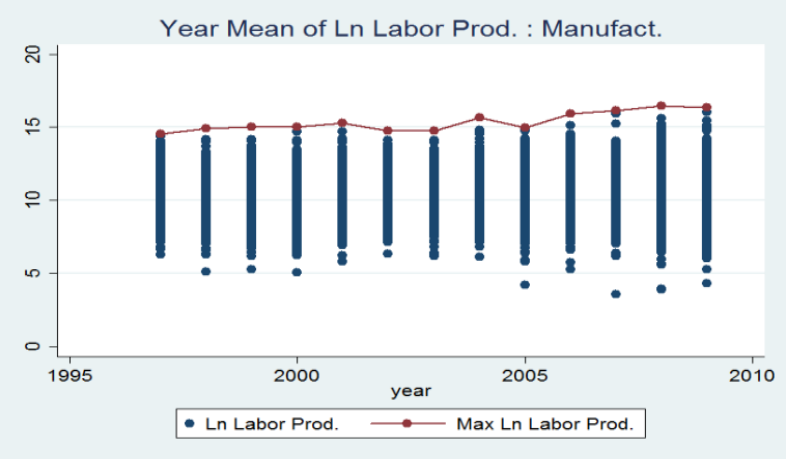
- *International vs domestic frontier, using labor productivity*

I measure labor productivity of Tunisian firm, which is measured by deflated sales revenue divided by the number of employees

$$\text{Ln labour prod.} = \ln(real\ revenue) - \ln(employment).$$

Graph 3 shows the labor productivity trend in Tunisia. The patterns of graph3 is similar to graph 1 in data section, which show the TFP level over time. Minor differences include less productive firms that further reduced their productivity level.

Graph C.3. Labour productivity level over time



Note: this figure shows the value of log labour productivity for each firm in manufacturing by year (blue dots), and maximum value for each year. Ln labour prod. $= \ln(real\ revenue) - \ln(employment)$.

- While only a few frontier firms slightly increased their TFP and only a few firms far away from the frontier have slightly reduced their TFP level, most firms show similar TFP level over time.
- Compared to using TFP in graph I, there might be a few less productive firms that decreased their productivity over time. Although this difference is marginal, it could be explained by those firms that have decreased their output, which are shown as decreased labour productivity, have invested less in capital inputs during the period of low output. Given that TFP is the residual of the production function, which

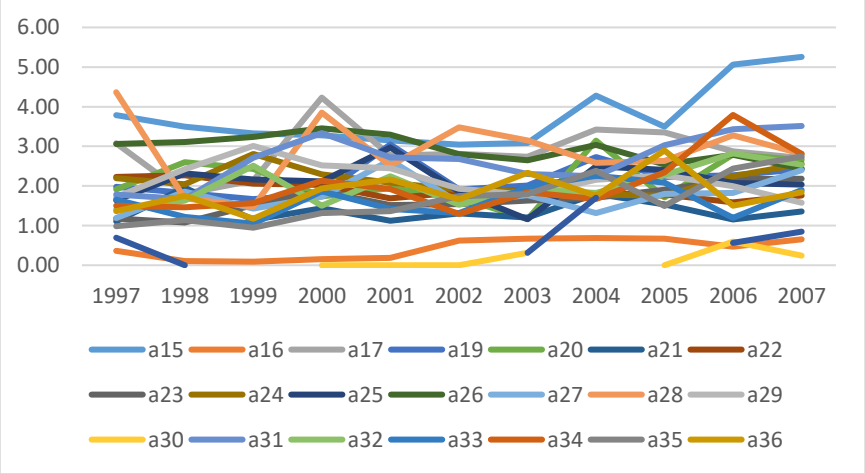
measures the relationship between inputs and outputs, if a firm reduces their inputs, the residual would decrease less, although output has decreased. This pattern is consistent with the previous literature which explains that firms that face major changes in output by economic shocks or reduced productivity could adjust their capital inputs more easily than their labour inputs, given the rigidity of labour markets.

Then, I measure an additional domestic technology gap using labour productivity of Tunisian Firms The technology frontier is measured by log c of the firm with highest labour productivity in industry i, time t and the gap is the distance from this technology frontier to the individual firm's log labour productivity of firm in industry i and time t.

- Domestic frontier, using labour productivity ($L_{\boldsymbol{DF}\,jt}$): a Tunisian firm that has the highest labour productivity in sector j, at time t

Graph 4 shows the trend of technology distance to domestic frontier, using log labor productivity.

Graph C.4. Distance to domestic frontier, using lalor productivity

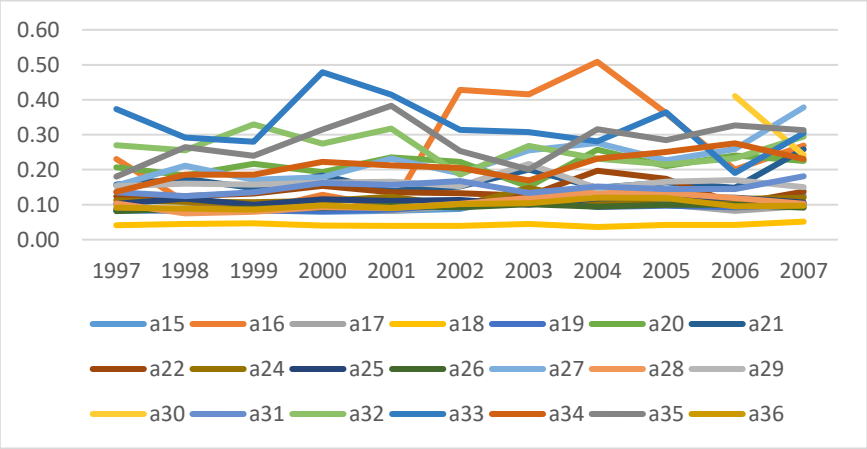


Note: Distance to domestic frontier, using labor productivity that is measured as $\frac{\text{Ln}\left(labor\ Prod_{jt}^{max}\right)}{\text{Ln}\left(labor\ Prod_{ijt}\right)}$. a18 deleted because it seems to be an outlier.

- Only a few industries are close to the frontier line, and the others become slightly further from the frontier line over time. While most of industries show a mean industry/frontier firm ratio in the range of 0.7-0.9, some firms are lagging behind.
- In graph 4, there seems that the technology distance to domestic frontier (using laor productivity) has been increasing over time, which is different from graph III (using TFP) in data section that provide relatively stagnated distance.

Graph C.5 shows the trend of standard deviation of technology distance to domestic frontier, using log labor productivity

Graph C.5. Standard deviation of distance to domestic frontier, using log labor productivity



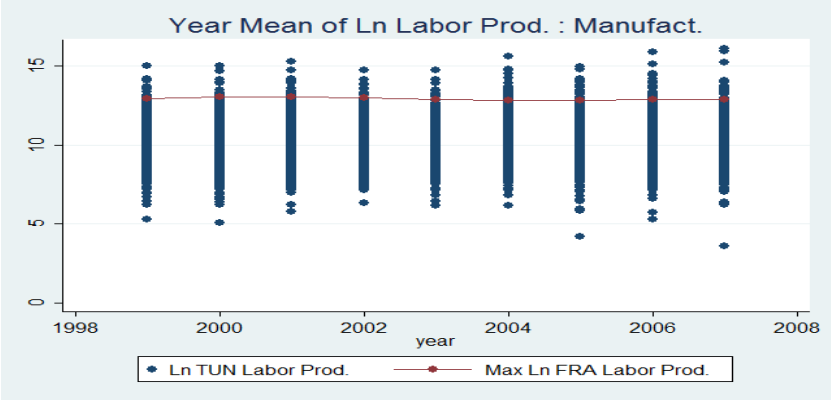
Note: a23 is an outlier and delated

Graph C.5 is similar to graph IV in data section, which shows the trend of standard deviation of distance, using TFP, in graph 5. Still, the sigma convergence patter is not clear.

Then I measure international frontier ($L_{FF\,jt}$), which is French industry-level labour productivity in sector j, at time t.

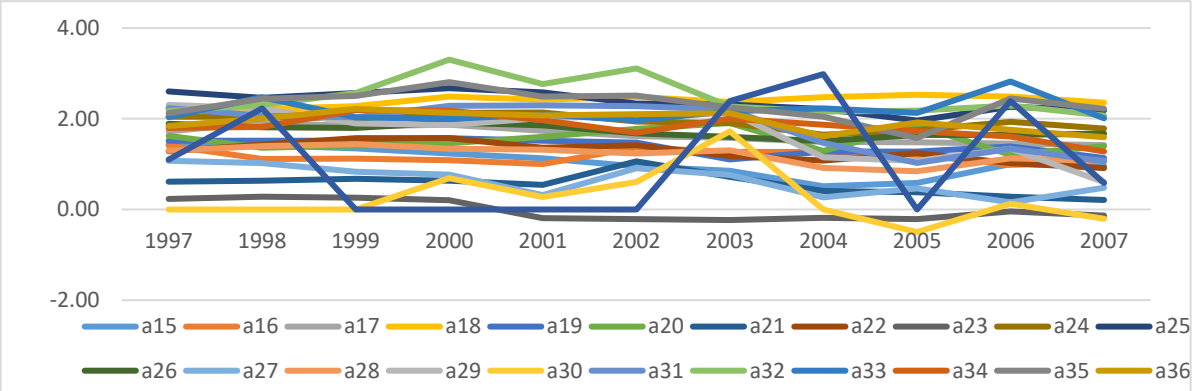
Graph C.6 shows Tunisian firms' labor productivity trend, which is blue dots, comparing to over time, comparing to international frontier ($L_{FF\,jt}$), which is the red line. Well performing firms in Tunisia shows higher labour productivity levels than the international benchmark, the average labour productivity in each industry in France. However, the findings from the following graphs are still consistent with the previous results.

Graph C.6. Labor productivity level over time, comparing to international frontier



- The red line is the French labour productivity average in manufacturing. Without considering industry, top-performing Tunisian firms show higher labour productivity level than the French average.
- When I use international frontier (French industry average labour productivity), that well performing firms in Tunisia show higher labour productivity level than the average French labour productivity.
- However, the message and findings from the following graphs are still consistent with the previous results.

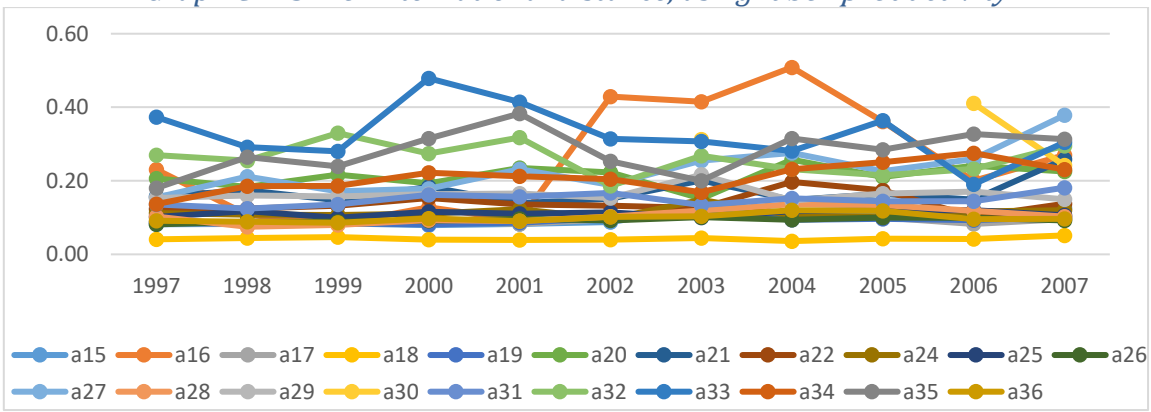
Graph C.7. International distance, using labour productivity, by 2-digit industry level



Note: Distance to international frontier, using labor productivity, measured as $\frac{\ln\left(labor\ Prod_{jt}^{FRA}\right)}{\ln\left(labor\ Prod_{ijt}^{TUN}\right)}$

- International distance, using labour productivity, seems to be slightly decreasing, although mostly sustained. This might be caused by the simple fact that the international frontier is lower than the domestic frontier, so easier to catch up.
- Still, there is large heterogeneity across industries, which are consistent with the previous graph using domestic distance, using TFP (graph III in data section) and using labor productivity (above graph C.4).

Graph C.8. S.D of international distance, using labor productivity



Note: a23 is an outlier and deleted

- Standard deviation of international distance has been almost sustained and show very similar pattern with the s.d. of domestic distance, using TFP (graph III in data section) and using labor productivity (above graph 4). There is sigma convergence in some sectors but not in others - no clear pattern of sigma convergence.

Appendix D. Additional result tables

Openness of frontier firms: table D.1-D.4 show whether frontier firms are more open than others, in terms of participating in exports and having foreign ownership. While frontier firms are more likely to receive FDI, the ratio of exporters in frontier firms (50.41) are similar to that in all manufacturing firms (51.36).

Table D.1. Manufacturing Firms' export participation in INS data

Export_stat	Obs	Percent	Cum.
0	8,013	48.64	48.64
1	8,460	51.36	100
Total		16,473	100

Table D.2. Frontier firms' export participation

export_stat	Freq.	Percent	Cum.
0	121	49.59	49.59
1	123	50.41	100
Total	244	100	

Table D.3. FDI firms among all manufacturing firms in INS data

FDI_stat	Freq.	Percent	Cum.
0	12,023	72.99	72.99
1	4,450	27.01	100
Total	16473	100	

Table D.4. FDI firms among frontier firms

FDI_stat	Freq.	Percent	Cum.
0	147	60.25	60.25
1	97	39.75	100
Total	244	100	

Table D.5 shows the suggested IV explains significant variations of export volume.

Table D.5. IV2 export volume first stage

	(1) IV2_OLS	(2) IV2_FE
IV2	3.700***	0.978*
	(0.000)	(0.030)
Constant	-88.486***	-24.956*
	(0.000)	(0.023)
Observations	11987	11987
R^2	0.360	0.260

Year dummy and industry dummy were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), p-values in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001

Table D.6 is the same with table 6 but using random effects than firm fixed effect. Hausman test reveals that fixed effect is more appropriate to use the above model.

Table D.6. RE Domestic GAP export Dummy

	(1) RE	(2) RE	(3) RE	(4) RE	(5) RE
Lag Exporter	-0.004		-0.010	-0.095***	-0.100***
	(0.732)		(0.372)	(0.000)	(0.000)
Lag Ln (GMM_TFP_Fj/GMM_TFP_ij)		0.110***	0.110***	0.095***	0.096***
		(0.000)	(0.000)	(0.000)	(0.000)
Lag Exporter*GMM TFP GAP				0.038***	0.039***
				(0.000)	(0.000)
Lag Innovation Investment					-0.001
					(0.282)
Lag FDI status					0.030*
					(0.013)
Constant	-0.008	-0.336***	-0.338***	-0.296***	-0.294***
	(0.657)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11428	11428	11428	11428	11428
R^2					
r2_o	0.002	0.047	0.047	0.048	0.048
rho	0.102	0.118	0.118	0.121	0.120

p-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, To perform Hausmann test, it is not allowed to cluster standard error.

Table D.7. Hausman tests results

Column	P-value: difference in coefficients not systematic	Suggested model
1	0.000	FE
2	0.000	FE
3	0.000	FE
4	0.000	FE
5	0.000	FE

Hausman test compares an estimator θ1 that is known to be consistent with an estimator θ2 that is efficient under the assumption being tested. The null hypothesis is that the estimator θ2 is indeed an efficient (and consistent) estimator of the true parameters. If this is the case, there should be no systematic difference between the two estimators. If there is a systematic difference in the estimates, you have reason to doubt the assumptions on which the efficient estimator is based. Also, Hausman test can also differentiate between fixed effects model and random effects model in panel data. In this case, Random effects (RE) is preferred if the null hypothesis cannot be rejected due to higher efficiency; otherwise, fixed effects (FE) is at least consistent and thus preferred.

Fixed-effect should be chosen, based on the results of comparing models from FE vs RE.

In table D.8, columns (1)-(2) provide the estimation results using OLS and column (3)-(4) provide the results using firm fixed effect. The results are very similar to table 13 in the result section.

Instrumenting initial export volume reduces the estimated coefficient of technology transfer to between 4.8% and 5.2% in Columns (1)-(4). The coefficient of the interaction term between previous export status and technology gap are in the range between 0.7% to 2% and statistically significant. Like as table 13, the coefficients get larger with firm fixed effects, as shown in Columns (3) and (4). Meanwhile, the estimated coefficient of export status show mixed results, become negative in column (3) and (4).

In column (1) and (2), the coefficients of IV on the residual are statistically significant but small and R^2 of test regression are close to zero, which ensure that the suggested instrument is not correlated with the residual of the primary instrument (instrument is valid). Again, the results using firm fixed effects, in column (3) and (4), requires careful interpretation, with larger coefficient of IV and R^2 in the test regression. Corrected standard error become smaller in column (1) -(4) as expected.

Table D.8. Different econometric techniques – IV 2SLS with export volume

Dep Var=TFP growth	(1) IV2 OLS	(2) IV2 OLS	(3) IV2 Panel	(4) IV2 Panel
Lag Exporter	0.004***	0.003***	-0.024**	-0.020**
	(0.001)	(0.001)	(0.003)	(0.003)
Tech Distance	0.052***	0.051***	0.048***	0.049***
(Lag Ln TFP_Fj/TFP_ij)	(0.000)	(0.000)	(0.001)	(0.001)
Lag Exporter×Tech Distance	0.007***	0.007***	0.020***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
Lag Innovation Investment		-0.001		-0.002
		(0.223)		(0.054)
Lag FDI status		0.032**		-0.017
		(0.002)		(0.024)
Constant	-0.090	-0.085	-0.348	0.038
	(0.066)	(0.090)	(0.248)	(0.900)
Observations	11422	11422	11422	11422
R^2	0.053	0.054	0.010	0.011
Rho*	N/A	N/A	0.600	0.600
Test regression – Coeff. of IV on the residual of second stage(equ.10)	-0.005***	-0.005***	0.162***	0.175***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2 of the test regression**	0.001	0.001	0.068	0.079

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity) and corrected. P-values in parentheses, Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, R^2 is reported but it is not important in 2SLS. * Rho is fraction of variance due to u_i. ** R^2 of the test regression is from the OLS of IV on residual of second stage regression.

Table D.9 and D.10 provide the above results of Table 14 but using different econometric techniques, including OLS and GMM. The results across different distance measures are

consistent with the results using OLS methods and similar to the results using GMM, which ensure the estimation results of above tables.

Table D.9. Comparisons of different distance – OLS, lag export dummy

Dep Var=TFP growth	(1) Domestic TFP -The highest	(2) Domestic TFP -The highest	(3) Domestic TFP – Top 1%	(4) Domestic TFP – Top 1%	(5) Domestic LP	(6) Domestic LP	(7) Intl LP	(8) Intl LP
Lag Exporter	-0.062***	-0.070***	-0.031	-0.041	-0.002	-0.008	-0.002	-0.007
	(0.001)	(0.000)	(0.196)	(0.097)	(0.887)	(0.659)	(0.904)	(0.653)
Tech Distance (LagLn TFPFj/TFPij)	0.085***	0.085***	0.084***	0.084***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Dom.LP Distance (TUN LP_Fj/LP_ij)					0.041***	0.042***		
					(0.000)	(0.000)		
Int. LP Distance (FRA LPFj/LPij)							0.062***	0.064***
							(0.000)	(0.000)
Lag Exporter ×Tech Transfer	0.025***	0.026***	0.011	0.012				
	(0.000)	(0.000)	(0.307)	(0.279)				
Lag Exporter× TUN LabourProd GAP					0.002	0.002		
					(0.641)	(0.645)		
Lag Exporter× FRA LabourProd GAP							0.009	0.008
							(0.214)	(0.287)
Lag Innovation Investment		-0.001		-0.000		0.001		0.001
		(0.486)		(0.715)		(0.206)		(0.102)
Lag FDI status		0.030**		0.035***		0.014		0.019
		(0.004)		(0.000)		(0.185)		(0.066)
Constant	-0.260***	-0.261***	-0.156***	-0.157***	-0.147***	-0.157***	-0.060***	-0.073***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Observations	11428	11428	9564	9196	11428	11428	11428	11428
R^2	0.048	0.049	0.038	0.044	0.015	0.015	0.025	0.025

Year and industry dummies were included but not reported. Standard errors are clustered, and robust (white correction for heteroskedasticity), *p*-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While the magnitude and direction of coefficient are similar for other distance measures, there are major changes in coefficients when I test the top 1% distance in column (3) and (4) table D.9. Compared to the estimated results provided in the result section, the coefficients of convergence get much larger for the distance with top 1% TFP. The coefficient of export become significant and positive while the coefficient of interaction

term between export and technology distance become negative and statistically significant.

Table D.10. GMM with Lag Export Dummy

	(1) Domestic TFP -the highest	(2) Domestic TFP-the highest	(3) Domestic TFP -top 1%	(4) Domestic TFP-top 1%	(5) Domestic LP	(6) Domestic LP	(7) Intl LP	(8) Intl LP
Lag Exporter	-0.266*	-0.276*	0.354	0.326	-0.114	-0.134	-0.048	-0.058
	(0.047)	(0.045)	(0.074)	(0.088)	(0.295)	(0.241)	(0.621)	(0.555)
Tech Transfer (LagLn TFP_Fj/TFP_ij)	0.081***	0.080***	0.740***	0.725***				
	(0.000)	(0.000)	(0.001)	(0.001)				
Lag Ln (TUN LP_Fj/LP_ij)					0.047**	0.045**		
					(0.002)	(0.003)		
Lag Ln (FRA LP_Fj/LP_ij)							0.101***	0.101***
							(0.000)	(0.000)
Lag Exporter ×Tech Transfer	0.094*	0.096*	-0.186*	-0.187 *				
	(0.033)	(0.031)	(0.034)	(0.031)				
Lag Exporter× TUN LabourProd GAP					0.023	0.027		
					(0.388)	(0.325)		
Lag Exporter× FRA LabourProd GAP							0.023	0.025
							(0.569)	(0.536)
Lag Innovation Investment		-0.001		-0.017***		0.001		0.001
		(0.207)		(0.001)		(0.608)		(0.392)
Lag FDI status		0.029		0.316***		0.016		0.020
		(0.116)		(0.001)		(0.342)		(0.213)
Constant	-0.259***	-0.268***	-4.364***	-4.009*	-0.165**	-0.148*	-0.090*	-0.107*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.025)	(0.011)	(0.024)
Observations	11428	11428	9564	9564	11428	11428	11428	11428
AR2	2.117	2.101	-2.43	-2.48	2.269	2.276	2.277	2.273
AR2 (p-value)	0.034	0.036	0.015	0.013	0.023	0.023	0.023	0.023
Sargan/hansen (p)	0.004	0.004	0.557	0.586	0.000	0.000	0.001	0.001
Diff in hansen (p)	0.604	0.608	0.617	0.628	0.717	0.550	0.957	0.965

With firm fixed effect. Year dummy and industry dummy were included but not reported. p-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Non-dynamic system GMM with lag 2 and 3. The instrument set for the differenced equation consists of the log of TFP growth, lagged export status, in levels, in periods $t-2$ and $t-3$ (among which the missing values are treated as 0 and the instrument for each period are collapsed) and the gap variable, interaction between gap and previous year export, year and industry dummies, differenced. The instrument set for the levels equation consists of the log of TFP growth, lagged export status, the gap variable, interaction between gap and previous year export, a constant and year and industry dummies.

III. Chapter 2. "Create" or "Buy"?, Internal vs. External Sources of Innovation and Firm Productivity

1. Introduction

The role of innovation in improving productivity might vary according to a country's relative position in technology advancement. Frontier countries might benefit more from policies that promote firms' internal innovation (create), while follower countries would gain more from policies favouring the adoption of existing technologies through innovation outsourcing (buy). However, in many countries, the government policies to promote innovation narrowly focus on "creating," regardless of considerations of the level of a country's technological advancement.

Moreover, despite rapidly growing innovation outsourcing (Narula 2004, Lacity and Willcocks 2013), [31] there is little systematic research and analysis of the effects of innovation outsourcing, and specifically, whether the outsourced innovation produces a different effect than in-house innovation on firms' productivity. The existing research on innovation outsourcing focuses largely on its impact on firms' innovation performance, such as the number of new products or registered patents, rather than on firms' overall performance, such as final output and productivity. A firm invests in innovation primarily to enhance its final output and productivity; however, up to now little has been known about effects of innovation outsourcing that spread beyond its direct effect upon a firm's innovation performance.

Additionally, research on representative firms in developing countries is particularly rare. Existing research focuses mainly on a few developed economies and on selected industries, such as high-technology industries, even though these may not be the most innovative industries in developing countries. Also, research using innovation survey

[31]. Innovation outsourcing is a rapidly increasing trend. For instance, the global business process outsourcing (BPO) market has been growing at 25 percent annually and was estimated as $309 billion in 2012 worldwide (Lacity and Willcocks 2013). Technological convergence, declining transaction costs of acquiring external knowledge, and shortening product cycle times have driven firms to outsource innovation (Narula 2004).

data is usually conducted for those firms that are more likely to invest in innovation or had responded in the affirmative for innovation outputs — which might lead to biased estimates of the effect of innovation for generic firms.

Although innovation has been widely recognized as a determinant of productivity[32], the role of innovation in improving productivity might vary according to a country's relative position in technology advancement. Specifically, countries with high level of technology advancement will grow faster by investing in innovation, while the follower group of countries will benefit more by adopting existing frontier technologies (Aghion 2004; Aghion, et al. 2013). Therefore, depending on their level of technology advancement, the growth rate of the economy will depend not only on innovation but also on "firms' ability to adopt or diffuse technology" throughout the economy (Griffith et al. 2004).

These considerations suggest the question of whether innovation policy should vary according to the level of a country's technological advancement. Meanwhile, in many countries, the government policies to promote firms' innovation narrowly focus on the internal innovation, such as tax benefits and subsidies to conduct in-house research and development (R&D) regardless of considerations of the level of a firms' technological advancement.

Particularly in a developing country like Tunisia, where firms are constrained by limited resources and skill levels, it is important to understand which sources of innovation is more efficient at improving productivity, thus, final output. However, the effect of innovation outsourcing on firm productivity is under-researched, even in developed economies, and to my knowledge, has never been examined in Tunisia.

[32]. In Schumpeterian growth theory, innovation is a major driver of economic growth and resource allocation from less innovative firms to more innovative ones. Firms innovate with the expectation of being rewarded with "rents", which would be decreased when other firms imitate those innovations, and eventually drive the them out of the market ("creative destruction") (Aghion 2004).

This paper fills this gap in our knowledge of the effect of innovation outsourcing on productivity of more general industries in developing countries by examining representative firms in the manufacturing sector in Tunisia. In this paper, I analyse the determinants of a firm's decision to invest in different sources of innovation, and the effects of these different sources on a firm's final output, via productivity. Then, I answer the following questions: are there any differences in the determinants of a firm's decision to create or to buy? Are the effects on productivity different between create and buy, and if so, which source of innovation is more effective in increasing final output via productivity?

The findings suggest that innovation policy in Tunisia should emphasize adoption and adaptation, rather that creation and innovation. To encourage firms' "buying," the government can promote exports and workers' skills, whereas incentives that encourage firms to hire more technicians or to acquire foreign investment might not be efficient ways to encourage "buying." Moreover, the fact that there is a minimum requirement (threshold) for innovation investment suggests that policies that aim to reduce this threshold or support firms around this threshold could catalyse the innovation investment.

The rest of the chapter is organized as follows. Section two provides the literature review and an analytical framework. Section three describes the data set and the key variables used, including the measurement of innovation variables. Section four provides the empirical strategy, and potential concerns and suggested solutions related to the empirical strategy. Section five presents the results, and section six provides the conclusion.

2. Literature Review

While innovation's positive effects on productivity are empirically supported in many developed economies[33], evidence is still rare in developing countries, where innovation's effect on productivity might be different from that in developed countries. Specifically, in developing countries, the cost of innovation might be higher because of greater distance from the technology frontier, and incentives to innovate might be lower because of lower expected rents of small domestic markets, as well as weak institutions such as patent law or intellectual properties law meant to protect against imitation by competitors.

In fact, because innovation is risky and costly, firms in developing countries might be better off improving their ability to acquire existing external knowledge (buy) instead of trying to innovate within the firms (create). Efforts for creation are mostly shown in a few developed countries and among a small number of firms, while buying account for a large part of productivity growth in developing countries (Fu et al., 2010).

However, tapping existing knowledge is not easy either. The adaptation of knowledge requires well-directed technological efforts, sufficient human and financial resources (Lall 1992; Cohen and Levinthal 1990)— essentially the same prerequisites as for internal innovation. Thus, internal innovation could play the role of absorptive capacity, the ability of firms to imitate external innovation (Griffith et al. 2004). There is an additional possibility that it might be better to use a combination of both sources of innovation, instead of only one source. (Cassiman and Veugelers 2006; Lokshin, et al. 2008).

[33] These empirical results are generally consistent with the earlier literature in that increased innovation inputs positively influence firm productivity (for instance, Crepon, Duguet, and Mairesse 1998). More recent literature documents that different innovation inputs lead to different types of innovation outputs, depending on the specific characteristics of a firm. For instance, R&D and IT investment lead to product innovation in high-technology industries and process innovations for exporters (Brynjolfsson and Hitt 2003: Inklaar and Timmer 2008). Also, the type of innovation seems to matter for productivity. Hall (2011) surveyed empirical work on the relationship between innovation and productivity and found that product innovation positively impacts output and productivity, but that the impact of process innovation is ambiguous.

In light of these considerations, which of create or buy contributes more to productivity (thus output) increases in developing countries is unclear. Understanding the effect of different sources of innovation will provide practical information to firms and policy makers.

However, research on the effect of different sources of innovation on firm performance, such as productivity and revenue, instead of innovation outcome, with representative firms in more general industries in developing countries is extremely rare. Moreover, most previous studies have focused only on a few developed economies and high-technology industries, even though those industries are not necessarily the most innovative, especially in developing countries. Further, among those few studies on developing countries, most of them were conducted only for those firms that responded in the affirmative to innovation outputs, which might produce biased results.

Different sources of innovation and their effects on productivity

I review previous literature on innovation outsourcing and provide views on why different sources of innovation might have different effects on firm productivity.

Despite the rapid acceleration of innovation outsourcing and increasing research on this trend in a number of fields, such as industrial organization and management, the latter so far has not explored systematically whether create and buy produce different effects on the final output and firm productivity, and what accounts for the differences. The existing findings are fragmented, and there is limited framework to analyse the create or buy decision on innovation outsourcing separately from decisions on general outsourcing, even though innovation outsourcing might be different from general outsourcing.

One advantage of innovation outsourcing, which also applies to general outsourcing, is short-term cost saving. Outsourcing can reduce production costs because of economies of scale and lower wages of outsourcing providers. However, there is a certain cost

associated with searching for outsourcing providers. Thus, literature in the field of management and industrial organization has tried to provide an analytical framework for firms' outsourcing decisions using a profit maximization model and its extension. Profit-maximizing firms decide whether or not to outsource by measuring the trade-off between "operating a larger organization with less specialization or conducting a costly search with contracting incompleteness" (Grossman and Helpman 2003, 2005).

There are several disadvantages in innovation outsourcing, as there are in general outsourcing. Outsourcing may damage firms' capability to innovate and the benefits of outsourcing is not guaranteed as the outcome of outsourcing could be affected by the complexity of production and integration processes (see, for example, Bengtsson and Berggren 2008; Chesbrough and Teece 2002; Ulrich and Ellison 2005). In fact, despite strong arguments for the advantages of outsourcing, previous studies show few positive or else contradictory effects of outsourcing on firm performance (Bengtsson et al. 2009[34]).

In addition to the abovementioned advantages and disadvantages that innovation outsourcing shares with general outsourcing, it also has certain differentiating characteristics, such as a diverse motif and risks, which influence the particular way it affects productivity.

Unlike general outsourcing, in most cases innovation outsourcing activities are identified for strategic reasons. Firms choose to outsource innovation in areas where they do not have in-house ability. They use innovation outsourcing as an instrument to acquire external knowledge, which could be subsequently integrated into a firm's own knowledge base, therefore, could improve firms' capacity to innovate. Also, firms may need to outsource innovation to gain the capacity to produce unique products or improve product quality. In fact, product innovation is conducted mainly for these strategic reasons; to obtain abilities to offer a variety of diversified products they

[34]. Related literature is cogently summarized in Bengtsson, et al. 2009.

otherwise do not have the capacity to produce. Gains from acquired abilities to produce new products may outweigh costs of innovation outsourcing (Quinn 1999; Chesbrough 2003; Fifarek et al. 2008).

However, unlike general outsourcing, innovation outsourcing exposes firms to certain risks, such information leakage, loss of control of innovation process, and introduction delay caused by internal resistance. Using a theoretical model, literature find that innovation outsourcing does not take sufficiently if information leakage cannot be monitored (Lai, Riezman, and Wang 2009 [35]). Further, given that the supplier of outsourced activities typically has more knowledge than the buyer, the buyer could lose control of the innovation process and the skills that they outsource (Quinn 1999). Materializing the benefits of innovation outsourcing requires much attention of top management, as decision to outsource innovation could face internal resistance from employees, particularly lower- to intermediate-level manager, who are accustomed to the traditional way of working and may fear loss of jobs (Lacity and Willcocks 2013). Moreover, benefits of engaging in innovation outsourcing materialize mostly in the long term with uncertainty. Innovation outsourcing helps firms establish a reputation and build relationships with other innovators, which all take time (Nelson and Winter 1977).

Meanwhile, innovation outsourcing's effect on productivity can be varied by the firm's level of technological advancement and its ability to adopt. As explained by the Schumpeterian Growth Theory, if the "follower" group of firms will benefit more by adopting existing technology from the frontier, while firms close to the technology frontier will grow faster by investing in innovation, it might be more efficient for firms in developing countries like Tunisia to acquire technology created externally (buy), as long as it is easy to adopt. However, if technology is difficult to transfer and adopt, firms must have the ability to learn from the external innovation (absorptive capacity), which

[35]. Lai, Riezman, and Wang (2009) uses a principal-agent model related to the cost-saving aspects of outsourcing, and analyses whether a firm under monopolistic competition should outsource R&D or not.

might not exist at firms in developing countries because of lower levels of initial technology; in these cases, innovation outsourcing might not be efficient.

Thus, given the diverse motif and risk of conducting innovation outsourcing and its complex characteristics, it is unclear whether innovation outsourcing would have a positive effect on firm productivity and final output in developing countries like Tunisia, and which type of innovation is more efficient in increasing firms' productivity.

Meanwhile, there is scarce empirical evidence for the effects of innovation outsourcing on firms' productivity and final output. The advantages and disadvantages of innovation outsourcing cited above are identified largely in case studies of a few selected firms in developed countries from managerial science literature. Though insightful, these findings are not readily generalized to other contexts. Also, as previously mentioned, although evidence from developing countries is particularly rare, the effect of innovation outsourcing on productivity increase could be different between developed and developing countries. Moreover, to my knowledge, there are few evidence-based explanations regarding what makes a firm create or buy, and whether different sources of innovations have different effects on firms' productivity and final outputs.

Are there any benefits to creating and buying jointly?

The finding that a firm needs to acquire absorptive capacity to benefit from an external source of innovation stimulated numerous investigations into a possible complementary effect of internal and external sources of innovation, given that internal innovation may play a role in the absorptive capacity of adopting external innovation. However, the evidence of the complementarity effect between both sources of innovation is mixed.

Earlier literature found that in-house innovation plays a role in absorptive capacity, which helps a firm to assimilate and integrate external innovation into its own production, and is thus a prerequisite to deriving benefit from innovation outsourcing (Cohen and Levinthal 1990; Griffith et al. 2004; Spithoven et al. 2011). Firms using both

sources of innovation have better innovation performance than those using only one source of innovation (Cassiman and Veugelers 2006). Conditional on a significant level of internal R&D, a firm can achieve higher productivity gains by combining both sources of R&D but with decreasing returns to scale (Lokshin et al. 2008).

However, a number of empirical studies report absence of a complementary effect or even a negative (supplementary) effect of using both sources of innovation. For instance, several studies document that internal and external innovation can substitute for each other, especially when resources are limited (Fikkert 1993; Basant and Fikkert 1996; Blonigen and Taylor 2000). A possible explanation is that, given a limited budget, an increase in either of one of the two options tends to reduce spending on the other. If the effect on innovation investment on productivity is not linear or requires a certain amount of investment (threshold) to produce a positive effect on the final outcome, splitting resources between two types of innovation would actually have a lower effect than consolidating resources on just one.

While it is difficult to generalize, evidence of complementary effects seems to be more common in studies on developed countries, and evidence of substitution effects seems to be mostly from studies on developing countries. For instance, complementary effects were documented in studies conducted on firms in Germany, Italy, the United Kingdom, Belgium, France, and Denmark, while those that document supplementary effects were conducted on firms in Andean-group countries, India, and China [36].

In addition, other studies find that the complementary or substitution effects could be changed depending on the ratio of the sources of innovation used, the internal innovation status of the firm, and the external environment. External innovation affects incentives to conduct internal innovation especially in the long-run. Innovation

[36]. The empirical evidence on supplementary effects includes Mytelka (1987) on Andean-group countries, Fikkert (1993) on Indian manufacturing firms, and Basant and Fikkert (1996) on Indian firm-level panel data. Also, a recent study by Hou and Mohnen (2013) found the complementary effect on Chinese manufacturing for only medium-size firms, but found a supplementary effect for rest of firms. There is more evidence of complementary and supplementary effects beyond this literature review.

outsourcing, such as R&D outsourcing, and innovation performance have an inverse U-shaped relationship, which is affected by the level of internal R&D and the level of R&D collaborations, both of which serve as "instruments to increase the effectiveness of R&D outsourcing" (Fu et al. 2010). Also, when learning is less demanding, internal innovation has little impact on firms' absorptive capacity (Cohen and Levinthal 1990).

3. Data

The data used in this study come from the annual enterprise survey, L'Enquête Nationale sur les Activités Économiques, which is conducted by the Tunisian Institute of National Statistics (L'Institut National de la Statistique, INS).

The data are collected for the period 1997 to 2009, with about 2,300 firms surveyed each year, including some 1,500 firms in the manufacturing sector. The survey coverage is extensive, as about 30 percent of firms with six or more employees in each sector, excluding agriculture, are included in the sample. In each year, a sampling method is applied which takes into account stratifications by industry and company size in terms of actual employees. I have confirmed that the sample includes representative Tunisian enterprises by comparing key firm characteristics of INS data with the aggregated information of firms listed by the Investment Promotion Agency (Agence de Promotion de l'Industrie, API).

The drawback of the INS data is that the survey provides a repeated cross-section, which accurately represents the Tunisian economy, but makes it difficult to apply econometric techniques for the panel data. However, approximately 300 (N) firms are repeatedly selected for 13 consecutive years (T), and most of the firms appear for at least 2 of the 13 years; therefore, the whole set of data is a rather weakly balanced panel, which allows me to use econometric techniques for the panel data.

The advantage of the INS data is that they provide rich information on firm characteristics (firm creation year, export status, ownership), balance sheets (revenue,

labor, capital, expenditure on intermediate goods), and production (goods category, exports, and ownership status), as well as other information included in standard firm-level surveys. Also, the INS data uniquely provide variables to identify internal and external innovation, which will be further described in the next subsection.

Since 2008, the INS has abridged questionnaires to reduce time and cost and to simplify the survey procedure. Consequently, questions related to internal and external innovation have been deleted. Therefore, I omitted observations for 2008 and 2009 and kept only those in manufacturing, with NACE codes between 15 and 36. I also omitted observations with missing information in labor, capital, material, and internal and external sources of innovation. Therefore, the total number of observations has been reduced to 16,471 for the period 1997 to 2007. A firm is repeatedly selected on average around four times during this period, which makes this data set similar to a weakly balanced panel that observes around 4,100 firms over a four-year period (the higher N, the small *T*), which is still a large enough sample to test the questions posed in this paper.

Innovation variables

The concept of innovation is broadly studied in economics and managerial science literature, and typically understood as introducing new production processes, new products, new management methods, and new organization of production activities. These concepts have been measured with various proxies, depending on available data.

In most innovation surveys, such as the Community Innovation Survey (CIS), innovation has been defined as a process, products, and organizational activities that are new-to-market or new-to-firm.[37] However, innovation surveys are relatively new and have been

[37]. There are several limitations to the CIS, although it provides direct measures of innovation. First, the definition of an innovative firm is somewhat ambiguous. It asks firms if they have undertaken activities new to market or new to firm to measure innovation, and if the firm answers in the affirmative, it is treated as an innovator. Second, the surveys provide limited information. They usually do not give information on multifactor productivity, although they sometimes provide data on labour productivity. They also do not

conducted in a relatively small number of samples, and mostly in developed countries. In Tunisia, an innovation survey similar to CIS was conducted in 2005, however, it targeted a specific group of firms that were most likely to innovate, which cause a sample selection bias.[38] Also, the survey was conducted only once in Tunisia, which makes it harder to understand the time trend of innovation effects or to apply the panel technique to remove potential effects related to time trend.

With general firm-level surveys, researchers have used different proxies for innovation. Many studies have used R&D investment amount as a proxy for innovation input. Fewer studies have used patents as a proxy for intermediate innovation output.

The INS data provide detailed information about expenses on innovation activities, such as conducting R&D, receiving consulting services, and purchasing royalties. Hence, I will use the expenses related to innovation activities as proxies for innovation inputs.

While the concept of innovation could include a wide range of activities, I follow a more conservative approach and construct an innovation variable using cost items that are directly related to technical innovation, such as the cost of conducting R&D, cost of receiving technical consulting services, and cost of purchasing royalties. Specifically, I consider cost of conducting R&D as internal innovation (create), and purchasing royalties and receiving technical consulting services as external innovation (buy). Then,

---

have detailed information, such as information on organizational innovation or detail expenditures on various kinds of innovation investments.

[38]. The innovation survey of Tunisia was carried out in 2005 by the Ministry of Scientific Research and Technology, modelling the CIS survey. According to the survey description, the sample was restricted to certain types of firms - manufacturing firms with high technology intensity and/or value addition, with firms with over 10 employees registered in the Agency for Investment Promotion (API) and the Institutes of National Statistics (INS). The survey was given to 739 firms likely to conduct innovative and/or R&D activity. Among these, 586 firms took the survey and 322 firms (around 55 percent) responded in the affirmative to innovation. The firms taking the survey were predominantly in textiles (19 percent of respondents), food and agro-processing (17 percent), electrical and equipment (17 percent), and IT (4 percent). The survey included questions about product and process innovation. Firms were asked if they have introduced a new product or process during the three years preceding the survey.

I create a total innovation (all) variable by calculating the total cost of these three activities. Therefore, my innovation variable is limited to innovation inputs on technical innovation. This narrow definition of innovation allows me to compare the effects of similar innovation activities between both sources of innovation.

These proposed innovation variables have commonly been used as innovation input variables in previous literature. Specifically, R&D and royalties are most widely used proxies for innovation. Receiving technical consulting services has also been recognized as innovation outsourcing in several studies, since if technology is uncodified, merely purchasing existing technology is insufficient to adopt the technology, and also requires consulting services[39] (Quinn 1999; Bloom and Van Reenen 2007, 2010).

Table 1 provides the mean value and number of observations of internal and external innovation variables from 1997 to 2007.

On average, approximately 62 percent of Tunisian firms engaged in either internal or external innovation between 1997 and 2007. During this period, about 36 percent of firms engaged in internal innovation, and about 58 percent in external innovation. Among those firms that invested in external innovation, most paid for consulting services, and only a few for royalties. This ratio of firms that engage in innovation is relatively large and similar to the ratios in developed economies, and similar to the result of a different survey in Tunisia.[40]

[39]. Also, recent literature finds that receiving consulting services enhances firms' productivity (Bloom and Van Reenen 2007, 2010; Bloom et al. 2012).

[40]. Around 55 percent of respondents responded affirmatively to innovation in Tunisian innovation survey 2005. Eurostat reveals that innovation existed in 51 percent of manufacturing firms and in 40 percent of services firms in the period 1994–96 in Europe (Pianta 2005). In the CIS survey, about 62 percent of firms claimed to innovate in 1993 in Belgium (Cassiman and Veugelers 2006).

Table 1. Innovation Variables, 1997 to 2007

Data		Create (Internal innovation)			Buy (External innovation)			All (Total innovation)		
Year	Number of firms	Mean log amount (TD)	Number of firms	Ratio (%)	Mean log amount (TD)	Number of firms	Ratio (%)	Mean log amount (TD)	Number of firms	Ratio (%)
1997	1,580	2.09	407	26	5.11	882	56	5.60	924	58
1998	1,574	2.95	573	36	5.73	1,010	64	6.47	1,093	69
1999	1,503	2.99	557	37	5.94	984	62	6.56	1,043	66
2000	1,777	2.80	632	36	5.63	1,101	70	6.25	1,170	74
2001	1,810	2.86	644	36	5.64	1,106	70	6.28	1,179	75
2002	1,427	3.06	525	37	5.69	852	54	6.38	907	57
2003	1,199	3.06	433	36	5.71	712	45	6.38	752	48
2004	1,352	3.49	572	42	6.26	879	56	6.96	926	59
2005	1,368	3.19	521	38	6.13	872	55	6.86	918	58
2006	1,501	2.88	518	35	5.77	932	59	6.60	993	63
2007	1,382	2.73	458	33	5.59	823	52	6.34	861	54
Mean	*1,498*	*2.92*	*531*	*36*	*5.75*	*923*	*58*	*6.43*	*979*	*62*

Note: TD=Tunisian dinar.

Table A.1 in appendix A provides innovation variables by two-digit industry level. There is large heterogeneity in the amount of innovation investment across industries, and even within manufacturing. Comparing innovators' share in entire firms (innovator's ratio) across the two-digit industry level, I found that innovators' ratios are not high in so-called "high-tech" industries, such as pharmaceutical or automobile industries, which are typically considered innovative. In fact, a large number of previous studies on innovation focused largely on these sectors. Meanwhile, those industries that are generally considered less technologically sophisticated, such as tobacco, furniture, apparel, and printing, have some of the highest innovator ratios, together with refined petroleum, chemicals and their related products (like rubber and plastic products), which are typically capital intensive and also Tunisia's main export items. This finding contradicts most of the previous studies, which consider high-tech industries to be technological leaders and innovation-intensive, even in developing countries.

The low level of innovators' share in high-tech industries might be explained by the fact that Tunisian firms might avoid investing in innovation activities in sectors where the technology gap with the more technologically advanced countries is large. Another possible explanation could be that those sectors are not necessarily tech-intensive in developing countries. In fact, I visited firms that are in high-tech industries, such as automobile and aerospace, and found that they produce only certain parts of automobiles or airplanes, such as seats and plastic materials for interior use, which might require a relatively low level of technology in the integrated global value chain. This suggests that two-digit industry level groups might be too aggregated, and the position of these firms in the relevant supply chain is more important. In other words, the more relevant factor is not industry level group but product or process level group. Therefore, firms in developing countries like Tunisia that belong to high-tech industries do not necessarily produce innovation-intensive products.[41]

Interestingly, there is no distinguishing feature between internal and external innovation across the two-digit industry level. In the sectors where more firms invest in internal innovation, more firms also invest in external innovation. However, the different characteristics of firms that invest in different sources of innovation will be further analysed in the next subsection.

Other variables

To test whether key factors that determine firms' innovation are different between internal and external innovation, I identified major determinants of innovation investment from previous literature. The explanatory variables include a vector of variables that could influence a firm's decision to invest in innovation.

[41]. In Tunisia, FDI is mostly driven by short-term, cost-saving benefits. This is in contrast to some other emerging markets, such as China and India, where FDI is driven by long-term benefits and strategic reasons. Foreign firms in the latter cases tend to invest in innovation by establishing local R&D centres and collaborate with local universities, as examples.

- Export: Previous literature has found that exporting can influence firms' innovation investment decisions. Exporting firms tend to invest more in innovation. Process and product innovation would increase export market entry. Interaction between R&D and exports could further influence productivity, and the decision to export is often accompanied by large R&D investment (Porter 1990; Grossman and Helpman 2003; Krugman 1991; Griffith, Redding, and Van Reenen 2004; Aw, Roberts, and Xu 2011; Bernard, Redding, and Schott 2011).

- FDI: Similarly, FDI might be another factor that could influence firms' investment in innovation. Foreign investors' knowledge and know-how are transferred to domestic partners, competitors, suppliers, and customers, which might also influence their decision to invest in innovation. However, inward FDI may produce a negative effect on innovation of local firms if the FDI firms substitute local innovation efforts with foreign ones. In fact, studies provide mixed results of FDI's effect on firms' innovation (Fu, Helmers, and Zhang 2012; Fu 2011).

- Firm age: Previous literature finds that younger firms are more likely to innovate (Huergo and Jaumandreu 2004; Balasubramanian and Lee 2008).

- Firm size (number of employees): Larger firms are more likely to invest in R&D. Specifically, large firms invest more in process R&D, while small firms invest more in product R&D (Acs and Audretsch 1991; Cohen and Klepper 1996).

- Skill (Average wage): Ability of labour, measured by average wage, is positively correlated with a firm's innovation, and influences firm productivity (Van Reenen 1996; Abowd et al. 2005; Fox and Smeets 2011). Number of technicians (technical staff ratio): Having more technicians could positively influence firms' innovation investment decisions since technical staff might be more directly involved in the process of how innovation is handled and of how innovation inputs are used in the production of final outputs.

- Competition: Market competition influences the level of firms' innovation investment. Previous studies reveal that firm entry spurs innovation in sectors close to the technology frontier, but discourages it in ragging sectors (Aghion et al. 2005; Aghion and Griffith 2008).

Details of the definition of the variables are presented in table 2.

Table 2. Summary Statistics of the Variables

	Variable	Definition	Obs.	Mean	S.D.	Min.	Max.
Dummy variables {Z}	Int only	Firms invest only in internal innovation	16,471	0.04	0.19	0	1
	Ext only	Firms invest only in external technology acquisition	16,471	0.30	0.46	0	1
	Innover	Firms invest in internal innovation	16,471	0.35	0.48	0	1
	Externer	Firms invest in external innovation	16,471	0.62	0.49	0	1
	Both	Firms invest in both sources of innovation at the same time	16,471	0.32	0.47	0	1
	All	Firms invest in any sources of innovation	16,471	0.65	0.48	0	1
Innov investment {U}	ln_n_innov	Log investment amount of any sources of innovation	16,471	6.00	4.65	0	16.37
	ln_n_inter	Log investment amount of internal innovation	16,471	2.93	4.21	0	16.25
	ln_n_exter	Log investment amount of external innovation	16,471	5.48	4.55	0	16.21
Inputs for production function	ln_revenue_d	Log amount of sales revenue, depreciated	16,457	13.91	1.65	6.17	21.50
	ln_labor	Log number of employees	16,471	3.98	1.23	0	8.48
	ln_capital_d	Log amount of capital assets beginning of the year, depreciated	16,015	13.42	1.83	4.61	20.57
	ln_interm_d	Log amount of intermediary inputs (materials), depreciated	16,167	12.73	2.23	1.60	20.19
Factors that influences innovation	Techstaff raito	Technical staff share among total employees	16,394	0.74	0.25	0	1
	Skills	Log average wage	15,369	8.39	0.68	2.28	12.47
	Firm age	Years since firm's creation	14,279	27.06	13.45	6	200
	Dominance	A firm's market share	16,457	0.01	0.06	0	1
	Export_stat	Export status dummy	16,471	0.51	0.50	0	1
	FDI_stat	FDI status dummy	16,471	0.27	0.44	0	1

The mean of the log investment amount of any sources of innovation, log investment amount of internal innovation, and log investment amount of external innovation are 6.00, 2.93, and 5.48, respectively, which is equivalent to TD 192,396[42] (US$101,725 or 3.4 percent of revenue), TD 45,883 (US$24,260 or 0.8 percent of revenue), and TD 146,513 (US$74,465 or 2.6 percent of revenue), respectively. For Tunisian manufacturing firms, the average sales revenue is TD 5,670,918 (US$2,998,365), the average wage is TD 4,225 per year (US$2,234) and average number of workers is 111. All values are in real terms, depreciated by the price index provided by the INS.

4. Empirical Strategy

In this section, I provide econometric strategies to answer the key questions posed in this paper, discuss potential concerns related to them, and provide solutions.

The questions I would like to answer are summarized here: first, what are the determinants of whether a firm will innovate at all, and further, whether they create, buy, or do both? Second, conditional on the response to question one, what determines the intensity of innovation? Third, how do the different types of innovation impact firm productivity?

These are difficult questions, as there are three fundamental issues to address. First, there are deep endogeneity problems between innovation and productivity. Second, the innovation data are censored. Lastly, there is a debate about whether to measure the impact of technology on output or directly on (a derived measure of) total factor productivity (TFP).

Therefore, in this section, I provide empirical models to answer the questions posed above and suggest solutions to address these three cross-cutting econometric problems.

[42] Tunisian Dinar (TD)

Determinants of create or buy

To understand whether the factors that influence firms' innovation investment are different between firms that create and firms that buy, I analyse the determinants of firms' innovation for both create and buy, using a Probit model as seen in equation (1). Denote firms by $i = 1,\ldots,$ *N*, industries by $j = 1, \ldots,$ *J,* and years by $t = 1, \ldots,$ *T.* The dependent variable is a dummy variable of whether there is investment in any innovation (all), internal innovation (innover), and external innovation (externer), respectively. To test whether there is any difference between those firms that invest in only one source of innovation and firms that invest in both sources of innovation, I have also created dummies of different exclusive categories — firms that have only internal innovation (int only), firms that have only external technology acquisition (ext only), and firms that invest in both internal and external sources of innovation (both).

Probit $Z'_{ijt} = \gamma X_{ijt} + \nu_{ijt}$, ($Z'_{ijt} = 1$, if $Z_{ijt} > 0$. Otherwise, $Z'_{ijt} = 0$) (1)

$Z_{ijt} = \{$ int only$_{ijt}$, internal$_{ijt}$, ext only$_{ijt}$, external$_{ijt}$, both$_{ijt}$, all$_{ijt}$ $\}$
$X_{ijt} = \{$firm size$_{ijt}$, tech staff ratio$_{ijt}$, skills$_{ijt}$, firm age$_{ijt}$, export status$_{ijt}$, FDI status$_{ijt}$, Dominance$_{ijt}$ $\}$

- Firm size $_{ijt}$: Log number of employees is used as a proxy of size of firm i in sector j and time t, in log form.
- Technical staff ratio$_{ijt}$: The number of technicians/number of total employees. Since technical staff is a relatively small number compared to total labour, there is no strong correlation between labour and the ratio variables, which allows the joint use of technical staff ratio and labor variables as the right-hand–side (RHS) .
- Skill$_{ijt}$: Log average wage of a firm i in sector j and time t, which is used as proxy of workers' skill.
- Firm age$_{ijt}$: The number of years since a firm i was created.
- Export status$_{ijt}$: Dummy variable that shows whether a firm exports or not.
- FDI status$_{ijt}$: Dummy variable that shows whether a firm has any foreign ownership.

- $\text{Dominance}_{\text{ijt}}$: A proxy for competition, and measured as a firm's share in the market. The indicator of dominance is constructed as $\text{dominance}_{\text{ijt}} = \frac{\text{revenue}_{\text{ijt}}}{\sum_{z=1}^{N} \text{revenue}_{\text{izt}}}$, where $\text{revenue}_{\text{ijt}}$ is the revenue of firm i at industry j and time t. N is the number of firms at industry j and time t.

$$v_{ijt} = \alpha_t + \alpha_j + \delta_{ijt}$$

- α_t : Time dummies (1997–2007)
- α_j : Industry dummies (NACE 15–36)
- δ_{ijt}: Idiosyncratic error, which varies across individual firms

Rather than using dummies, I then use innovation intensity (investment amount) at my left-hand side (LHS) for the abovementioned six categories of firms to capture information based on intensity, using firm fixed effects (FE) methods. The RHS variable remains the same.

$$\ln Z_{\text{ijt}} = \beta_1 X_{\text{ijt}} + v'_{ijt} \quad (2)$$

where $v'_{ijt} = \alpha_t + \alpha_j + \varepsilon'_{\text{ijt}}$

- $\varepsilon'_{\text{ijt}}$: Idiosyncratic error, which varies across individual firms

Meanwhile, if a firm that would have invested in innovation decides not to under a certain threshold ($z = 0$), the observed innovation value Z_{ijt} is censored around zero. To address this issue, I consider using an econometric technique for the censored dependent variable, such as Tobit. I will further discuss the potential censoring problem and solution in the next subsection.

Does innovation affect final output?

To identify the effect of innovation on productivity, I adopt a production function approach that describes the relationship between factor inputs and output. Specifically, I use the standard Cobb-Douglas production function, where output is a function of the

inputs the firm employs, such as labor, capital, and material, as well as its productivity. One advantage of using the production function is that it provides not only the coefficient for the variable of interest but also the coefficients of other factor inputs, which allow comparison of the relative size of the coefficient for variable of interest. Also, it reduces the problem of having to correct for other sources of firm heterogeneity that influence both innovation and overall performance, by including (controlling for) key factor inputs as regressors.

I consider innovation investment as a factor input and add the identified innovation variables in the production function. In this functional form, innovation is treated as an input, the same as labor, capital, and material. The residual is now unobservable, which takes out the effect of innovation inputs.

All variables are quantity terms (number of workers) or proxies for quantity terms that are measured by value terms divided by price index, as in previous literature.[43] For the LHS, I use gross output, measured by sales revenue deflated with the output deflators constructed from the INS's Producer Price Index (PPI). Since there are no separate deflators for material and innovation, I use these output deflators for material and innovation inputs. For the capital input, I have constructed the deflators from the Gross Fixed Capital Formation (GFCF) of the National Account.

The empirical specification and description of variables can be written as follows:

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln I_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (3)$$

- Y_{ijt} : The real output of firm i operating in sector j at time t, which is calculated by the sales revenue deflated by subindustry-level deflators from the PPI obtained from INS.

[43]. Industry-level price indexes are usually applied to deflate firm-level sales and input expenditures in production function estimates.

- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by GFCF, from the National Account.
- L_{ijt} : Number of workers.
- M_{ijt}: The value of physical material inputs used directly for production, deflated by PPI deflators.
- I_{ijt} : Sum of the innovation investment (all), which is the cost of R&D, cost of consulting services, and cost of royalty payment for firm i in sector j at time t, deflated by PPI deflators. The subindustry of the PPI index was used as its output subindustry.
- Θ_{ijt}: A vector of control variables that are the dummies of export and FDI status.
- α_t : Time dummies (1997–2007).
- α_j : Industry dummies (NACE 15–36).

To answer the main research question, which source of innovation contributes more to productivity, I divide the innovation variables into internal and external innovation as seen in equation (4), and I simply compare coefficient of β_4 and β_5 in equation (4).

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln \text{Internal } I_{ijt} + \beta_5 \ln \text{External } I_{ijt} + \beta_6 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (4)$$

To test whether the effect on productivity is different between those firms that invest in one source of innovation and firms that invest in both sources, I add the interaction term between internal and external innovation as seen in equation (5). This is because the β_4 in equation (4) actually includes not just those firms investing in internal innovation, but also those that invest in both sources of innovation. By adding the interaction term, the distinct effects of different categories of firms can be separated. In equation (5), β_4 provides the potential effect of investing only in internal innovation; the overall effect on internal innovation is $\beta_4 + \beta_6$. The same holds for β_5 and $\beta_5 + \beta_6$ for the firms that invest only in external innovation and the overall effect on external innovation.

In previous literature, the interaction term of both sources of innovation has been used to measure whether there is any complementarity in using both sources at the same time (Cassiman and Veugelers 2006). Therefore, the coefficient of β_6 in equation (5) can also provide information about whether there is any synergy of using both sources of innovation.

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln \text{Internal } I_{ijt} + \beta_5 \ln \text{External } I_{ijt} + \beta_6 \ln \text{Internal } I_{ijt} \times \ln \text{External } I_{ijt} + \beta_7 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (5)$$

There are three major problems with the above econometric specifications: first, if the innovation decision is endogenous, and thereby correlated with the error term; second, if the innovation variables are censored, and third, if the effect on final output is an indirect measure of the effect on the firm's productivity.

Simultaneity between innovation investment and productivity

Simultaneity bias (or endogenous input selection): If a firm's knowledge of its productivity influences its decisions to invest in innovation and the amount to invest, the estimated coefficient of innovation might be biased. Specifically, in the above specification, if more productive firms invest in innovation, the estimated coefficient of innovation might be biased upward since the innovation investment might be correlated with unobserved productivity shocks. Therefore, the above functional form using ordinary least squares (OLS) fails to convincingly isolate the causal effect of innovation on firm productivity.

To control for simultaneity between productivity and innovation, I applied the generalized method of moments (GMM) in the above specification. GMM deals with the simultaneity issue by using the previous year of observations of the dependent variable and the endogenous variable (here, innovation investment) as its own instrument, removing them from the regression equation (using the differenced equation with

lagged levels as instruments) or removing them from the instruments (using differences as the instrument in a levels regression). The INS dataset has a relatively short time (T = 11, max, from 1997 to 2007, but most have less than 11 years of observations) and a larger firm dimension (N = 16,471, unbalanced), which is an advantage of using GMM.

In addition to innovation variables, I consider material as an endogenous variable, as in previous literature (Ackerberg et al. 2006). Firms can quickly adjust their material inputs based on their knowledge of productivity and final output, while it takes more time to adjust labour and capital inputs. Therefore, I use lagged values of the dependent variable, innovation variables, and material as its own instrument, by removing them from the regression equation (using the differenced equation with lagged levels as instruments) and from the instruments (using differences as instruments in the levels regression).

Due to gaps in innovation variables for previous years in the weakly balanced INS data, using a dynamic equation significantly reduces the number of innovative firms that can be tested. A dynamic model that has lag dependent variable and/or lag factor inputs as additional regressors requires further lags of those additional regressors when they are used. Therefore, I use a static equation, which is a long-run description, since it might take some time for inputs, such as innovation investment, to influence the output. To understand the short-run effects, my estimation required an assumption that the current year's innovation investment of a firm reflects the previous years' innovation investment. This might be a valid assumption given that the overall number of innovative firms and the amount of innovation investment has been stable over the data period.

In addition to using GMM, I also considered other econometric techniques widely used in previous literature to deal with simultaneity issues in firm-level analysis; these include Olley and Pakes (OP) (1996) and Levinsohn and Petrin's (LP) (2003) semi-parametric estimator. However, critical assumptions of OP methods on monotonicity of investment in productivity might not hold when introducing an innovation status

variable (Van Biesebroeck 2003; De Loecker 2007, 2013). Also, the INS data are weakly balanced; thus, there is no information about those firms that enter into and exit from the market, which is important in controlling the selection bias in OP methods. Meanwhile, the current method of LP (such as the levpet command in Stata) is developed for one proxy variable (material) and one endogenous variable (capital) when using revenue as the dependent variable, and does not allow the addition of innovation as another endogenous variable; (it is possible, however, to manually code this method to have an additional endogenous variable). For these reasons, OP and the current method of LP are not the most suitable methods for analysing innovation effects for INS data; thus, I used GMM instead of these two semi-parametric methods.

As mentioned above, the OLS estimate would be biased upward, and the fixed effects (FE) estimate of coefficients would be biased downward.[44] However, those estimation results are still useful since they provide an upper and lower range of the estimated results. Also, the current LP estimation is still closer to true estimation than OLS and FE, since it disregards simultaneity issues of other factors inputs, such as capital, in estimating the production function, even though it does not remove the simultaneity issue in my interest variable, innovation. Therefore, I will report the results from OLS, FE, and the current LP methods to ensure my estimated results using GMM are within the credible range.

In case the innovation variables are censored

If there are costs to seeking out innovation activities, and innovation activities require a certain scope to be materialized, firms would invest in innovation activities only when their investment amount is above a certain threshold. Many firms that are not investing in innovation would have invested in innovation without these threshold constraints. In the INS data, about 40 percent of firms reported zero innovation investment, therefore, the innovation variable might be censored at zero.

[44]. How FE provides an estimate with a downward bias is explained well in Van Beeren 2012.

Therefore, I consider a firm's decisions to innovate as two-fold: first, whether to invest in innovation at all, and if so whether to invest in internal or external innovation (or both), and second, how much to invest. I used the Type II Tobit model (selection in censored data) with three-stage equations. The first equation of the model explains the propensity to invest in overall innovation (all), invest in internal source of innovation (internal), and in external innovation (external). Those firms that reported having positive innovation investment are defined as innovator, creator, and buyer. The second equation explains the investment amount in each source of innovation activity (if a firm invests). Therefore, the first two equations estimate the predicted investment amount for those firms that could have invested if the cost of searching were zero or if there is no minimum requirement to invest in innovation (no threshold). Then, in the third stage, I used the predicted value of the innovation investment amount, instead of the observed innovation amount, in the main regressions. The empirical model is therefore as follows:

First stage: Decision equation (Probit model)

$$Z^*_{ijt} = \gamma X_{ijt} + v_{ijt,} \text{ and } z_{ijt} = 1 \text{ if, } z^*_{jt} > 0, \; z_{ijt} = 0 \text{ if } z^*_{ijt} = < 0 \qquad (6)$$

The first stage is shown in equation (6), which is the propensity of the decision to invest in innovation, and then, which source (create or buy) of innovation. I used the Probit model to understand the determinants of firms' innovation decisions in each source. As mentioned above, *X* is the vector of factors that could influence the probability of firms investing in innovation, where *Z* is a vector of dummy variables for investing in each type of innovation:

X_{ijt} ={ firm size $_{ijt}$, $technical\ staff\ ratio_{ijt,}$ $Skill_{ijt}$, $firm\ age_{ijt}$, $export\ status_{ijt}$, $FDI\ status_{ijt}$, $Dominance_{ijt}$ },

Z_{ijt} = {invest in any source of innovation (all), invest in internal innovation (innover), and invest in external innovation (externer)}.

Second stage: Predict innovation investment amount, considering censoring issue (Tobit model)

$U^*_{ijt} = \gamma' Q_{ijt} + \sigma\lambda_{ijt} + \mu_{ijt}$, and $U_{ijt} = U^*_{ijt}$ if $z_{ijt} = 1$, $U_{ijt} = 0$ if $z_{ijt} = 0$ (7)

$\nu_{ijt} = \alpha_t + \alpha_j + \varepsilon_{ijt}$, $\mu_{ijt} = \alpha'_t + + \alpha'_j + \varepsilon'_{ijt}$, t=1, …, T, j= 1, …J and I = 1, … N
and $\varepsilon_{ijt} = \rho_1 \varepsilon_{ijt-1} + \tau_{ijt}$, $\varepsilon_{ijt} = \rho_2 \varepsilon'_{ijt-1} + \tau'_{ijt}$, $\tau_{ijt} \sim N(0, \sigma^2_{\tau})$, $\tau'_{ijt} \sim N(0, \sigma^2_{\tau'})$

Equation (7) is for the second stage, which is to predict the innovation investment amount, considering the potential censoring issue, using the Tobit model. Here, *U* is the vector of the log amount of innovation investment. *Q* is a vector of explanatory variables for innovation investment decision and innovation amount equations, which is essentially the same vector as *X.* Using the same vector of variables does not raise any identification issues in the Tobit model (Crepon, Duguet, and Mairesse 1998).

U_{ijt} = {log total innovation amount (all), log internal innovation amount (create), log external innovation (buy)}.

Q_{ijt} = {firm size$_{ijt}$, techstaff ratio$_{ijt,}$ skill$_{ijt}$, age$_{ijt}$, export stat$_{ijt}$, FDI stat$_{ijt}$ dominance$_{ijt}$},

σ is the standard deviation, and λ is the inverse Mills ratio. The components α_t and α'_t are time dummies; α_j *and* α'_j are industry dummies; and ε_{ijt} is an idiosyncratic error, which varies across individual firms. Hence the model allows unobserved heterogeneity, first order state dependence, and serial correlation in the error components.

When a firm that would have invested in innovation decides not to innovate, under a certain threshold (z = 0), the observed innovation value *i* is zero. The significance of the presence of these potential censoring effects is indicated by the Rho statistics in the generalized Tobit model, which reflects the correlation between the error terms of the two equations (μ and υ).
I then use the predicted innovation investment amount ($\widehat{U}_{ijt}$), which is measured in the second stage, and plug it into the main specifications, which are equations (3) to (5). Now, equations (3) to (5) become equations (8) to (10).

In the third stage, I plug in the predicted innovation investment amount ($\widehat{U}_{ijt}$) into the main equations:

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln \widehat{All}_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (8)$$

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln \widehat{internal}_{ijt} + \beta_5 \ln \widehat{external}_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (9)$$

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln \widehat{internal}_{ijt} + \beta_5 \ln \widehat{external}_{ijt} + \beta_6 \ln \widehat{internal}_{ijt} \times \ln \widehat{external}_{ijt} + \beta_7 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (10)$$

Meanwhile, it should be noted that the use of the Tobit model for potentially censored regressors produces different effects than the selection bias of a sample. If the analysis is made only for firms with innovation inputs or outputs, this could lead to a sample selection bias since the characteristics of innovative firms might be different from those firms that are not. To deal with this selection bias, previous literature also used a selection model with a two-stage estimation procedure, which is a similar econometric strategy to the above specification, such as Probit and Tobit specifications for the interval data on outputs to measure the probability of investment in innovation and input the estimated probability into the production function (Lokshin et al. 2018; Crepon, Duguet and Mairesse 1998). However, unlike the innovation surveys or samples of only innovators, my data include representative Tunisian firms, both innovators and non-innovators. Therefore, sample selection bias is not an issue with the INS data.

Having Total Factor Productivity (TFP) as a dependent variable

There might be questions about why I analyse the effects of different sources of innovation on final output, Y, instead of on productivity itself. In fact, some literature has used TFP as the dependent variable to measure the effect of innovation-related activities on productivity. That literature typically conducted these analyses with two steps: first, measuring TFP as residual of the standard production function, and second,

testing innovation's effect on the measured TFP (for example, Brynjolfsson and Hitt 2003). This is a direct way to measure innovation's effect on productivity.

However, the product function with *Y* as a dependent variable is essentially the same as with TFP as a dependent variable. In a standard product function, the residual (ϵ_{ijt}) consists of productivity, A_{ijt}, the Hicksian neutral efficiency level of firm (average TFP), and ϵ', standard i.i.d. error term, capturing unanticipated shocks to production and measurement error.

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \Theta_{ijt} + \alpha_t + \alpha_j + \epsilon_{ijt} \quad (11)$$

$$\epsilon_{ijt} = \text{A}_{\text{ijt}}, + \epsilon'_{ijt}$$

In equation (6), adding innovation — typically considered a key driver of productivity — as an input of the product function makes innovation a part of TFP (A_{ijt}).

$$\text{A}_{\text{ijt}} = f'(I_{ijt}) \quad (12)$$

Therefore, using specification (12) is essentially making equation (11) into equation (13), which is my specification.

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \Theta_{ijt} + \alpha_t + \alpha_j + f'(I_{ijt}) + \epsilon'_{ijt} \quad (13)$$

In my view, measuring an innovation input's effect on output might be a better approach than measuring its effect on productivity for several reasons. First, measuring the innovation effect on TFP requires the assumption that innovation investment, such as investment in R&D or in IT equipment, does not affect the output directly but indirectly through productivity, which is not necessarily true. Also, having innovation as an input in the production function could automatically control other input intensity in production. Moreover, the coefficient of innovation could also provide the relative importance of innovation by allowing a comparison of the elasticity of innovation input to that of other key input variables. Lastly, the production function approach has been widely used; therefore, the limitations related to the econometric issues are well

understood, and a number of solutions based on the latest econometric techniques have been suggested. In fact, most literature has used Y as the dependent variable and innovation as inputs in the production function to analyse the effect of innovation on productivity.

Therefore, I will measure the effects of innovation inputs on final output, which is an indirect measure of productivity, as a main specification. In addition, as a robustness check, I will undertake the abovementioned two-stage approach, and measure TFP as a residual of the product function, and then use TFP as LHS variable, and test my results for consistency.

I measure TFP as the residual of a Cobb-Douglas production function, which has an output that is a function of the inputs the firm employs — the same equation of basic specifications as equation (3), but without an innovation term in the RHS. The empirical specification of estimation TFP can be written as follows:

$$\ln Y_{ijt} = A_{ijt} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \delta_t + \delta_i + \xi_{ijt} \quad (14)$$

- Y_{ijt} : The real output of firm *i* operating in sector *j* at time *t,* which is calculated by the sales revenue deflated by subindustry deflators from the Producer Price Index.
- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by GFCF, from the National Account.
- L_{ijt} : Number of employees.
- M_{ijt} : The value of material inputs adjusted for changes in material inventories, deflated by subindustry deflators from the Producer Price Index.
- A_{ijt}: The Hicks neutral efficiency level of firm (TFP of firm) measured as the residual of the model/stochastic error term.
- δ_t : Time dummies for 1997–2007.
- δ_i: Firm fixed effect.
- ξ_{ijt}: Standard i.i.d. error term capturing unanticipated shocks to production and measurement error.

I use the generalized method of moments (GMM) in TFP estimation for consistency, by controlling simultaneous input selection issues when input is correlated with the error term (A_{ijt}). The INS dataset has a relatively short time dimension (T = 11 max, after omitting information after 2008, but most firms have less than 11 years of observations) and a larger firm dimension (more than 16,000 manufacturing firm observations, although many are repeated several times), therefore, is suitable for GMM.

With INS data, for each of the NACE two-digit industries in manufacturing (NACE 15–36), I obtained TFP estimation, with non-dynamic system GMM with 2 and 3 lags for instruments. One drawback of using a weakly balanced INS data set is that the dynamic model will significantly reduce the number of observations; therefore, I used the non-dynamic GMM model. Specifically, I treated all factor inputs — labor, capital, and material — as endogenous; so, factor inputs are instrumented by their own lag and differenced. Therefore, previous year information has already been used as an instrument. Meanwhile, a dynamic model that has lag-dependent variables and lag factor inputs as additional regressors requires one additional lag in instruments, which significantly reduces the number of observations. Likewise, further lags in instruments significantly reduce the number of observations; so, I used 2 and 3 lags in instruments. After omitting those observations that were missing values in key variables, such as revenue and employment, I obtained approximately 15,800 TFP measurements out of about 16,471 firm observations.

As a robustness check, I use this estimated TFP as a dependent variable, $A_{\mathrm{ijt}} = f'(I_{ijt})$, as described as below.

$$\ln A_{ijt} = \beta_1 \ln All_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \tag{15}$$

$$\ln A_{\mathrm{ijt}} = \beta_1 \ln Internal_{\mathrm{ijt}} + \beta_2 \ln External_{\mathrm{ijt}} + \beta_3 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \tag{16}$$

$$\ln A_{\mathrm{ijt}} = \beta_1 \ln Internal_{\mathrm{ijt}} + \beta_2 \ln External_{\mathrm{ijt}} + \beta_3 \ln Internal_{\mathrm{ijt}} \times \ln External_{\mathrm{ijt}} + \beta_4 \Theta_{ijt} + \alpha_{\mathrm{t}} + \alpha_{\mathrm{j}} + \varepsilon_{ijt} \tag{17}$$

5. Results

Determinants of innovation investment

Table 3 presents estimation results of equation (1), with firm fixed effects. It shows how each determinant is associated with each source of innovation decision, while controlling for firm-specific, time-invariant unobserved bias (FE). I provide the results of the Probit estimation using pooled regression in table B.1, appendix B.

Table 3. Determinants of Innovation Decision, Panel Firm Fixed Effects

Dep. Var. $\{Z'_{ijt}\}$	(1) Internal Only	(2) Internal All	(3) External Only	(4) External All	(5) Both	(6) All
Firm size	-0.007	0.015	0.021	0.043**	0.022	0.036*
	(0.269)	(0.328)	(0.146)	(0.005)	(0.138)	(0.015)
Tech staff ratio	0.003	-0.003	0.049*	0.043	-0.006	0.046
	(0.741)	(0.914)	(0.023)	(0.076)	(0.796)	(0.058)
Skill	-0.009	0.006	0.026	0.041**	0.015	0.032*
	(0.179)	(0.689)	(0.091)	(0.009)	(0.289)	(0.037)
Export status	0.004	0.021	0.037*	0.055**	0.017	0.058***
	(0.605)	(0.189)	(0.012)	(0.001)	(0.281)	(0.000)
FDI status	0.001	0.005	-0.026	-0.022	0.004	-0.021
	(0.898)	(0.781)	(0.167)	(0.284)	(0.818)	(0.299)
Firm age	-0.000	0.001	-0.001	0.000	0.001	0.000
	(0.665)	(0.275)	(0.290)	(0.874)	(0.233)	(0.963)
Dominance	-0.002	0.289	-0.258	0.033	0.291	0.031
	(0.943)	(0.408)	(0.385)	(0.915)	(0.401)	(0.920)
# of obs.	13,257	13,257	13,257	13,257	13,257	13,257
# of dep.=1	534	5,225	4,222	8,913	4,691	9,447
# of group	3,332	3,332	3,332	3,332	3,332	3,332
R^2, within	0.002	0.005	0.006	0.010	0.006	0.011
Rho	0.458	0.647	0.610	0.601	0.659	0.598

Note: Firm fixed-effects (within) regression; *t* statistics in parentheses, standard errors are clustered and robust; year and industry dummies are included but not reported. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

Columns (2) and (4) show the factors that influence the probability of firms engaging in internal and external sources of innovation respectively. Column (6) shows probability of investment in any source of innovation (all). I added columns (1), (3), and (5) to see whether there are any differences between those firms investing in only one source of innovation and those investing in both sources at the same time.

The determinants of a firm's decision to invest in innovation are different between internal and external innovation. Tests for the difference of coefficients are conducted, and the null hypothesis that coefficients of the regressions from different columns are systematically the same is rejected at the 1 percent significance level between columns (1) and (3), and between columns (2) and (4).

The above estimation includes 9,447 firms that invested in any sources of innovation. Among them, 4,691 invested in both sources of innovation. Approximately 8,913 firms invested in external innovation, and of those, 4,222 invested exclusively in external sources of innovation. A total of 5,225, firms invested in internal innovation, but only 534 invested in only internal sources of innovation.

All the coefficients of columns (1) and (2) are statistically insignificant, which implies that there are no systemic factors that encourage firms' investment in internal innovation. In addition, those firms that invest in only one type of innovation shows less systemic patterns that encourage firms' investment decision, compared to those firms that invest in both sources of innovation. Specifically, most coefficients in column (1), (3) and (5) are insignificant, except for the positive and significant coefficients of technical ratio and export for those firms that invest in only external sources of innovation as shown in column (3).

The estimation results in columns (4), and (6) show that being large, paying higher wages, and participating in exports are positive determinants of firms' investment in both external sources of innovation and any type of innovation. Interestingly, FDI is associated with decreased likelihood of investment in innovation, and has a negative

coefficient; however, this coefficient is statistically insignificant. Also, technical staff ratio, dominance, and firm age are not statistically significant determinants of all innovation and external innovation decisions.

Table 4. Determinants of Innovation Intensity, Panel Firm Fixed Effects

Dep. Var. $\{Z_{ijt}\}$	(1) Internal Only	(2) Internal All	(3) External Only	(4) External All	(5) Both	(6) All
Firm size	-0.041	0.210*	0.274*	0.564***	0.291*	0.523***
	(0.391)	(0.048)	(0.011)	(0.000)	(0.016)	(0.000)
Tech staff ratio	0.064	0.052	0.438*	0.308	-0.101	0.401*
	(0.437)	(0.776)	(0.019)	(0.117)	(0.627)	(0.046)
Skill	-0.069	0.182	0.320**	0.574***	0.240	0.491***
	(0.174)	(0.106)	(0.005)	(0.000)	(0.060)	(0.000)
Export status	0.047	0.196	0.354**	0.533***	0.198	0.599***
	(0.408)	(0.122)	(0.006)	(0.000)	(0.169)	(0.000)
FDI status	-0.014	0.018	-0.245	-0.137	0.096	-0.163
	(0.852)	(0.912)	(0.148)	(0.441)	(0.611)	(0.368)
Firm age	-0.001	0.009	-0.004	0.004	0.010	0.005
	(0.660)	(0.225)	(0.624)	(0.576)	(0.243)	(0.566)
Dominance	0.018	5.747**	-1.145	2.207	4.613*	3.486
	(0.984)	(0.004)	(0.577)	(0.308)	(0.044)	(0.114)
# of obs.	13,257	13,257	13,257	13,257	13,257	13,257
# of group	3,332	3,332	3,332	3,332	3,332	3,332
R^2, within	0.002	0.004	0.006	0.011	0.062	0.011
Rho	0.429	0.583	0.585	0.569	0.632	0.560
F test (u_i = 0)	1.95	3.39	2.83	3.49	3.37	3.48
Prob > *F*	0.000	0.000	0.000	0.000	0.000	0.000

Note: Firm fixed-effects (within) regression. The dependent variable is the log investment amount of different sources of innovation as noted in each column. *t* statistics in parentheses, standard error are clustered and robust; year and industry dummies are included but not reported. Rho reports fraction of variance due to u_i. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent.

Table 4 provides the above specification with the firm fixed effects, but with dependent variables of actual investment amounts in different sources of innovation, as seen in

equation (2). The advantage of using the innovation amount as a dependent variable rather than using a dummy variable for innovation is that the results reflect the information on innovation intensity (investment amount to innovation) with firm FE. Table B.2 in appendix B provides the estimation results of the same specification as table 1.4, but using random effects rather than firm fixed effects. Hausman test results (table B.3) reveal that fixed effect is more appropriate to use in the above model.

Although the direction and statistical significance of coefficients of table 4 are similar to those in table 3, the results of table 4 are different from those of table 3, which explains that the decision related to innovation (whether to innovate or not) and decisions related to innovation intensity (how much to innovate) are not exactly the same.

Similarly to the results in table 3, for firms that invest only in internal sources of innovation, widely recognized determinants of investing in innovation do not influence their innovation intensity decision. In column (1), all coefficients are statistically insignificant, implying that none of the abovementioned factors would increase the innovation investment amount for those firms that invest in internal innovation only.

Meanwhile, large firms with a big market share (dominance) will have a larger amount of overall internal innovation, as seen in column (2). In fact, dominance has a very large effect on internal innovation investment amount, since a 1 percent increase of market share is associated with a 5.74 percent increase of the internal innovation investment amount. The other determinants, including technical staff ratio, FDI status, and firm age, will not augment firms' internal innovation amount.

For firms that invest only in external sources of innovation, firm size, average wage and export status have positive and significant effects on external innovation amount, as seen in column (4). Meanwhile, the coefficient of technical staff ratio also becomes positive and statistically insignificant for the firms that invest in external innovation only and that invest in any sources of innovation, as shown in column (3) and (6).

The above results of table 3 and 4 are largely consistent with the findings of previous studies, although a few are in contrast to previous findings.

Firm size, measured by log number of labor, matters for the decision to invest in both source of innovation and innovation intensity, except for firms that invest in only one source of innovation. This finding is consistent with previous literature that finds firm size to be one of the determinants of innovation (Souitaris 2002), and that the biggest firms have an advantage when undertaking innovative activities (González and Jaumandreu 1998).

Workers' skill, measured by log average wage, also has a positive coefficient for both sources of innovation decisions, except for firms that invest in only one source of innovation. Also, skill has positive effects on innovation intensity of external sources. The magnitude of the coefficient for skill is as large as the coefficient for firm size in table 4. This might suggest that not only the quantity of labour, but also the quality of labour is important for making the decision to invest in innovation. While the coefficients of firm size and skill are similar in both internal and external innovation in the Probit model, both coefficients are larger for internal innovation than external innovation in the fixed effects model. Larger firms with more skilled employees are more likely to invest in internal innovation.

Participating in exports also has a positive effect on both sources of innovation and innovation intensity (except for internal innovation intensity). The coefficient for export is larger for the external innovation decision than for the internal innovation decision. The coefficient of export on external innovation intensity is significant while the coefficient on internal innovation intensity is insignificant. Exporters might need more advanced technology, which might not exist in-house, or they may have better exposure to external markets or other firms, which might help them to buy external innovation.

Again, a test for the difference of coefficients is conducted, and the null hypothesis that coefficients of the regressions from the mentioned columns are systematically the same

is rejected at the 1 percent significance level between columns (1) and (3), and between columns (2) and (4), which confirms that the determinants of investing in innovation are different between internal and external sources of innovation.

Table A.2 in appendix A provides more details on firms' innovation investment by level of their export status: full exporters, which export all of their production; partial exporters, which export some of their production but sell the remaining production on the domestic market; and non-exporters. Partial exporters invest the most in innovation, followed by full exporters, and lastly, non-exporters. Full exporters and partial exporters invest much more in external innovation than in internal innovation.

Table A.3 in appendix A shows the innovator's ratio by FDI status. Interestingly, firms with joint ownership between foreign owner and domestic owner (partial FDI) invest more in innovation than fully domestic firms (no FDI), while those firms that are fully owned by foreign owner (full FDI) invest in innovation much less.

The low level of innovation investment of full FDI firms might be explained by the specific characteristics of foreign investment in Tunisia. FDI in Tunisia is mainly provided by a few European countries, such as France and Italy, and is concentrated heavily in the export processing zones (EPZs), known as the offshore regime, where foreign firms receive a tax incentive to export products back to Europe. The main purpose of their investment in Tunisia is cost saving, from both cheaper labor and tax incentives in natural resource–related industries, or from outsourcing a relatively simple part of the process, like textiles, in the production value chain. In fact, research on EPZs in developing countries found that foreign firms operating in EPZs mostly engaged in process trade based on cheap unskilled or semi-skilled labor available in the host country and did not generate linkages with the local economy. This situation might explain the lesser likelihood of innovation investment for FDI firms.

The negative effects of FDI on technological upgrading in domestic firms have been documented previously. Competition with foreign subsidiaries may reduce local firms'

R&D efforts (OECD 2002). FDI firms may remain enclaves in developing countries, without effective linkages with the local economy. However, these negative effects are more relevant for competitor firms or other firms in the domestic market, rather than those firms that receive FDI. Therefore, there are many preconditions, such as a firm's absorptive capacity and business environment, necessary for an effective technology transfer process to occur through FDI.

The findings above are consistent with previous studies investigating determinants of innovation in Tunisia. Surveys on selected industries, such as ICT and pharmaceutical industries, document the lack of innovation efforts in those so-called high technology industries (Harbi et al. 2009, 2012; Yacoub 2013). Also, a study using the innovation survey confirms that firm size has a positive effect on innovation (Ayadi et al. 2009).[45] Moreover, quality of labour has a positive effect on innovation, whereas FDI has a negative impact on innovation in Tunisia (Gabsi et al. 2008; Karray and Kriaa 2008). Their findings are consistent with the abovementioned results.

Which source of innovation is the more efficient way to increase productivity?

Table 5 presents the main results of the paper and provides estimation results of equations (3), (4), and (5), using GMM with lag 2 and 3.

The instrument set for the differenced equation consists of the log of revenue, the log of innovation investment (for all, internal and external innovation), the log of material input, in levels, in periods *t*-2 and *t*-3 (among which missing values are treated as 0, and the instruments for each period are collapsed), the log of labour and capital inputs, export and FDI status, and year and industry dummies, differenced. The instrument set for the levels equation consists of the log of revenue, the log of innovation investment

[45] The innovation survey used a small sample of firms that were highly likely to innovate, and therefore, cannot provide information for general firms in Tunisia. Also, the studies that use the innovation survey analyse the determinants of innovation output, not innovation efforts. Therefore, I cannot directly compare my results with those studies; however, they still provide valuable information to cross-check the characteristics of Tunisian firm behaviour related to innovation.

(for all, internal and external innovation), the log of materials, labour, and capital inputs; export and FDI status as a constant; and year and industry dummies.

Table 5. Innovate Internally or Externally? Using GMM

Dep. Var. ln revenue	(1) All	(2) Internal vs. external	(3) Synergies
ln_labor	0.355***	0.357***	0.362***
	(0.000)	(0.000)	(0.000)
ln_capital	0.005	0.001	0.017
	(0.899)	(0.988)	(0.674)
ln_mateiral	0.640***	0.639***	0.642***
	(0.000)	(0.000)	(0.000)
ln_all	0.027**		
	(0.003)		
ln_internal		0.013	0.046
		(0.189)	(0.274)
ln_external		0.021*	0.030*
		(0.048)	(0.045)
ln_int×ln_ext			-0.006
			(0.207)
export_stat	0.244***	0.242***	0.241***
	(0.000)	(0.000)	(0.000)
FDI_stat	0.275***	0.275***	0.280***
	(0.000)	(0.000)	(0.000)
# of obs.	15,735	15,735	15,735
# of groups	4,255	4,255	4,255
sum of coefficient	1.105	1.106	1.02
AR2 (p-value)	0.001	0.001	0.002
Hansen (p-value)	0.000	0.000	0.000

Note: Year and industry dummies were included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity).; p-values in parentheses. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

The test results require a careful interpretation of GMM results. Test results for the AR2 are close to zero, which leads me to reject the null hypothesis that the differenced residuals in period t and t-2 are uncorrelated — therefore, autocorrelation in these levels might be a concern in this system GMM measurement. The Sargan/Hansen test of overidentifying restrictions for GMM estimators also rejects the null hypothesis that the instruments are exogenous. This might have been caused by the fact that the instrument is exactly identified. The difference-in-Sargan/Hansen test fails to reject similar results that these additional instruments are valid.

The coefficient of materials (intermediary inputs) is quite large, around 0.64 in columns (1) to (3), implying that Tunisian firms engage predominantly in relatively low value added activities. While the coefficient of labour is significant and around 0.36 in columns (1) to (3), the coefficient of capital is close to zero and statistically insignificant. A very small coefficient for capital is not unusual in previous research on firm-level TFP analysis in developing countries (for instance, see Van Beveren, 2012). The coefficient of factor inputs reflects both input and scale elasticities related to output.

Control variables, participating in exporting activity (export) and having foreign ownership (FDI) have positive and significant effects on final output. Interestingly, the positive effect of FDI on output is in contrast to its effects on innovation decisions and innovation intensity. FDI would not increase either a firm's decision to innovate or the intensity of its innovation investment, but would still increase its final output.

I used the generalized method of moments (GMM) in TFP estimation to provide consistent estimation by controlling simultaneous input selection issues when input is correlated with error term (A_{ijt}). For instance, when there is an exogenous price shock, if material is considered more easily adjustable than labour and capital, then material is more strongly correlated with the error term. Therefore, material is biased upward and labour and capital are biased downward. Instruments can be used to nullify this bias; however, in general it is hard to find such instruments. Therefore, researchers use GMM

with lagged variables of output and inputs as instruments, as those are already included in the firm-level data. GMM thus provides a consistent estimate by removing the simultaneity issue that is caused by the endogenous input choice in TFP estimation.

Overall, results show that overall innovation (all) has a positive and statistically significant effect on output productivity, controlling for simultaneity issues between innovation and final output. In particular, external innovation has a positive and statistically significant effect on output productivity. Meanwhile, the coefficient of internal innovation is statistically insignificant at the 5 percent level, which is surprising and contrasts with previous literature that finds a positive effect of internal innovation on productivity (for example, see Griffith et al. 2004). In addition, a complementary effect between internal and external innovation is not found for Tunisian manufacturing firms.

Specifically, column (1) shows that overall innovation (all) has a positive and statistically significant effect on output productivity, controlling for simultaneity issues between innovation and final output. The coefficient of innovation (all) variable is 0.027, implying that a 1 percent increase of innovation investment would be associated with a 2.7 percent increase in final output, controlling for other inputs and export/FDI status, and the simultaneity issue that could be raised when firms with greater output invest more in innovation.

Column (2) shows the effect of each individual source of innovation on output productivity. External innovation has a positive and statistically significant effect on output productivity, despite the pros and cons of innovation outsourcing and their complex characteristics. In fact, the coefficient of external innovation is 0.021, so external innovation contributes the most to the effect of overall innovation on output productivity seen in column (1). This finding is particularly important, since to date there has been little empirical evidence that quantifies the effect of innovation outsourcing on firms' output productivity, particularly in developing countries.

The insignificant coefficient of internal innovation might be explained by a number of factors. First, if innovation investment requires a certain threshold amount to successfully enhance firms' productivity, it may be that current internal innovation has not yet reached the threshold. Second, Tunisian firms' outsourced innovation might be relatively simple, so it does not require a high absorptive capacity, which can be measured by the internal innovation investment.

Otherwise, internal innovation efforts might not be good proxies of absorptive capacity in Tunisia. As found in a previous study, if technology is difficult to transfer, firms must have a certain prerequisite capacity to learn and adopt the external source of innovation (absorptive capacity). Lastly, it may be that internal innovation is not used efficiently within the firms. In fact, the previous study found that Tunisia's relatively large spending on R&D has not increased innovation outcomes at the national level, due to the inefficient innovation environment (World Bank 2010[46]). In any case, it has been more efficient for Tunisian manufacturing firms to simply acquire technology created externally to enhance their output productivity during the period of data coverage.

The results are consistent with the previous study on Tunisia.

Using the innovation survey, Ayadi et al. (2009) concluded that Tunisian firms must benefit from external knowledge sources to exhibit either product or process innovation. Internal innovation, specifically investment in internal R&D, plays a limited role in generating product innovation but no effect on process innovation. Harbi, Amamou, and Anderson (2009) conducted surveys on 60 Tunisian ICT firms and found that internal innovation, specifically R&D, is negatively associated with firms' performance. Later, Harbi, Amamou, and Anderson (2012) conducted surveys on 92 small Tunisian ICT

[46] Tunisia spent an estimated 1.25 percent of its GDP on R&D in 2009. That and the number of researchers per million people are typical proxies showing innovation inputs; in Tunisia they are above regional average. However, innovation outcomes are disappointing in Tunisia, which shows a low number of international patent applications and low utilization of the results of research by firms, with both indicators below the regional average (WB 2010).

companies and found that although some innovation cultural values were positively related to firm performance, others appeared counterproductive. Specifically, high performance firms favoured directly managing and controlling employees, and placed a strong emphasis on cost control, rather than on creating a supportive environment to nurture external knowledge sources.

Column (3) provides estimation results when the interaction terms of both sources of innovation are added. The coefficient of external innovation becomes larger than in column (2), showing that external innovation's effect on output productivity is larger for those firms that invest in only external sources of innovation than for firms that invest in both internal and external sources of innovation. The coefficient of internal innovation remains statistically insignificant.

Meanwhile, the coefficient of the interaction term is close to zero and statistically insignificant, implying that there is no synergy in using both sources of innovation simultaneously. This result further supports the argument that internal innovation does not play a role in absorptive capacity in Tunisia, in contrast to earlier studies that argue it does by adapting external innovation. Therefore, there is a complementary effect between internal and external sources of innovation.

Results from table 5 might suggest that, in a developing country like Tunisia where firms face resource constraints and have limited internal skills and capability to innovate, it is better to increase investment exclusively in external innovation rather than dividing scarce resources between the two sources of innovation.

These results contradict some previous studies that find complementary effects for using both sources of innovation. For instance, Lokshin, et al. (2008) found complementarity in Dutch manufacturing firms, and Cassiman and Veugelers (2006) found it in Belgian manufacturing firms.

My results contrast those studies, probably because of sample selection bias of previous studies that narrowly focused on firms that innovate. For instance, Lokshin, et al. (2008) conducted their studies only on 304 Dutch manufacturing firms that answered that they were innovating.

More importantly, there might be differences in the way innovation works in developing and in developed countries. Specifically, firms in developing countries, such as Tunisia, have a lower level of innovation investment to start with. At the early stages of technology development, much more investment is required; therefore, there is an increasing rate of return. But after a certain threshold, firms would reach the level close to the technology frontier, which might cause a diminishing rate of return and explain the complementarity of using both sources of innovation. If Tunisian firms face resource constraints and their available investment amount is below the threshold, it is better for them to invest in one source of innovation, especially the one that contributes more to output productivity — "buying".

In fact, complementary effects are identified mostly in developed economies.[47] In the case of developing countries, the complementary effect was found only conditionally or only when certain characteristics hold. For instance, Hou and Mohnen (2013) documented complementary effect only for firms with 100 to 300 employees, however, for more general firms, they found a substitution effect between both sources of innovation in increasing labour productivity in Chinese manufacturing firms.

[47]. For instance, using a similar specification of the above regression on manufacturing firms, Lokshin et al., (2008) found positive and significant coefficients of the interaction term of both sources of innovation. They concluded that it is more efficient to divide the resources into both sources of innovation because a decreasing rate of return on innovation creates synergies between two sources of innovation. They added quadratic terms of each source of innovation in their specification to allow the decreasing or increasing returns to scale in both sources of innovation. They found that the existence of a decreasing rate of return, especially at high levels of internal and external R&D. In the case of the data they used, productivity grew by increasing the share of external R&D in total R&D (probably because of low level of external R&D relative to the internal R&D).

The findings of table 5 suggest that Tunisian firms with limited budgets for innovation would gain more by buying innovation, rather than creating in-house, and that there are no synergies of using both sources of innovation at the same time.

While research on the effect of innovation outsourcing on firm productivity on more general industries with representative firms in developing countries is extremely rare, previous literature provides explanations as to why no complementary or even a negative (supplementary) effect has been observed.

Internal and external innovation substitute for each other, especially when resources are limited (Basant and Fikkert 1996; Blonigen and Taylor 2000). Given a limited budget, an increase in either of the two options tends to reduce the spending incurred on the other option. If the effect on innovation investment on productivity is not linear or requires a certain amount of investment (threshold) to make a positive effect on the final outcome, splitting two types of innovation would actually have a lower effect than consolidating only one type of innovation. While it is difficult to generalize, existing evidence from studies shows that complementary effects tend to be more obvious in developed countries, whereas substitution tends to be more common in the analysis of developing countries.

In addition, other studies argue that complementary or substitution effects could be changed depending on the ratio of different sources of innovation used jointly, the firm's initial internal innovation condition, and its external environment. The level of firms' internal R&D and the breadth of R&D collaborations serve as instruments to increase the effectiveness of R&D outsourcing (Fu 2010). If learning is less demanding, internal innovation has little impact on absorptive capacity. In the extreme case in which external knowledge can be imitated without any expertise, a firm's internal R&D would have no effect on its absorptive capacity (Cohen and Levinthal 1990).

Table 6 provides estimation results from different econometric methods, such as ordinary least squares (OLS), fixed effects (FE), and Levinsohn and Petrin (LP), to estimate equations (3) to (5).

Table 6. Innovation Impact on Output, OLS, FE, and LP

Dep. Var.	OLS			FE			Levinsohn and Petrin (LP)		
ln revenue	(1) All	(2) Int.vs. ext.	(3) Synergy	(4) All	(5) Int.vs. ext.	(6) Synergy	(7) All	(8) Int.vs. ext.	(9) Synergy
ln_labor	0.393***	0.392***	0.391***	0.206***	0.205***	0.206***	0.352***	0.352***	0.351***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln_capital_d	0.198***	0.197***	0.196***	0.196***	0.196***	0.196***	0.320	0.272	0.207
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.058)	(0.061)	(0.174)
ln_mateiral	0.397***	0.396***	0.396***	0.307***	0.307***	0.307***	0.359*	0.402***	0.491***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.001)	(0.000)
ln_all	0.015***			0.005***			0.014***		
	(0.000)			(0.000)			(0.000)		
ln_internal		0.007***	0.002		0.005***	0.000		0.007***	0.004
		(0.000)	(0.558)		(0.000)	(0.953)		(0.000)	(0.193)
ln_external		0.012***	0.010***		0.003**	0.002		0.011***	0.010***
		(0.000)	(0.000)		(0.001)	(0.098)		(0.000)	(0.000)
ln_int×ln_ext			0.001**			0.001*			0.000
			(0.007)			(0.011)			(0.180)
Eexport_stat	0.198***	0.198***	0.197***	0.055***	0.055***	0.055***	0.178***	0.177***	0.177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FDI_stat	0.253***	0.253***	0.252***	-0.032	-0.033	-0.033	0.207***	0.207***	0.206***
	(0.000)	(0.000)	(0.000)	(0.089)	(0.083)	(0.079)	(0.000)	(0.000)	(0.000)
N	15,735	15,735	15,735	15,735	15,735	15,735	15,735	15,735	15,735
Sum of coeffi	1.004	1.004	0.996	0.715	0.717	0.711	1.045	1.043	1.064

Note: Year and industry dummies were included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity); p-values in parentheses: Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

The estimation results of table 6 confirm that table 5 GMM estimation results are in the credible range. As mentioned previously, estimation results using OLS and FE techniques can provide an upper and lower range within which to compare the estimation results of GMM in table 6, which aim to remove the simultaneity effects of innovation and final output.

The LP method, which uses the previous year's intermediate input (material) as a proxy for productivity shock and as an instrument to capital to remove the simultaneous effect of factor inputs and productivity, is currently developed for one proxy variable (material) and one endogenous variable (capital) when using revenue as the dependent variable, and does not allow the addition of other endogenous variables, such as innovation investment. Therefore, it still does not remove the simultaneous effect between innovation investment and final output; however, the estimation results using the LP technique are still closer to a true estimation than either OLS or FE, since it gets rid of simultaneity issues of other factor inputs, such as capital, in estimating the production function.

As expected, the coefficients of labour get larger when using OLS and smaller when using FE, compared to those in table 6. The coefficient of labour using LP is quite similar to the coefficients using GMM in table 6. The coefficients of capital are positive and statistically significant when using OLS and FE, but become insignificant when using LP when the simultaneous effect of factor inputs and final output are removed, which is consistent with the above results using GMM. This might imply that capital investment in Tunisia is highly correlated with the output; therefore, there could be an upward bias in the capital coefficient in OLS and FE estimation.

In contrast, the coefficients of intermediate inputs get larger when using LP, which is also consistent with GMM estimation, although the coefficients of intermediary inputs with GMM get even larger, which might result from different assumptions of endogenous variables and different estimation methods in LP and GMM. Overall, the factor inputs coefficients using OLS, FE, and LP confirm that estimation results using GMM are in the

credible range. The control variables, export and FDI, have significant and positive effects on final output, except for the coefficient of FDI, which is insignificant when using FE; these results are also consistent with table 5.

The coefficients of the overall innovation investment (ln_n_innovationi) are statistically significant and are 0.015 using OLS, 0.005 using FE, and 0.014 using LP. These coefficients are smaller than 0.027, the result in column (1) in table 5, implying that the innovations' effect on final output (via productivity) is actually larger when the simultaneous effect between innovation and final output is considered.

As seen in columns (2), (5), and (8), both internal and external innovation have positive and significant effects on final output. The magnitude of the coefficient of external innovation is larger when using OLS and LP, but smaller when using FE. The results are different from the results in column (2) in table 5, where internal innovation does not significantly impact the final outcome, while external innovation does.

However, when adding the interaction terms between the internal and external innovation investment amount, the coefficients of internal innovation become insignificant when using OLS, FE, and LP, as seen in columns (3), (6), and (9), which is consistent with the results of column (3) in table 5. Significantly, the coefficients of the interaction term are in columns (3) and (5), but the magnitude is very small (close to zero), and this coefficient becomes insignificant in column (9) when using LP, which is consistent with the results of table 5.

The above results using OLS and FE support that the main results found using GMM are in the credible range. Also, the results using typical LP are consistent with the GMM results, which supports the fact that the difference of coefficients between OLS, FE and GMM result from removing the simultaneous effects of inputs and output.

I also consider a translog production function, which is a flexible functional form of the production functions, to avoid the rigid assumptions of the Cobb-Douglas production

function, such as a linear relationship between factor inputs and output, and perfect substitution between production factors (in other words, perfect competition on the production factors market). However, it is not included in the final results due to the high collinearity among regressors.[48]

Using equation (3) in the translog function[49], I find that, when other inputs are in the mean, the marginal effect of labour is 0.309, the marginal effect of capital is 0.158, the marginal effect of intermediate inputs is 0.694 and the marginal effect of innovation is -0.072. Likewise, equations (4) is measured with a translog function. When other inputs are in the mean, the marginal effect of labour is 0.296, the marginal effect of capital is 0.104, the marginal effect of intermediate inputs is 0.690, the marginal effect of internal innovation is -0.036, and the marginal effect of external innovation is -0.068. The negative coefficients for innovation variables seem to be caused by collinearity among explanatory variables, which is a major constraint to estimating the translog production function.

Meanwhile, if a firm that would have invested in innovation decides not to under a certain threshold (z = 0), the observed innovation value Z_{ijt} is censored around zero. To address this issue, I use Tobit for the censored dependent variables.

Table 7 provides results using Tobit regression as described in equations (9) and (10). Tobit regression coefficients are estimated in a similar way to Probit regression coefficients in pooled regression, except that the linear effect is on the uncensored latent variable, not the observed outcome.

---

[48] The translog production function can be used for the second order approximation of a linear-production function and allows to estimate not only the elasticity of input but also the elasticity of scale, which is equal to the marginal product (Ferguson, 1979; Klacek, et al., 2007). However, the collinearity among regressors in the translog specification is concern if the sign of at least one estimated parameter is opposite to the sign of the correlation between the resultative variable and the analysed explanatory variable (Pavelescu, 2010b).

[49] For instance, equations (3) is now measured as Y=f(K,L,I,T) = l k m t l2 lk lm lt k2 km kt m2 mt t2 lkm lkt lmt kmt lkmt y97-y07. The marginal product of innovation is a non-linear function of other inputs: dY/dN= _b[t]+_b[lt]*l+_b[kt]*k+2*_b[t2]*t+_b[mt]*m+_b[lkt]*lk+_b[lmt]*lm+_b[kmt]*km+_b[lkmt]*lkm.

Table 7. Determinants of Innovation Using Tobit Methods

Dep. Var. $\{ U_{ijt} \}$	(1) Internal	(2) External	(3) All
Firm size	1.881***	0.957***	0.912***
	(0.000)	(0.000)	(0.000)
Tech staff ratio	-1.491***	0.060	0.045
	(0.000)	(0.835)	(0.869)
Skills	2.758***	1.547***	1.467***
	(0.000)	(0.000)	(0.000)
Export_stat	0.861***	0.830***	0.880***
	(0.000)	(0.000)	(0.000)
FDI_stat	-0.980***	-0.756***	-0.687***
	(0.000)	(0.000)	(0.000)
Firm age	-0.008	-0.018***	-0.017**
	(0.282)	(0.001)	(0.001)
Dominance	-4.911**	2.377	1.743
	(0.007)	(0.054)	(0.156)
Observations	13,257	13,257	13,257
*N*_uncensored	4,995	8,384	8,875
*N*_left censored	8,262	4,873	4,382
Pseudo R^2	0.028	0.014	0.013
Log pseudo likelihood	-23,400	-32,568	-33,724
Sigma	8.919	6.530	6.343
Sigma standard error	0.069	0.053	0.053

Note: Year and industry dummies are included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity); *p*-values in parentheses: Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

As expected, the direction and statistical significance of coefficients in table 7 are similar to the results in columns (2), (4), and (6) in table B.1 in Appendix B. Meanwhile, the magnitude of coefficients is changed when considering the censoring issue in table 7. For instance, the positive effects of firm size, average wage, and export become much larger in table 7 than in table B.1. Also, the negative coefficient of technical staff ratio and

dominance on internal innovation investment, and negative coefficient of FDI on any type of innovation become much larger in table 7, compared to table B.1.

Among the observations of 13,257 firms, the uncensored observations are 4,995, 8,384, and 8,875; observations left censored, which are for the firms that reported zero innovation investment, are 8,262, 4,873, and 4,382, depending on sources of innovation, in columns (1) to (3). The pseudo *R*-squared is between 0.013 and 0.028, which is less than the *p*-value of *R*-squared in table 3 — that is, between 0.020 and 0.056. Sigma value, which is in the range 6.343 to 8.919 in columns (1) to (3), is comparable to the root mean squared error in an OLS regression that estimates the average of the squares of the difference between the estimator and what is estimated.

The significance of the Tobit "sigma" parameter confirms that the results of the Tobit model fit the data better than the linear model. This finding supports the assumption that there is a minimum required innovation investment, which is systematically related to determinants of innovation. This is similar to González and Jaumandreu 1998, who found the existence of sizeable thresholds for R&D among Spanish manufacturing firms and argued that the thresholds are systematically related to determinants of innovation, that is, demand and technological factors.[50]

Table 8 provides the estimation results of equations (11), (12), and (13) system GMM with lag 2 and 3, while using the predicted value of innovation investment, obtained from the Tobit regression above.

[50]. González and Jaumandreu (1998) used a Tobit model to analyse i) whether to undertake R&D or not and ii) if undertaking R&D, how much to undertake, with an assumption of existence of a minimum required R&D investment under which firms do not find it profitable to invest. They applied this framework to 2,000 Spanish manufacturing firms, many of which had no R&D investment.

Table 8. Innovation Impact on Output, GMM, and Predicted Value

Dep. Var. ln revenue	(1) All	(2) Internal vs. external	(3) Synergies
ln_labor	0.041 (0.473)	-0.112 (0.340)	-0.162 (0.167)
ln_capita	-0.070 (0.137)	0.009 (0.906)	0.050 (0.495)
ln_material	0.247*** (0.000)	0.215*** (0.000)	0.189*** (0.001)
Innov_hat	0.857*** (0.000)		
Inter_hat		-0.275 (0.180)	-0.230 (0.249)
Exter_hat		1.374** (0.001)	1.477*** (0.000)
Int_ext_hat			-0.026 (0.062)
Export_stat	-0.529*** (0.000)	-0.768** (0.002)	-0.870*** (0.000)
FDI_stat	0.530*** (0.000)	0.652*** (0.000)	0.643*** (0.000)
# of obs.	12,764	12,764	12,764
# of group	3,210	3,210	3,210
Sum of coeff.	1.075	1.211	1.298
AR2 (p-value)	0.000	0.001	0.003
Hansen(p-value)	0.000	0.000	0.001

Note: Year and industry dummies were included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity); *p*-values in parentheses. * = 5 percent, ** = 1 percent, *** = 0.1 percent

Of primary interest in this table are the coefficients of the predicted value of innovation investments. Like table 5, overall innovation (innov_hat) and external innovation have positive and statistically significant effects on final output, while internal innovation and the synergy between two sources of innovation are statistically insignificant.

Surprisingly, the magnitude of the coefficients became much larger when using the predicted value, so that the coefficient of overall innovation is 0.857 in column (1), and external innovation is 1.374 in column (2) and 1.477 in column (3), which makes the 1 percent increase in either external or overall innovation investment have a larger effect on final output than the 1 percent increase of other factors, such as intermediary inputs. Also, an increase in innovation investment has a larger effect on final output than a firm receiving foreign investment or becoming an exporter.

Therefore, the overall and external innovation effects on final output become much larger when considering the minimum requirement of innovation investment (threshold); however, internal innovation still has an insignificant effect on final output, and there is no synergy in investing in both sources of innovation. The results of table 9 further support the results of table 5.

When predicted values of innovation are used, the coefficients of labour become insignificant, and the coefficients of capital remain insignificant. Meanwhile, the coefficients of intermediary inputs are still positive and statistically significant. The coefficients of exports now become negative while FDI status still remains positive and significant.

Table 9 provides the estimation results for using TFP instead of final output (revenue) as a dependent variable, which is a direct test of the effect of different sources of innovation on productivity.

Table 9. Using TFP as a Dependent Variable, GMM

Dep. Var Ln TFP $_{ijt}$	(1) Innov	(2) Internal vs. external	(3) Synergies
ln_all	0.063***		
	(0.001)		
ln_internal		0.024	0.034
		(0.110)	(0.307)
ln_external		0.045*	0.039*
		(0.015)	(0.047)
ln_int×ln_ext			-0.001
			(0.853)
Eexport_stat	0.635***	0.611***	0.528***
	(0.000)	(0.000)	(0.000)
FDI_stat	0.807***	0.782***	0.704***
	(0.000)	(0.000)	(0.000)
# of obs.	15,735	15,735	15,735
# of group	4,255	4,255	4,255
AR2 (p-value)	0.607	0.534	0.509
Sargan (p-value)	0.000	0.000	0.000
Hansen (p-value)	0.001	0.002	0.000

Note: Year and industry dummies are included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity); *p*-values in parentheses, Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

The instrument set for the differenced equation consists of TFP, the log of innovation investment (for all, internal, and external innovation), in levels, in periods *t*-2 and *t*-3 (for which missing values are treated as zero, and instruments for each period are collapsed), export and FDI status, and year and industry dummies, differenced. The instrument set for the levels equation consists of TFP, the log of innovation investment (for all, internal and external innovation), export and FDI status, a constant, and year and industry dummies.

Test results for the AR (equation 2) are quite large, between 0.509 and 0.607, and fail to reject the null hypothesis that the differenced residuals in period t and t-2 are uncorrelated; therefore, autocorrelation in levels might not be a serious concern in this system GMM measurement. However, the p-value of the Sargan/Hansen test of over-identifying restrictions for GMM estimators is close to zero, rejecting the null hypothesis that instruments are exogenous. This might have been caused by the fact that the instrument is exactly identified. The difference-in-Sargan/Hansen test fails to reject similar results that these additional instruments are valid.

Overall innovation has a positive and significant effect on TFP, as seen in column (1) in table 9. The coefficient of internal innovation is statistically insignificant, while the coefficient of external innovation is positive and statistically significant in column (2). Lastly, using both sources of innovation at the same time (synergy) does not have a significant effect on TFP. These results are also consistent with the results of table 1.5, which support innovation effects on final output via TFP.

6. Conclusion

In this paper, I first identified the determinants of innovation investment and analysed whether those determinants are different for internal and external sources of innovation for a large number of representative samples of Tunisian manufacturing firms from 1997 to 2007.

As in previous literature on determinants of innovation, my estimation results showed that in Tunisia, larger firms that pay higher wages and participate in exports are more likely to invest in innovation. Meanwhile, having more technicians and a larger market share are statistically insignificant determinants of all and external innovation decisions, and they reduce the probability of firms engaging in internal innovation. Firm age has a negative and significant coefficient, but its magnitude is small and close to zero.

Interestingly, FDI firms are less likely to invest in innovation, although FDI has a positive

effect on final output, which might be explained by the fact that most foreign investment in Tunisia is driven by cost-saving purposes rather than longer-term strategic vision, which is consistent with previous findings of the negative effects of FDI on technological upgrading in domestic firms (OECD 2002). Determinants of innovation investment work in the opposite way for firms that invest in only one source of innovation, implying that those firms that invest in only one type of innovation are very different from those that invest in both sources of innovation.

The major determinants of the innovation decision are consistent using either the Probit model or firm fixed effects in panel data. Also, the estimation results with innovation intensity (innovation investment amount) as a dependent variable reveal that the decision related to innovation (whether to innovate or not) and the decision related to innovation intensity (how much to innovate) behave similarly for external innovation but quite differently for internal innovation investment in Tunisia.

I then tested which sources of innovation contribute more to final output (via productivity) in Tunisian manufacturing firms. The results are summarized below.

First, innovation, overall, has a positive and statistically significant effect on final output via productivity increase (output productivity). However, different types of innovation investment have different effects on productivity. The coefficient of the innovation (all) variable is 0.027, implying that a 1.0 percent increase in innovation investment would be associated with a 2.7 percent increase in final output, controlling for other inputs and export/FDI status as well as simultaneity issues between innovation and final output using GMM methods.

Second, internal innovation has an insignificant effect on final output, while external innovation has a positive and statistically significant effect on the same. Specifically, when testing the effect of each individual source of innovation on final output, it is found that the coefficient of external innovation is 0.021, which demonstrates that external innovation contributes most to the overall effect on output productivity. These results

are also documented in previous studies on Tunisian firms using a different data set, such as the innovation survey. Hence, it was more efficient for Tunisian manufacturing firms simply to acquire foreign technology created externally to enhance their output productivity during the period of data coverage.

Third, external innovation's effect on final output is larger for those firms that invest in only external sources of innovation than for firms that invest in both sources of innovation. When the interaction terms for internal and external innovation investment are added, the coefficient of external innovation becomes larger while the coefficient of internal innovation remains insignificant.

Fourth, there is no synergy from using both sources of innovation simultaneously. The coefficient of the interaction term is close to zero and statistically insignificant. This result might suggest that internal innovation does not play a role in firm absorptive capacity in Tunisia. The results further support my argument that for a developing country like Tunisia, where firms face resource constraints and have limited internal skills and limited capability to innovate, it is better to invest more in only external innovation, rather than dividing resources between the two sources of innovation.

Fifth, the Tobit model estimation result supports the assumption that a minimum innovation investment is required. When considering the censoring issue of innovation variables, using Tobit methods to analyse determinants of innovation investment, the direction and statistical significance of the coefficients are consistent with the main specification, but the magnitude of the coefficients becomes larger. It appears that the Tobit model fits the data considerably better given that a large number of observations have been left censored (zero innovation investment) and the significant sigma values of Tobit regression. In fact, sizable thresholds exist, which are systematically related to determinants of innovation, that is, demand and technological factors.

Lastly, the overall and external innovation effects on output productivity become much larger when considering this minimum requirement of innovation investment

(threshold), using the predicted value from the Tobit regression. Meanwhile, internal innovation and synergy of using both sources of innovation still have an insignificant effect on final output when using the predicted values.

The above results are also borne out through other econometric methods, such as OLS, FE, and LP, confirming that the GMM results are in the credible range. Also, the results were consistent when I used TFP as a dependent variable, which confirms the innovation effect on productivity via TFP.

The paper provides insights for innovation policy design. In many countries, the government's innovation policy—such as tax benefits and subsidies to conduct R&D—focuses too narrowly on promoting internal innovation, without considering the level of a country's technological advancement.

My findings suggest that innovation policy in Tunisia should emphasize technology adoption over technology creation. In a developing country like Tunisia, where firms are constrained by limited resources and skill level, it is important to understand which sources of innovation are more efficient at improving final output. In particular, innovation policies should focus on facilitating firm purchases of foreign technology and external innovation, since external innovation contributes most to the overall effect on output productivity, and there is no synergy in using both sources of innovation simultaneously. To encourage firms' investment in external innovation, the Tunisian government can promote exports and workers' skills (average wage can be a proxy of workers' skills), but providing incentives, such as subsidies, to firms to hire more technicians, and FDI promotion are not the best ways to encourage firms' investment in innovation.

Moreover, the fact that there is a minimum requirement (threshold) for innovation investment suggests that policies that aim to reduce this threshold or to support firms around this threshold could catalyze the innovation investment of certain firms. Such policies could include government's co-financing or risk-sharing of firms' innovation

investment (that is, through governments' matching grants or guarantee schemes) and tax benefits for target firms around this threshold. Lastly, the finding that so-called "high-tech" industries are not the most innovative industries in Tunisia suggests that they should not be the main focus of innovation policy. The findings expressed in this paper are particularly important, since there is little empirical evidence that quantifies the effect of innovation outsourcing on firm output productivity, especially in developing countries.

The finding of this paper raises a number of questions regarding innovation policies, which could serve as potential areas for further research. For instance, given my findings that internal innovation has an insignificant effect on firms in Tunisia, it would be interesting to investigate why Tunisian firms continue to invest in internal innovation, and how they can make these investments more impactful on their output productivity. Further, though I find that policies to reduce the innovation threshold or support firms around it could catalyze innovation investment, methods for identifying this threshold and the firms around it must still be developed. This finding could suggest practical policy implications; for instance, many governments provide support to firms through matching grants or subsidies for innovation, but do not use systematic mechanisms for identifying target firms that could maximize the effects of their support. Lastly, if the effect of innovation on productivity varies according to a firm's position relative to the technology frontier, what is the threshold level of technological advancement that determines whether it will benefit more from "creating" or "buying" innovation? The same question applies at the country level, in innovation policy design.

References

Abowd, J. M., J. Haltiwanger, R. Jarmin, J. Lane, P. Lengermann, K. McCue, and K. Sandusky. 2005. "The Relation among Human Capital, Productivity, and Market Value: Building Up from Micro Evidence." In *Measuring Capital in the New Economy* 153–204. Chicago: University of Chicago Press.

Acemoglu, D. 2009. "When Does Labor Scarcity Encourage Innovation?" National Bureau of Economic Research (NBER) Working Paper Series, Working Paper 14809, Cambridge, MA.

Acemoglu, D., P. Aghion, C. Lelarge, J. Van Reenen, and F. Zilibotti. 2007. "Technology, Information, and the Decentralization of the Firm." *Quarterly Journal of Economics* 122 (4): 1759–99.

Acemoglu, D., and J. Linn. 2004. "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry." *Quarterly Journal of Economics* 119 (3): 1049–90.

Ackerberg, D., K. Caves, and G. Frazer. 2006. "Structural Identification of Production Functions," Mimeo, RandR Econometrica.

Acs, Z. J., and D. B. Audretsch. 1991. R&D, "Firm Size and Innovative Activity. Innovation and Technological Change: An International Comparison," In Innovation and Technological Change: An International Comparison, ed. Z. J. Acs and D. B. Audretsch, 39–59. Ann Arbor, MI: University of Michigan Press.

Aghion, P. 2004. "Growth and Development: A Schumpeterian Approach." *Annals of Economics and Finance* 5: 1–25 (2004).

Aghion, P., U. Akcigit, and P. Howitt. 2013. "What Do We Learn from Schumpeterian Growth Theory?" National Bureau of Economic Research (NBER) Working Paper Series, Working Paper 18824, Cambridge, MA.

Aghion, P., Griffith, R. 2008. "Competition and growth: reconciling theory and evidence". Zeuthen Lectures. MIT Press: Cambridge, US.

Antràs, P., and E. Helpman. 2004. "Global Sourcing." *Journal of Political Economy* 112 (3): 552–80.

Arnold, J., and B. Javorcik. 2005. "Gifted Kids or Pushy Parents? Foreign Direct Investment and Plant Productivity in Indonesia." World Bank Policy Research Working Paper 3597

Aw, B., M. Roberts, and D. Xu. 2011. "R&D Investment, Exporting, and Productivity Dynamics." *American Economic Review* 101 (4): 1312–44.

Ayadi, M., M. Rahmouni, and M. Yildizoglu. 2009. "Determinants of the Innovation Propensity in Tunisia: The Central Role of External Knowledge Sources." No. halshs-00368560.

Balasubramanian, N., and J. Lee. 2008. "Firm Age and Innovation." *Industrial and Corporate Change.* 17 (5): 1019–47.

Basant, R., and B. Fikkert. 1996. "The Effects of R&D, Foreign Technology Purchase, and Domestic and International Spillovers on Productivity in Indian Firms." *Review of Economics and Statistics* 78 (2): 187–99.

Bengtsson, L., and C. Berggren. 2008. The Integrator's New Advantage — Reassessing Outsourcing and Production Competence in a Global Telecom Firm. *European Management Journal* 26: 314–24.

Bengtsson, L., R. Von Haartman, and M. Dabhilkar. 2009. "Low-Cost versus Innovation: contrasting Outsourcing and Integration Strategies in Manufacturing." *Creativity and Innovation Management* 18 (1): 35-47.

Bernard, A. B., and J. B. Jensen. 2004. "Why Some Firms Export." *Review of Economics and Statistics* 86 (2): 561–69.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott. 2011. "The Empirics of Firm Heterogeneity and International Trade." National Bureau of Economic Research (NBER) Working Paper Series, Working Paper 17627, Cambridge, MA.

Blonigen, B., and C. Taylor. 2000. "R&D Intensity and Acquisitions in High-Technology Industries: Evidence from the U.S. Electronic and Electrical Equipment Industries." *Journal of Industrial Economics* 48: 47–70.

Bloom, N., Eifer, B., Mahajan, A., McKenzie, D. and Roberts, J. (2012), Does Management Matter? Evidence from India", The Quarterly Journal of Economics

Bloom, N., and J. Van Reenen. 2007. "Measuring and Explaining Management Practices across Firms and Countries." *Quarterly Journal of Economics* 122 (4): 1351–408.

Bloom, N. and Van Reenen, J. 2010. "Why Do Management Practices Differ across Firms and Countries?" Journal of Economic Perspectives, 24(1)

Bloom, N., and Van Reenen, J. 2011. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." NBER Working Paper No. 16717.

Blundell, R.W., and Bond, S.R., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115– 143.

Blundell, Richard and Stephen R. Bond. 2000. "GMM Estimation with Persistent Panel Data: An Application to Production Functions." Econometric Reviews, 19(3): 321-40.

Brynjolfsson, E., and L. Hitt. 2003. "Computing Productivity: Firm-Level Evidence." *Review of Economics and Statistics* 85 (4): 793–808.

Cainelli, G., R. Evangelista, and M. Savona. 2004. "The Impact of Innovation on Economic Performance in Services." *The Service Industries Journal* 24 (1): 116–30.

Cassiman, B., and E. Golovko. 2010. "Innovation, Exports and Productivity." *International Journal of Industrial Organization* 28 (4): 372–76.

Cassiman, B., and R. Veugelers. 2002. "R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium." *American Economic Review* 1169–84.

Cassiman, B. and R. Veugelers. 2006. "In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition." *Management Science* 52 (1): 68–82.

Chesbrough, H. W., and D. J. Teece. 1996. "When Is Virtual Virtuous? — Organizing for Innovation." *Harvard Business Review* (Jan.–Feb.): 65–73.

Cohen, W. M., and S. Klepper. 1996. "Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D." *The Review of Economics and Statistics* 232–43.

Cohen, W. M., and D. A. Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35 (1).

Crépon, B., Duguet, E., and Mairessec, J. 1998. Research, Innovation And Productivi [Ty: An Econometric Analysis At The Firm Level. *Economics of Innovation and New technology*, 7(2), 115-158.

Dankbaar, B. 2007. "Global Sourcing and Innovation: The Consequences of Losing Both Organizational and Geographical Proximity." *European Planning Studies* 15: 271–88.

De Loecker, J. 2013. "Detecting Learning by Exporting." *American Economic Journal: Microeconomics* 5 (3): 1–21.

Fifarek, B. J., F. M. Veloso, and C. I. Davidson. 2008. "Offshoring Technology Innovation: A Case Study of Rare-Earth Technology." *Journal of Operations Management* 26: 222–38.

Foster, L., J. Haltiwanger, and C. Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review* 98 (1): 394–425.

Fox, J. T., and V. Smeets. 2011. "Does Input Quality Drive Measured Differences in Firm Productivity? * *International Economic Review* 52 (4): 961–89.

Fikkert, B. 1993. "An open or closed technology policy? The effects of technology licensing, foreign direct investment and technology spillovers on R&D in Indian industrial sectors' firms", *unpublished PhD dissertation*, Yale University, New Haven, CT.

Fu, X. 2008. "Foreign Direct Investment, Absorptive Capacity and Regional Innovation Capabilities: Evidence from China." *Oxford Development Studies* 36 (1): 89–110.

Fu, X. 2011. Processing Trade, FDI and the Exports of Indigenous Firms: Firm-Level Evidence from Technology-Intensive Industries in China. *Oxford Bulletin of Economics and Statistics,* 73(6), 792-817.

Fu, X. 2012, "How does openness affect the importance of incentives for innovation?", *Research Policy*, 41, 512-523

Fu, X. and Gong, Y. 2010. "Indigenous and foreign innovation efforts and drivers of technological upgrading: evidence from China," *World Develop*ment, 39(7), pp. 1213–1225.

Fu, X., C. Helmers, and J. Zhang. 2012. "The Two Faces of Foreign Management Capabilities: FDI and Productive Efficiency in the UK Retail Sector." *International Business Review* 21 (1): 71–88.

Fu, X., and R. Hoyes. 2003. "The Role of Management Practices in Closing the Productivity Gap: A Literature Review." University of Cambridge, *Centre for Business Research,* Memo.

Fu, X., C. Pietrobelli, and L. Soete. 2010. "The Role of Foreign Technology and Indigenous Innovation in Emerging Economies: Technological Change and Catching Up." *World Development* 39 (7): 1203–12.

Gabsi, F., H. Mhenni, and K. Koouba. 2008. "Innovation Determinants in Emerging Countries: An Empirical Study at the Tunisian Firms Level." MPRA Paper No. 17940

Girma, S. 2005. "Absorptive Capacity and Productivity Spill-Overs from FDI: A Threshold Regression Analysis." *Oxford Bulletin of Economics and Statistics* 67 (3): 281–306

González, X., and J. Jaumandreu. 1998. "Threshold Effects in Product R&D Decisions: Theoretical Framework and Empirical Analysis." FEDEA Working Paper 78.

Griffith, R., S. Redding, and J. Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics* 86 (4): 883–95.

Grimpe, C., and U. Kaiser. 2010, "Balancing Internal and External Knowledge Acquisition: The Gains and Pains from R&D Outsourcing." *Journal of Management Studies* 47 (8): 1483–509.

Grossman, G. M., and E. Helpman. 2003. "Outsourcing versus FDI in Industry Equilibrium." *Journal of the European Economic Association* 1 (2–3): 317–27.

Grossman, G. M., and E. Helpman, E. 2005. "Outsourcing in a Global Economy." *The Review of Economic Studies* 72 (1): 135–59

Hall, B. H. 2011, "Innovation and Productivity." National Bureau of Economic Research (NBER) Working Paper Series, Working Paper 17178, Cambridge, MA.

Harbi, S., M. Amamou, and A. R. Anderson. 2009. "Establishing High-Tech Industry: The Tunisian ICT Experience." *Technovation* 29 (6): 465–80.

Harbi, S., M. Amamou, and A. R. Anderson. 2012. "Innovation Culture and the Economic Performance of Tunisian ICT Firms." *International Journal of Entrepreneurship and Innovation Management* 16 (3): 191–208.

Hou, J., and P. Mohnen. 2013, "Complementarity between In-House R&D and Technology Purchasing: Evidence from Chinese Manufacturing Firms." *Oxford Development Studies* 41 (3): 343–71.

Huergo, E., and J. Jaumandreu. 2004. "Firms' Age, Process Innovation and Productivity Growth." *International Journal of Industrial Organization* 22 (4): 541–59.

Inklaar, R., Timmer, M. P., and Van Ark, B. 2008. "Market services productivity across Europe and the US." *Economic Policy*, 23(53), 140-194.

Javorcik, B. S. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spill overs through Backward Linkages." *The American Economic Review* 94 (3): 605–27.

Karray, Z., and M. Kriaa. 2008. “Innovation and R&D investment of Tunisian Firms: A Two Regimes Model with Selectivity Correction.” In *ERF 15th Annual Conference*-Equity and Economic Development. Cairo, Egypt.

Krugman, P. 1991. “Geography and Trade.” Cambridge, MA: *MIT Press.*

Lacity, M. and L. Willcocks. 2013. “Outsourcing Business Processes for Innovation.” *MIT Sloan Management Review* (Spring).

Lall S. 2000. Selective Industrial and Trade Policies in Developing Countries: Theoretical and Empirical Issues. Working Paper No. 48. *Queen Elizabeth House*, University of Oxford

Lai, E., R. Riezman, and P. Wang. 2009. “Outsourcing of Innovation.” *Economic Theory* 38 (3): 485–515.

Lewin, A. Y., S. Massini, and C. Peeters. 2009. “Why Are Companies Offshoring Innovation: The Emerging Global Race for Talent.” *Journal of International Business Studies* 40 (6): 901–25.

Levinsohn, J., and A. Petrin. 2003. “Estimating Production Functions Using Inputs to Control for Unobservable.” *Review of Economic Studies* 70 (2): 317–41.

Liu, X., and T. Buck. 2007. “Innovation Performance and Channels for International Technology Spillovers: Evidence from Chinese High-Tech Industries.” *Research Policy* 36 (3): 355–66.

Lokshin, B., R. Belderbos, and M. Carree. 2008. “The Productivity Effects of Internal and External R&D: Evidence from a Dynamic Panel Data Model.” *Oxford Bulletin of Economics and Statistics* 70 (3).

Lööf, Hans, and Almas Heshmati. 2001. “On the Relationship between Innovation and Performance: A Sensitivity Analysis.” *SSE/EFI* Working Paper Series in Economics and Finance 446, Stockholm School of Economics.

Mairesse, J., and P. Mohnen. 2002. "Accounting for Innovation and Measuring Innovativeness: An Illustrative Framework and an Application." *American Economic Review* 92 (2): 226–30.

Mol, M. J. 2005. “Does Being R&D-Intensive Still Discourage Outsourcing? Evidence from Dutch Manufacturing.” *Research Policy* 34: 571–82

Mytelka, L. K. 1987. “Licensing and technology dependence in the Andean group”, *World Development*, 6(4), pp. 447–459.

Narula, R. 2004. “Understanding Absorptive Capacities in an ’Innovation Systems’ Context: Consequences for Economic and Employment Growth.” *Danish Research For Industrial Dynamics*, Working Paper No 04-02

Nelson, R. R., and S. G. Winter. 1977. “In Search of a Useful Theory of Innovation.” In *Innovation, Economic Change and Technology Policies,* 215-45. Birkhäuser Base.

OECD (Organization for Economic Cooperation and Development). 2002. *Science and Technology Industry Outlook.* Paris: OECD.

Olley, G. S., and A. Pakes, 1996. “The Dynamics of Productivity in the Telecommunications Equipment Industry.” *Econometrica* 64 (6): 1263–97.

Porter, M. 1990. *The Competitive Advantage of Nations.* London: Macmillan.

Pianta, M. 2005. "Innovation and Employment" In *The Oxford Handbook of Innovation.* ed. J. Fagerberg, D. Mowery and R. Nelson, 568–98. Oxford: Oxford University Press.

Roodman, D. 2006. How to do xtabond2: an introduction to “difference” and “system” GMM in Stata, Working Paper Number 103, *Centre for Global Development.*

Schumpeter, J. A. 1934. “Theory of Economic Development: An Enquiry into Profits, Capital, Interest and the Business Cycle.” *Innovation and Economic Performance in Services,* 457*.* Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1942. “Capitalism Socialism and Democracy.” New York: *Harper Brothe*r.

Sharma, M., M. Lacity, and L. Willcocks. 2012. “A Catalyst for Innovation.” *Accenture Outlook.*

Simar, L., and P. W. Wilson. 2011. “Two-Stage DEA: Caveat Emptor.” *Journal of Productivity Analysis* 36: 205–18.

Simonen, J., and P. McCann. 2008. “Firm Innovation: The Influence of R&D Cooperation and the Geography of Human Capital Inputs*.” Journal of Urban Economics* 64 (1): 146–54.

Souitaris, V. 2002. “Technological trajectories as moderators of firm-level determinants of innovation.” *Research policy*, 31(6), 877-898.

Spithoven, A., B. Clarysse, and M. Knockaert. 2011. “Building Absorptive Capacity to Organise Inbound Open Innovation in Traditional Industries.” *Technovation* 31 (1): 10–21.

Ulrich, K. T., and D. J. Ellison. 2005. "Beyond Make-Buy: Internalization and Integration of Design and Production." *Production and Operations Management* 14: 315–30.

Van Reenen, J. 2012. "Total Factor Productivity Estimation: A Practical Review." *Journal of Economic Surveys* Volume 26, Issue 1, pages 98–128.

Van Biesebroeck, J., 2003. "Exporting raises productivity in sub-Saharan African manufacturing firms." NBER Working Paper 10020 (October).

Van Reenen, J. 1996. "The creation and capture of rents: wages and innovation in a panel of UK companies." *The Quarterly Journal of Economics*, 195-226.

Westergren, U. H., and J. Holmström. 2012. "Exploring Preconditions for Open Innovation: Value Networks in Industrial Firms." *Information and Organization* 22 (4): 209–26.

World Bank. 2010. "Tunisia Development Policy Review: Towards Innovation-Driven Growth", Report N. 50847, The World Bank Group.

Yacoub, N. 2013. "Assessing Pharmaceutical Innovation in Tunisia: An Empirical Survey on Firms' Knowledge-Capital and an Analysis of the National Sectorial Innovation System." *African Journal of Science, Technology, Innovation and Development* 5 (2): 103–18.

Appendix A. Summary Statistics

Table A.1 Top 15 Industries with the Most Innovating Firms

Industry	# of firms	Internal innovation		External innovation		Total innovation	
		Mean (Ln)	# of firm	Mean (Ln)	# of firms	Mean (Ln)	# of firms
Basic metals	235	3.22	90	6.17	148	6.79	154
Chemicals and chemical products	787	4.90	433	7.07	560	7.90	597
Coke, refined petroleum products, and nuclear fuel	44	6.32	25	7.56	29	8.56	30
Electrical machinery and related items	598	3.54	242	5.50	331	6.32	354
Fabricated metal products, except machinery and equipment	871	3.22	365	5.81	587	6.50	621
Food products and beverages	2030	2.75	656	5.29	1136	5.92	1192
Furniture; manufacturing, etc	791	2.61	267	5.56	508	6.20	540
Machinery and equipment, etc	382	3.48	159	6.27	251	6.88	263
Medical, precision, and optical instruments, watches, and clocks	101	2.55	31	5.52	57	5.98	57
Motor vehicles, trailers, and semi-trailers	253	3.61	102	6.07	164	6.83	170
Office machinery and computers	11	6.02	7	8.40	9	8.82	9
Other non-metallic mineral products	1256	2.75	424	5.40	714	6.17	782
Other transport equipment	131	3.11	47	5.75	81	6.58	87
Pulp, paper, and paper products	254	3.33	106	6.15	154	6.66	164
Radio, television, and communication equipment	167	3.96	73	6.49	112	7.68	123
Rubber and plastic products	637	4.18	329	6.82	469	7.48	491
Textiles	1,246	2.74	418	5.54	742	6.20	789
Tobacco products	46	4.15	22	7.38	31	7.96	32
Wearing apparel; dressing and dyeing of fur	4,947	2.33	1,428	5.66	3,043	6.29	3,205

Wood and products of wood and cork, except furniture; articles of straw and plaiting	275	2.79	101	5.31	172	6.04	187
Publishing, printing, and reproduction of recorded media	430	2.71	151	5.79	267	6.51	288
Recycling	16	2.50	5	5.16	10	5.62	10
Tanning and dressing of leather; luggage, handbags, saddlery, harness, and footwear	965	2.73	359	5.39	578	6.08	621

Note: To identify industries with the most innovating firms, I have measured the innovator's ratio (the number of firms that invest in innovation within the two-digit industry /total number of firms within the two-digit industry). This table presents the top 15 industries with the highest innovator's ratio within the manufacturing sector.

Table A.2 Innovator's Ratio by Exporting Status

Year	ln_n_internalino (%)		ln_n_externalino (%)		ln_n_innovationinv (%)	
	Full/Partial	Full/None	Full/Partial	Full/None	Full/Partial	Full/None
1998	58.7	79.4	91.3	117.0	89.2	108.4
1999	86.2	123.0	101.7	128.1	102.0	124.8
2000	62.4	92.3	83.6	108.6	85.4	109.3
2001	68.6	107.7	87.2	109.4	88.1	109.6
2002	80.2	113.0	95.3	119.7	97.2	119.6
2003	73.7	123.5	89.5	124.6	90.7	122.9
2004	74.5	113.2	85.0	108.3	87.4	107.8
2005	74.1	105.6	89.6	108.4	92.9	108.7
2006	66.6	130.2	89.1	117.0	87.0	113.0
2007	62.5	129.9	80.9	118.2	83.6	115.3

Note: Higher than 100 percent indicates that exporters invest more on innovation inputs. Full describes firms that export entire production; partial describes firms that export some of their production and sell the rest at the domestic market; and none describes firms that sell only in domestic markets.

Table A.2 provides more details on innovation investment by level of export status, among full exporters, partial exporters, and nonexporters. Interestingly, partial exporters invest the most in innovation, followed by full exporters. Nonexporters invest in innovation the least. Full exporters and partial exporters invest much more in external innovation than in internal innovation.

Table A.3 Innovator's Ratio by FDI status (Full/Partial/None)

Year	ln_n_internalino (%)		ln_n_externalino (%)		ln_n_innovationinv (%)	
	Full/Partial	Full/None	Full/Partial	Full/None	Full/Partial	Full/None
1997	83.60	151.96	93.11	120.61	98.88	125.32
1998	65.21	103.22	92.95	108.83	92.61	107.71
1999	65.30	107.84	90.02	109.09	89.88	109.75
2000	62.39	87.31	94.54	104.59	92.54	104.76
2001	79.40	91.20	106.10	107.55	104.99	105.91
2002	119.20	107.53	105.17	112.37	110.10	112.96
2003	80.33	105.21	97.86	109.55	103.75	112.14
2005	76.13	99.31	107.28	108.66	103.96	108.55
2006	96.38	131.09	114.64	117.35	108.09	117.19
2007	67.78	94.80	97.49	106.33	99.40	105.96

Note: Higher than 100 percent indicates that firms with FDI invest more. Full describes firms that have 100 percent foreign ownership; partial describes joint ventures of foreign and domestic firms; and none describes firms that are locally owned.

Table A.3 shows the innovator's ratio by FDI status. Firms that have joint ownership between foreign owner and domestic owner (partial FDI) invest more in innovation than fully domestic firms (No FDI), while those firms fully owned by foreign owners (full FDI) invest far less in innovation.

Appendix B. Additional Results

Table B.1 is essentially the same as table 1.3 but presents estimation results of the determinants of firms' innovation for both create and buy, using pooled regression of the Probit model.

Table B.1 Determinants of Innovation Decision Using Probit Model

Dep. Var. $\{Z_{ijt'}\}$	(1) Internal Only	**(2) Internal All**	(3) External Only	**(4) External All**	(5) Both	**(6) All**
Firm size	-0.089***	**0.186*** **	-0.144***	**0.075*** **	0.219***	**0.055*** **
	(-3.90)	**(14.28)**	(-10.69)	**(5.87)**	(16.70)	**(4.26)**
Tech staff ratio	0.022	**-0.162** **	0.320***	**0.086**	-0.166**	**0.093**
	(0.24)	**(-3.11)**	(5.73)	**(1.69)**	(-3.15)	**(1.77)**
Ln (ave wage)	-0.104**	**0.303*** **	-0.135***	**0.185*** **	0.356***	**0.165*** **
	(-3.02)	**(14.33)**	(-6.46)	**(9.19)**	(15.73)	**(7.78)**
Export status	0.025	**0.091** **	0.044	**0.130*** **	0.090**	**0.139*** **
	(0.46)	**(3.09)**	(1.43)	**(4.41)**	(2.99)	**(4.70)**
FDI_stat	-0.033	**-0.169*** **	-0.043	**-0.197*** **	-0.169***	**-0.212*** **
	(-0.57)	**(-5.41)**	(-1.35)	**(-6.38)**	(-5.23)	**(-6.74)**
Firm age	0.000	**-0.001**	-0.003**	**-0.003** **	-0.001	**-0.003** **
	(0.09)	**(-1.08)**	(-2.88)	**(-3.20)**	(-1.36)	**(-3.21)**
Dominance	-2.526*	**-0.746** **	0.610*	**0.083**	-0.794**	**-0.012**
	(-2.11)	**(-3.02)**	(2.03)	**(0.31)**	(-3.16)	**(-0.05)**
# observations	13,257	**13,257**	13,257	**13,257**	13,257	**13,257**
# dep > 0	534	**5,225**	4,222	**8,913**	4,691	**9,447**
R^2	0.024	**0.056**	0.034	**0.021**	0.069	**0.020**

Note: t statistics in parentheses. Standard errors are clustered and robust; year and industry dummies are included but not reported. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

Like as table 1.3, columns (2) and (4) show the factors that influence the probability of firms engaging in internal and external sources of innovation, respectively. Column (6) shows probability of investment in any source of innovation (all). I added columns (1), (3), and (5) to see whether there are any differences between those firms investing in only one source of innovation and those investing in both sources at the same time.

The determinants of firm's decision to invest in innovation are different between internal and external innovation. Tests for the difference of coefficients are conducted, and the null hypothesis that coefficients of the regressions from different columns are systematically the same is rejected by 1 percent significant level between columns (1) and (3), and between columns (2) and (4).

The estimation results are quite different from the results of Probit estimation with firm fixed effect in table 1. Particularly, many coefficients in column (1), (3) and (5) are statistically significant, which implies that firm specific information matters a lot for the decision of investing only one source of innovation or jointly invest in both type of innovation. In addition, many coefficients in column (2) are also statistically significant, implying that firm specific information matters for the decision of investing in internal innovation.

Meanwhile, the direction and statistical significance of coefficients for external innovation and all innovation are similar to those in table 1.3, as shown in columns (4) and (6). Firms that is larger, pay higher wages, and participate in exports are more likely to invest in external innovation or any type of innovation. Interesting, the coefficient of FDI is associated with less likelihood of investment in innovation. Firm age has a negative and statistically significant coefficient in columns (4) and (6), but the magnitude is small and close to zero. Technical ratio and dominance are not statistically significant determinants of all innovation and external innovation decisions; however, they reduce the probability of firms engaging in internal innovation.

Columns (1) and (3) show that the abovementioned factors, which enhance the likelihood of firms' investment in innovation, work the opposite way for firms that invest in only one source of innovation. Column (5) shows the estimation results of those firms that invest in both sources of innovation at the same time, and the direction of the coefficient in column (5) is predominantly the opposite of columns (1) and (3). Firms that are large and pay high wages are less likely to invest either only in internal innovation or only in external innovation, as seen in columns (1) and (3), but more likely to invest in both sources of innovation as seen in column (5). Participating in exports and having foreign ownership do not have a significant effect on a firm's decision to invest in one source of innovation, either internal or external, as seen in columns (1) and (3); while exporting has a positive effect, and FDI has a negative effect on a firm's decision to invest in both sources of innovation, as seen in column (5).

Having more technicians does not have a significant effect on a firm's decision to invest in only internal sources of innovation, but has a positive and significant effect on a firm's decision to invest in only external sources of innovation, as seen in columns (1) and (3). The negative coefficient of technical staff ratio in column (5) is largely driven by those firms that invest in an internal innovation source as seen in column (2). This finding is somewhat unexpected since one would expect that technicians would directly engage in decisions on innovation; however, this result might be attributed to the fact that the main role of technical staff in Tunisian firms is dealing with external sources of innovation, rather than engaging in their own R&D. This finding might suggest that Tunisian firms face limited resource constraints; therefore, having technicians could supplement their investment on internal innovation.

Interestingly, firms with a larger market share do not make substantial effort to innovate internally but rely instead on only external sources of innovation. The larger market share (dominance) has a negative and significant effect on a firm's decision to invest in only internal sources of innovation, as seen in column (1). Actually, the magnitude of the coefficient is far too large, but this might be driven by the fact that only a small number of firms invest in internal innovation (only 534 firms have value 1 and the rest, 0). In

contrast, the market share has positive and significant effect on a firm's decision to invest in only external sources of innovation, as seen in column (3). Firms with larger market share are less likely to invest in both sources of innovation, as seen in column (5). Again, firm age does not have a significant effect on internal, internal only, and both sources of innovation. It has a negative and significant effect on external sources of innovation, but the magnitude is very small and close to zero.

Table B.2 is essentially the same as table 1.5 but uses random effects rather than firm fixed effect. Hausman test results reveal that fixed effect is more appropriate in the above model.

Table B.2 Determinants of Innovation: Random Effects

	(1) ln_Internal Only	(2) ln_Internal All	(3) ln_External Only	(4) ln_External All	(5) ln_Both	(6) ln_All
Firm size	-0.027	0.710***	-0.092*	0.688***	0.799***	0.697***
	(-1.59)	(14.74)	(-2.19)	(12.80)	(16.45)	(12.71)
Tech staff ratio	0.017	-0.379*	0.528***	0.106	-0.499**	0.142
	(0.29)	(-2.43)	(3.83)	(0.63)	(-3.15)	(0.83)
Ln (ave wage)	-0.044	0.780***	-0.039	0.865***	0.914***	0.848***
	(-1.75)	(11.38)	(-0.65)	(11.46)	(13.16)	(11.03)
Export status	0.030	0.315**	0.257**	0.549***	0.280**	0.612***
	(0.83)	(3.21)	(2.98)	(5.13)	(2.82)	(5.61)
FDI_stat	-0.009	-0.090	-0.083	-0.266*	-0.110	-0.255*
	(-0.22)	(-0.80)	(-0.84)	(-2.14)	(-0.96)	(-2.01)
Firm age	0.001	0.003	-0.008*	-0.007	0.002	-0.006
	(0.40)	(0.86)	(-2.38)	(-1.57)	(0.43)	(-1.42)
Dominance	-0.376	2.425*	0.388	2.726*	2.593*	2.598*
	(-0.98)	(2.18)	(0.40)	(2.17)	(2.32)	(2.03)
Observations	13,257	13257	13,257	13,257	13,257	13,257

Note: t statistics in parentheses. Significance level: * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Table B.3 Hausman Test Results

Column	*P*-value: difference in coefficients not systematic	Better estimation model
1	1	RE
2	0.000	FE
3	0.000	FE
4	0.000	FE
5	0.000	FE
6	0.000	FE

Note: RE = Random effects. Overall, fixed effects should be chosen; based on the results of comparing the six models from FE vs. RE; RE fails to outperform in five out of six cases.

The Hausman test compares an estimator θ1 that is known to be consistent with an estimator θ2 that is efficient under the assumption being tested. The null hypothesis is that estimator θ2 is indeed an efficient (and consistent) estimator of the true parameters. If this is the case, there should be no systematic difference between the two estimators. If there is a systematic difference in the estimates, there are reasons to doubt the assumptions on which the efficient estimator is based. The Hausman test can also differentiate between the fixed effects model and the random effects model in panel data. In this case, random effects (RE) is preferred if the null hypothesis cannot be rejected due to higher efficiency; otherwise, fixed effects (FE) is at least consistent and thus preferred.

IV. Chapter 3. Measurement and Performance of Service Firms, and Foreign Ownership

1. Introduction

Service is the largest sector in the global economy, representing 70 percent of the world's value-added, over half of employment, and 20 percent of global trade measured in volume and 50 percent as measured in value-added (Fontagne et al 2011; Iacovone, Mattoo, and Zahler 2013; OECD 2013). As countries develop, their share of services in GDP and in employment rises. The share of service exports in total exports has expanded to 70 percent among mid- and high-income economies. The service sector is the major driver of growth in OECD countries (Marel 2010; Iacovone et al. 2013).

As services become more tradable, service-led growth becomes more important even for developing countries. The lower- and middle–income country group has the largest positive trade balance in modern services, such as communications services. Even countries that have historically focused on manufacturing are experiencing rapid service growth (for example, more than 50 percent of China's GDP is now attributed to services). Developing countries' share of world services exports almost doubled for the past two decades (Sáez 2014; OECD and WTO 2013; World Bank national accounts data 2016).

However, despite its importance, we know little about this sector, largely due to the lack of data, but also because of conceptual and methodological difficulties in measuring the sector's performance. Existing literature on services is narrowly focused on the indirect effect that policy changes in the services sector have on the manufacturing sector, instead of analyzing the effect on the services sector itself. For instance, changes of a service firm's ownership through privatization and liberalization could improve performance of downstream manufacturing sectors (Arnold, Javorcik, and Mattoo 2011; Francois and Woerz 2008; Eschenbach and Hoekman 2006). Also, efficiency gains in service inputs, such as IT, logistics, electricity, and financial services, increase productivity in manufacturing (Freund and Weinhold 2004; Arvis et al. 2016; Arnold,

Mattoo, and Narciso 2008; Jensen 2011). This literature considers service as an intermediate input for other production, but does not investigate how policy changes in the services sector impact the performance of the sector itself.

Moreover, our information about this sector may be flawed. Services have long been thought to be less productive, to hire fewer employees, and to pay lower wages than manufacturing, and have been seen as contributing to the productivity slowdown of the early post–World War II period (Jensen 2011; Gallouj and Savona 2009; Baumol 1967; Baumol, Blackman, and Wolff 1985). However, this assumption of poor performance in services is based on the still-evolving theory of service value, specifically, the misdefinition of service output and the consequent incorrect measurement of service productivity (Gallouj and Savona 2009). For instance, service activities were assumed without evidence to have "technological stagnancy," and considered "peripheral" activities that were crowding out manufacturing, which was believed to be associated with higher living standards and industrialization (Baumol 2002, 2001, 1967; Clark 1940; Fourastié 1949; Cohen and Zysman 1987).

There is now a potential for more careful work on understanding the services sector and its performance at the micro-level. As firm-level data become more readily available, new opportunities to understand performance of service firms emerge. Moreover, assumptions of low performance of service firms have been widely challenged. It is found that Baumol's technological stagnancy assumptions for services, which were based on the assumption of zero price elasticity of demand for services, often do not hold (Baumol 2001; Oulton 2001).

A distinct characteristic of the services sector is high protection, which results in limited foreign participation with a high proportion of state ownership. Many developing countries pursue policies that restrict the access of foreign services suppliers to domestic markets (Fontagne et al. 2011; Hoekman and Braga 1997; Boardman and Vining 1989). While firms owned by foreign investors through foreign direct investment (FDI) are typically considered more efficient than domestic firms in developing

countries, evidence of more efficient FDI than non-FDI firms is extremely rare in the services.

While existing literature focuses on the effect of policy change in the services sector on other sectors and on the aggregated level,[51] and assumes lower performance of the services sector by definition, understanding how changes in the services sector—such as in firm ownership—influence its performance is necessary.

In this paper, I investigate the measurement of service firm performance and the effect of ownership on the estimated performance of Tunisian service firms. Specifically, I review the methodological issues in measuring performance in services and suggest two different aspects of the performance of service firms in Tunisia—total factor productivity (TFP) and markups. Using these performance measures, I examine the service firms' performance in Tunisia by subsectors and over time. Lastly, I investigate whether variations in these measures of performance can be explained in terms of ownership types, such as foreign and joint ownership, in Tunisian service firms.

For a number of reasons Tunisia is a particularly interesting country case for analyzing the effect of foreign ownership on service firm performance. Despite the importance of the services sector in the Tunisian economy (that is, its value-added contributes about 60 percent of GDP[52]), this sector faces high protection with complex entry regulations for firms. The government's industrial policies have narrowly focused on the manufacturing sector, while disregarding services. For instance, while Tunisia has multiple international treaties to promote trade in goods, it has not yet joined the trade agreement for services or fully implemented the joint agreement.[53] As a result, the level of competition is particularly low in key subservice sectors, with limited foreign

51. For instance, Arnold, Javorcik, and Mattoo 2011; Francois and Woerz 2008; Alfaro 2003; Inklaar, Timmer, and Van Ark 2008.
52. Data source: World Development Indicators 2016.
53. Although Tunisia has been a member of the World Trade Organization (WTO) since 1994, the actual negotiation of the WTO agreements on services trade has not taken place. Also, services were excluded under the major trade agreements such as the Association Agreement with the European Union.

participation and a large presence of state-owned enterprises (SOEs)—driven by a variety of investment restrictions, foreign exchange controls, and limits on movement of foreign personnel. Therefore, without actual evidence of firm ownership's effect on service firm performance, it was typically assumed that changes of firm ownership through privatization and liberalization would improve service firm performance and the overall competitiveness of the economy.

The contribution of this paper is three-fold.

First, this paper provides suggestions on how to measure service firm performance, TFP and markups. Specifically, I review the conceptual and methodological difficulties in measuring performance in services, and suggest how to mitigate those challenges in the proposed service firm performance measures.

Second, using these performance measures, I provide analysis of Tunisian service firm performance. Specifically, I show TFP and markups of service firms by subsectors and over time, and identify distinct characteristics of service firms, such as large heterogeneity across and within subsectors. Understanding service firm performance is particularly important in Tunisia as service consists of 60 percent of the economy but is rarely studied.

Finally, using these performance measures, I investigate whether variation in firm performance can be explained by foreign ownership in the Tunisian services sector, which, with complex entry barriers for foreign firms, has limited foreign ownership. Although earlier literature projected more efficient foreign firms than others, as well as performance gains by liberalization,[54] systematic evidence of these effects is rare. This is one of the first attempts to provide such an analysis. Moreover, this paper focuses on ownership's effect on the service firm's performance; thus, it differs from previous

54. Saghir 1993; Kikeri, Nellis, and Shirley 1994; Harik, Sullivan, and Patton 1992.

studies that focus on service ownership's effect on other sectors, such as manufacturing. The findings of this paper contribute to the literature on FDI and firm performance.

The rest of the chapter is organized as follows. Section 2 provides the literature review. Section 3 describes the data set and descriptive information. Section 4 provides the empirical strategy. Section 5 presents the results, and section six provides the conclusion.

2. Literature Review

There are a number of differences between the production processes of the service and manufacturing sectors, which makes it difficult to apply existing performance measurements (developed for manufacturing firms) to service firms. A summary of the main differences between the two sectors follows.

The services sector tends to be highly heterogeneous, thus, significant differences in performance across sub-sectors are to be expected. It comprises activities that require large capital investments and have high fixed costs, such as electricity distribution and railroads; activities that require a high level of skills, such as banking and business-related services; and activities as diverse as restaurants and IT services. Since there is no standardized input-output process, each industry faces its own problem of services measurement (Pires, Sarkar, and Carvalho 2008; Triplett and Bosworth 2003).

In services, market demand heavily influences the production process and final outputs. Many services require the proximity of the consumer to the producer, as customers play an active role in influencing productivity and output quality by providing information about their needs (Hoekman and Kostecki 2009; Ostrom et al. 2010). Also, if demand is low, the producer's resources will be underutilized, thus reducing internal efficiency. The same is true for manufacturing, but to a lesser degree, as intermediate inputs for manufacturing can be storable, and inventories can be used to offset this effect.

There is large heterogeneity in quality in services. Changes in inputs and production processes affect the perceived quality of the output (Hoekman and Kostecki 2009; Grönroos and Ojasalo 2004). Quality of service products varies even within the narrowly defined subservice category, therefore, quantity-based performance measurements, such as productivity, might be partial measurements because a changed set of inputs easily alters the perceived quality of the output. For instance, if a retail store reduces the number of staff, productivity per worker will increase, but the customer's perceived quality of the store could be reduced and revenue may go down. Therefore, service performance should reflect the perceived quality (Grönroos and Ojasalo 2004).

Additionally, services may have different input intensities than manufacturing. Existing literature finds that technology investment and high-skilled labor stimulate innovation more in services than in manufacturing, which in turn would increase productivity (Vandenbussche, Aghion, and Meghir 2006). Firm size seems to be less relevant for productivity (Pires, Sarkar, and Carvalho 2008), which may imply that economies of scale are less important for services. Services firms tend to be more reliant on consumer-led nontechnological innovation (Iacovone, Mattoo, and Zahler 2013).[55]

2.1. Service Firm Performance Measurement

How to measure performance of service firms?

Due to the abovementioned differences between the two sectors, there are conceptual and methodological issues in applying traditional firm performance measurements (developed for manufacturing) to services. In this context, some business literature has explored alternative ways to measure service firm performance.

55. Iacovone, Mattoo, and Zahler 2013 provide examples of nontechnological innovation as product design, work environment, or management structure, rather than science and technology–led (introduction of new products/processes in the market, expenditure related to R&D, physical equipment acquisition, and training).

For instance, profit, a simple measurement of revenue divided by cost, is suggested as a performance measure to capture both quantity and quality dimensions, and output and input elements (Vuorinen et al. 1998; Grönroos and Ojasalo 2004).[56] However, in my view, profit might not be a better measurement than internal efficiency measures, such as productivity, as it is hard to separate direct costs and sales associated with specific production, and it is less informative than productivity. For instance, a standard measurement of TFP from the Cobb-Douglas production function provides information about input intensities and returns to scale. These studies on profit also state that their main purpose is to point out key elements to consider in measuring service firm performance, rather than to suggest a solution. However, their views that revenue can capture the quality component measured as unit price is important to consider.[57]

Some other studies have used labor productivity to measure service firm performance (Fixler and Siegel 1999; Fernandes and Paunov 2012). However, as in the manufacturing sector, the single-factor productivity measure is inferior to multifactor measures because it cannot capture the effects of other inputs in productivity analysis. Specifically, the marginal productivity of labor would change as the amount of other inputs available to the firm change; thus, holding constant other inputs' effects is crucial in measuring labor productivity. Therefore, labor productivity gives only partial information on how inputs are transformed into final output (Fu and Hoyes 2003).

A. Total Factor Productivity

Despite the abovementioned differences between service and manufacturing, TFP is still a useful way to measure firm performance, even in services. The productivity concept is

56. Grönroos and Ojasalo (2004) argued that service performance should reflect not only "how effectively service inputs are transformed to service outputs (internal efficiency)", but also "how well the quality of the service process and its outcome are perceived (external efficiency)".

57. The studies argued that the perceived service quality flowing from a given resource structure as inputs in the service production process creates sales at a certain level. If the resource structure is changed, the cost level changes and so do perceived quality and the revenue of service providers. Therefore, the productivity of service processes can be measured as the ratio between revenues (external efficiency) and costs (internal efficiency). However, they also raised concerns about revenue since it is not always a good measure of "external efficiency" as it may be regulated in (monopolistic) markets or subsidized by firms.

built on the proportion of output that is directly attributable to inputs, such as labor (L), capital (K), intermediate input (M), and technology (W). This last term, W, is TFP, which shows how effectively inputs are transformed into outputs, while assuming constant quality of output.

This assumption of constant quality of outputs raises concerns about TFP estimation even in the manufacturing sector. For example, both Mercedes and Kia produce the same product—automobiles—yet the quality of the two products might not be the same. Meanwhile, service quality could be a lesser concern in some service products. For instance, a mortgage loan from Citi Bank and from Lloyds Bank could be considered as the same product if pricing and conditions are the same. The heterogeneous quality issue is less a concern for the service sector, which can standardize quality. Thus, the issue of reflecting quality in productivity measurements is not specific to the type of industry; but is related to whether the production process and products can be standardized and to the variances of consumer preferences for such products.

TFP provides important information (that is, input intensities, and returns to scale) and has been used widely in previous analyses; thus, its methodological limitations and suggestions for improvements have been widely discussed. As mentioned in Griliches (1992), "Productivity analysis raises similar difficulties in both services and goods"; and in Fu and Hoyes (2003), "Despite all the econometric and measurement problems associated with TFP, given the theoretical considerations regarding factor complementarities and marginal productivities, this measure of productivity is the preferred one."

In this regard, I consider TFP as a measure of service firm performance, while investigating methods to improve this measurement to reflect the services sector's characteristics, such as heterogeneity in quality, and influence of market demand on production and outputs.

One option to improve TFP measurement for service firms might be to decompose the quality and market demand factors from revenue information by controlling for proxies of quality (for example, variance of price) and market competition (for example, a firm's market share) in estimating TFP. However, in the absence of such data, using firm-fixed effects (FE) could partially control the heterogeneity across service firms within each subgroup, although this cannot capture time-variant heterogeneity.

Another option is comparing TFP across firms within a disaggregated-level subsector, or at an even more narrowly defined product level, and comparing the time trend of TFP—such as growth rather than the levels—could also allow valuable comparison within a firm or within subsector/product categories, given the similar input choices and production processes within the sectors. However, it might not be particularly informative to compare TFPs across very different industries.

In addition, estimating TFP separately at a disaggregated level, such as narrowly defined subsectors or products, could reduce concern about heterogeneity in product quality by allowing the production process to vary across different industries/products.

Lastly, revenue-based TFP (TFPR) could actually be a practical way for measuring service firm performance**.** While the concept of TFP is quantity-based (TFPQ), information on the prices of every good produced and factors of production used in each firm are rarely available. Therefore, researchers have relied on price indexes to deflate outputs and inputs, and measure TFPR even in the manufacturing sector, which could potentially lead to an omitted price bias. [58] However, the measurement of quantity is not feasible for service inputs and outputs, and the price and quantity cannot be separated because defining "one unit of a service" is difficult (Grönroos and Ojasalo 2004).

58. If the market is not perfectly competitive, which is most likely, "prices reflect idiosyncratic demand shifts or market power variation rather than quality or efficiency differences" (Foster 2007). Thus, high productivity firms may not be particularly technologically efficient. Also, in the real world, firms in the same industry are offering differentiated products using different inputs (for example, taxi vs. Uber), thus, the productivity comparison across those firms will be misleading (Katayama, Lu, and Tybout 2009**;** Reynolds et al. 2005; Foster, Haltiwanger, and Syverson 2005; Hottman, Redding, and Weinstein 2014).

However, it is important to note that TFPR captures information beyond productivity. Price information reflected in TFPR captures product quality and market power, which are expected to have larger effects in service than in manufacturing. For instance, TFPQ is negatively correlated with establishment-level prices, while TFPR is positively correlated with prices (Foster, Haltiwanger, and Syverson 2005). This is because decreases in price could result from increased productivity regardless of product quality changes. Also, if the market is not perfectly competitive—which is likely—prices reflect demand shifts or market power variation (Reynolds et al. 2005; Foster, Haltiwanger, and Syverson 2005),[59] which might have larger effects in services than in manufacturing.

Since product quality and market power are important aspects of service firm performance, TFPR is useful for services, but it is divergent from the initial concept of TFP, which is TFPQ. Thus, despite these efforts to improve TFP measurement for service firms, there are still conceptual issues in estimating TFP in services due to large varieties of quality and influences of consumer demand in final output; such problems also exist in manufacturing to some extent.

Additionally, TFP might be only one of several possible idiosyncratic factors that describe firms' performance. Therefore, I explore an alternative way of measuring firm performance—markups.

B. Markup

An alternative measure for service firm performance is markup, which is the percentage difference between the marginal cost and the selling price. Markups provide information on firms' market power. In a perfectly competitive market, markup should be 1, since marginal cost should be equal to marginal revenue, which is the price. In a monopoly,

59. The imperfect competition and heteronomous products also apply to the input (Katayama, Lu, and Tybout 2009; Hottman Redding, and Weinstein 2014)

price is the consumer's willingness to pay for the product.[60] Therefore, the divergence of markups from 1 reflects the firm's market power—the ability to charge prices above marginal costs.

A direct way of measuring the markups would be simply to compute the ratio of the price over marginal cost. As I do not have direct measures of marginal cost, I make a set of assumptions about firms' behavior and production technology to estimate the marginal cost. Specifically, I assume firms are cost-minimizing, and technology is described by the Cobb-Douglas production function, following the De Loecker (2011) and De Loecker and Warzynski's (2012) empirical framework to estimate markup, as summarized below.[61]

Deriving an expression for markups

A cost-minimizing firm i at time t produces output using the following production technology:

$$Q_{it} = Q_{it}(L_{it}, M_{it}, K_{it}, \omega_{it})$$

L_{it} denotes labor inputs, M_{it} is intermediate inputs, and K_{it} is capital assets. $Q_{it}(\cdot)$ is continuous and twice differentiable with respect to its arguments. Assuming that producers active in the market are cost-minimizing, the associated Lagrangian function is below.

60. In other words, in a monopoly, price depends on the elasticity of demand. In a market, price (P) is defined as $P=[e/(1+e)]/MC$, where e is the elasticity of demand. In a competitive market the elasticity of demand is infinite; therefore, $P=MC$; however, in a monopoly, the price is the markup on marginal cost where the markup is $e/(1+e)$.

61. A firm i's share of expenditures on labor in total sales is equal to the share of expenditures in total costs (Hall 1998). Any departure from the perfect competitive model will drive a wedge between both shares, measured as markup, $Mi = Pi/ Ci$.

$\mathcal{L}(L_{it}, M_{it}, K_{it}, \lambda_{it}) = w_{it}L_{it} + p_{it}M_{it} + r_{it}K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot))$, where w_{it}, p_{it} and r_{it} denote a firm's input price for labor, material, and capital.

The first order condition for labor input, free of any adjustment costs is

$\frac{\partial \mathcal{L}_{it}}{\partial L_{it}} = w_{it} - \lambda_{it}\frac{\partial Q_{it}(\cdot)}{\partial L_{it}} = 0$, where the marginal cost of production at a given level of output is λ_{it} as $\frac{\partial \mathcal{L}_{it}}{\partial Q_{it}} = \lambda_{it}$. Rearranging terms and multiplying both sides by $\frac{L_{it}}{Q_{it}}$,

$$\frac{\partial Q_{it}(\cdot)}{\partial L_{it}}\frac{L_{it}}{Q_{it}} = \frac{1}{\lambda_{it}}\frac{w_{it}L_{it}}{Q_{it}}$$

The left-hand–side variable is the output elasticity of labor input, which can be denoted as θ_{it}^{L}. This implies that a cost-minimization firm decides its optimal labor input (employment) when the output elasticity of labor input is equal to wage price, multiplied by number of labor share in production, divided by marginal cost of production at a given level of output.

Define markup μ_{it} as the fraction of price and marginal cost $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$,

$$\theta_{it}^{L} = \mu_{it}\frac{w_{it}L_{it}}{P_{it}Q_{it}} \text{ and } \mu_{it} = \theta_{it}^{L}\left(\frac{w_{it}L_{it}}{P_{it}Q_{it}}\right)^{-1} \quad (1.1)$$

Here I use labor input in estimating markups. However, this marginal cost of production can be derived from the first-order condition for any nondynamic input variables, such as material input. For instance, using the output elasticity of material input, θ_{it}^{M}, markup $\mu_{it} = \theta_{it}^{M}\left(\frac{p_{it}M_{it}}{P_{it}Q_{it}}\right)^{-1}$, which should be the same as markup estimated using labor input.[62]

62. De Loecker and Warzinski (2012) show that markups estimation using different input variables are similar, and the small difference observed is due to the adjustment costs of inputs (for example, cost of hiring and firing workers). They consider capital stock, Kit, as a dynamic input in production; therefore, they do not use capital input variables in estimating markups.

Estimating the first term—output elasticity from the production function—requires a measure of output (and input) quantity that does not pick up price differences across firms. Although a few recent firm-level data sets provide such information, this is unavailable in most firm-level data sets. Therefore, researchers were forced to use deflated revenue as proxies of output. If the price information is not fully removed in estimated markups, markups may include more information than competition, such as the perceived quality of service products and a firm's ability to produce differentiated goods. However, De Loecker and Warzynski (2012) show that although deflated revenue could potentially affect the level of markups, it does not affect the correlation between markups and firm-level characteristics or how markups change over time.

Estimating the latter term does not require separation of the price information of input and output from input expenditures and revenues. Most firm-level data sets provide such information.

In my view, this measure of markups is particularly useful in the services sector, where (1) it is sometimes not possible to separate price and quantity information from revenue despite significant heterogeneity of quality across products and subsectors, and (2) detailed output price (and even price deflator) and quantity information are limited. Moreover, as De Loecker and Warzynski 2012 explain, unlike previous studies on markups, this measure of markups does not require a demand function; thus, it does not require very detailed market-level data with information on prices, characteristics of products, and consumer-level attribution. Lastly, this measure of markups provides firm-specific markup information.

2.2. Foreign Ownership and Firm Performance

In this section, I review the previous literature to investigate foreign ownership's effect on firm performance. Evidence of ownership's effect on firm performance is mixed and particularly rare in the services sector. Ownership could affect the firm performance

through various channels, such as increased competition through liberalization, and through changes of governance and incentives, as summarized below.

Services are less liberalized than manufacturing, globally. A distinct characteristic of the services sector is high protection, which results in limited foreign participation with a high proportion of state ownership. Many countries restrict the access of foreign services suppliers to domestic markets. As a result, many service sectors, such as air and rail transportation, and financial institutions, have monopoly or regulated duopoly market structures (Fontagne et al. 2011; Hoekman and Braga 1997; Boardman and Vining 1989).

Researchers and policy makers often assume that liberalization would lead to a productivity gain in the services sector. FDI is considered an important vehicle for productivity gains in the services sector, as foreign services are best transferred through personal contact between the service provider and client; and foreign investors' knowledge is transferred to domestic partners, competitors, and suppliers via management skill and know-how (Fu, Helmers, and Zhang 2012; Arnold, Javorcik, and Mattoo 2011; Markusen, Rutherford, and Tarr 2005; Griffith, Redding, and Simpson 2004; Dehejia and Wahba 2002).

However, evidence of FDI's positive effect on the service firm is extremely rare. Most studies focus on FDI's impact on downstream manufacturing, instead of services sectors' performance itself. For instance, service liberalization improves firm performance in downstream manufacturing sectors and technology-intensive industries (Arnold, Javorcik, and Mattoo 2011; Francois and Woerz 2008). Liberalization of backbone services was correlated with productivity growth in transition economies in Eastern European (Guerrieri and Meliciani 2005; Eschenbach and Hoekman 2005).

Existing studies that focus on FDI's effect on the services sector are few and mostly conducted at the aggregated level using industry-level data, and find mixed effects of FDI in services. For instance, FDI's effect on growth is ambiguous in services although it was

positive in manufacturing and negative in the primary sector (Alfaro 2003). After liberalization of the Indian banking industry, anticipated TFP growth did not materialize probably because actual implementation of deregulation did not take place (Kumbhakar and Sarkar 2003). Entry regulations negatively affect productivity in telecommunications industry, but not in other services industries (Inklaar, Timmer, and Van Ark 2008).

The only firm-level analysis on FDI's effect on services sector performance I find shows that FDI has a positive effect on productivity in services, and service firms benefit at an earlier stage of the internationalization process than do manufacturing firms (Marel 2010; Love 2009).

Such limited information is in marked contrast to literature available for the manufacturing sector, where FDI's effect on firm performance has been extensively investigated. Given that the production process and supplier-customer relationships might be very different between services and manufacturing, while existing literature focuses on the effect of policy change in the services sector on other sectors, understanding how changes in the services sector—such as in firm ownership—influence its performance is also necessary.

2.3. Tunisian Services Sector

Tunisia is an interesting country case to investigate service firms' performance and the impact of firm ownership on performance for a number of reasons.

The services sector is important for the Tunisian economy as its value-added contributes about 60 percent of GDP and makes up one-third of household consumption and 18 percent of intermediate demand.[63] Understanding service firms' characteristics and

63. Data source: Service Value-Added data are obtained from World Development Indicators(WDI)2015; Konan and Maskus 2006; Tunisian input-output table 1994 from INS

performance is crucial in understanding the Tunisian economy as a whole. The traditional sectors, such as tourism and construction are the largest sectors; however, modern services, such as business-related services, have emerged in recent decades. Appendix A provides descriptive information on Tunisian service firms and highlights their key differences from manufacturing firms.

Tunisia, however, practices relatively high protectionism in the services sector. The government's industrial policies have focused narrowly on the industrial sector, while neglecting services.[64] Although its export-promotion policies began relatively early, support for the services sector began only in the 2000s and was limited to a few subservice sectors, such as tourism.[65] While Tunisia has multiple international treaties to promote trade in goods,[66] it has not yet joined the trade agreement for services or fully implemented the joint agreement. For instance, Tunisia drafted its Services Trade Reform Plan in 1994; however, actual negotiation within the context of WTO agreements on service trade has not yet taken place. Additionally, services were excluded from the major trade agreements, such as the Association Agreement with the EU. Commitments under the General Agreement on Trade in Services (GATS) were few and generally represented preservation of status quo policies.

64. Government support to promote industries mostly excludes the services sector. For instance, the tax incentives on imports of raw materials and components for exporters under the Investment Code exclude service firms (Choi et al. 2012).

65. Tunisia started an export-oriented industrial policy relatively early. In the 1970s, Tunisia established an industry promotion agency (API), an export promotion center (CEPEX), and tax benefits for manufacturing and offshore regimes. In the 1980s, the government reduced tariffs and restrictions related to imports while privatizing state-owned enterprises through the Structural Adjustment Program. In the 1990s, Tunisia joined several trade agreements, including a free trade agreement (FTA) with the EU, a free trade zone with the EU and Arab world, alongside accession to the GATT and WTO. The government set up the Industrial Modernization Program to support increased productivity in manufacturing firms. In the 2000s, the government established an industrial upgrading program that supports regulatory reforms, techno-park creation, and SME financing.

66. In 1995, Tunisia entered into a FTA with the EU, allowing gradual tariff removal for industrial products with the EU, the largest export destination (over 85 percent of industrial exports are shipped to the EU). Since 1995, Tunisia has been a member of the WTO and has also signed trade agreements with neighbouring countries (Egypt, Morocco, Jordan, and Turkey), although the trade volume with these countries is insignificant due to weak infrastructure and similar export baskets.

As a result, the Tunisian services sector shows less participation from foreign investors with larger state ownership compared to the manufacturing sector. The INS data show that only around 6.5 percent of service firms have some foreign share, while around 29.0 percent of manufacturing has some foreign share. Meanwhile, approximately 15 percent of service firms have some state share, while this share was only about 3 percent for the manufacturing firms.

With barriers to firm entry, the level of competition is particularly low in the services sector, which may lead to poor performance in the sector and in the overall economy. Reduced competitive pressure may hinder firms' adoption of existing technologies and prevent entry of new firms with potentially higher performance and/or new technology in many subservice sectors. It was revealed that prices in the services sector in Tunisia were about four times those in Morocco, a neighbouring country (World Bank 2010).

Given that services are an important input of production processes elsewhere in the economy (see, for instance, Arvis 2016; Freund and Weinhold 2004), Tunisia's weak service performance may limit its overall competitiveness in relation to neighbouring countries. In fact, the services sector's contribution to manufacturing production in Tunisia is much smaller than world average and in neighbouring countries, as revealed in the INS input-output table.[67]

Therefore, previous studies have argued that increasing competition through liberalization would increase economic activity in all sectors, not only in the services sector, and raise real returns to both capital and labor (Konan and Maskus 2006; Nucifora, Doemeland, and Rijkers 2014).

67. In the INS input-output table from 1994, services are 18 percent of intermediate demand in Tunisia while, Services are at more than 30 percent of the value-added of trade in manufacturing in world average (OECD and WTO 2013). The communications services comprise only 1 percent of production in Tunisia, whereas they make up 4 percent of GDP in Morocco (Varoudakis and Rossotto 2004).

However, the effect of such liberalization efforts on firms' performance and market competition are not known. The government has made some effort to liberalize service firms, but it has done so with a number of limitations, without systematic evidence of the effects of such efforts (Saghir 1993; Belev 2000; Savona 2004).[68]

This paper will provide analysis of Tunisian service firms—in terms of their performance by subsectors and over time, as well as identify their unique characteristics. This paper will also investigate if ownership affects firm performance in the services sector.

3. Data and Descriptive Information

The data used in this study are from the annual enterprise survey, Enquête Nationale sur les Activités Économiques (ENAE), which is conducted by the INS. The data are collected for the period 1997 to 2009, with an average 2,700 firms surveyed each year, including an average of 1,138 firms in the services sector (NACE 45–95).

The survey coverage is extensive, as firms accounting for about 30 percent of total firms with six or more employees in multiple sectors, including services, are included in the sample. In each year, a sampling method was applied, taking into account stratifications by industry and company size in terms of employees. To confirm that INS data include representative firms, key firm characteristics of the INS data are compared with the aggregated information of firms listed by the Investment Promotion Agency (IPA).

The INS data provide rich information on firm ownership, balance sheets (revenue, labor, capital assets, intermediate material, tax, and subsidy), and other characteristics

68. In 1986, the government adopted a Structural Adjustment Program, which required reforms included restructuring of the public sector. Privatization started in as early as 1987, starting with loss-making small firms in the 1980s, and expanding to include even profitable large ones in diverse industries in the 1990s. By 1995, around the period INS data were first compiled, there were 58 privatized enterprises, and most of them are in the services sector, excluding those in which the state kept majority shares. Most privatization involved changes in management. Between 2000 and 2008, the main transaction was the sale of some shares of Tunisie Telecom to a foreign firm, according to the Privatization Database 2011.

(firm creation year, location, industry), which permits an investigation of the effect of state ownership on firm performance.

The drawback of the INS data is that the survey provides a repeated cross-section that is representative of the Tunisian economy but does not readily permit application of econometric techniques for panel data. On the other hand, many observations of firms appeared over at least 2 years during the 13 years; thus, the whole set of data is a rather weakly balanced panel. Therefore, econometric techniques for panel data must be applied with caution.

In 2004, 2008, and 2009, the INS used simplified questionnaires and did not ask for firm ownership information. Therefore, observations from these years were not used, but were for the remaining 10 years. To avoid outliers, subsectors that have fewer than 50 observations, such as financial and insurance (NACE 65, 66, 67), water and air transport (NACE 61, 62), mail services (NACE 64), and R&D (NACE 73), were dropped. Similarly, education, health, and public administration (NACE 75) were omitted because these sectors typically provide not-for-profit services and have very different characteristics than other sectors. The remaining 11 subservice sectors are included. Lastly, the observations with missing information in revenue and key input variables, such as labor, capital, and material, are removed.

After these omissions, the total number of observations in the services sector was reduced from a total 14,789 firm observations to 8,939. Among these, 3,207 are firm observations. Firms are repeatedly selected at an average of about 4.78 times during the data coverage period. Meanwhile, 1,454 firms (45 percent of firms) appear just once. Thus, the panel technique can be applied only to a subset of the data.

Table 1 provides the number of observations by subservices. Retail and wholesale (NACE 50), construction (NACE 45), and hotel and restaurant (NACE 55) have the highest number of observations.

The INS data provide information about firm ownership, such as foreign, private, public, and semi-public ownership share. The sum of these ownership shares is equal to 100. Using this information, I generate state ownership variables as the sum of public and semi-public variables, and create ownership categories: private, foreign, and state ownership.

Table 1. Observations by Subservice Sectors

INS subsector	NACE	Description	Obs.
Construction	45	Construction	1,603
Retail and wholesale (commerce)	50	Sales and repair of motor vehicles	863
	51	Wholesale and commission trade, excluding motor vehicles	1,792
	52	Retail trade and repair of personal goods	843
Hotel and restaurant	55	Hotels and restaurants	1,460
Transport and communication	60	Land transport	470
	63	Transport services, travel agency activities	561
Real estate and rental	70	Real estate activities	332
	71	Renting of machinery/equipment without operator	118
Business services	72	Computer and related activities	105
	74	Other business services	792
Total			8,939

Table 2 shows summary statistics and changes of ownership variables.

Table 2. Ownership Variables

	Share			Status (dummy)		
Variable	**FDI**	SOE	Private	**FDI**	SOE	Private
Number of obs. (var > 0)	**592**	771	8,237	**592**	771	8,237
Number of firms (var > 0)	**214**	183	3,043	**214**	183	3,043
Number of obs. with change = 1	**150**	163	271	**87**	83	120
Number of firms with change = 1	**96**	86	154	**67**	58	84
% of change = 1 if var > 0	**25.34**	21.14	3.29	**14.70**	10.7 7	1.46

Note: FDI = Foreign direct investment; SOE = State-owned enterprise.

While most firms are privately owned, there is a small FDI and large SOE presence in the Tunisian services sectors. Around 92 percent of observations have at least some private ownership. Around 9 percent of observations have some state ownership, while only 6

percent of firms show some foreign ownership. Meanwhile, for the manufacturing firms in the INS data set, 29 percent of observations have at least some foreign share, but only 2 percent of observations report at least some state share. This smaller FDI and larger SOE presence in services, compared to manufacturing, is consistent with expectations, given the complex regulation and entry barrier in Tunisia's services sector.

There are few changes in firms' ownership structure over time. There are 592 observations (214 firms) with foreign ownership, implying that FDI firms appear 2.8 times on average during the data coverage period, which is relatively small. Among those, 150 observations (96 firms) changed their foreign share. Foreign share increased for 32 firms and decreased for 29 firms. Thirty-five firms reported both increase and decrease of foreign shares during the data coverage.

In appendix A, graphs A.2 to A.7 show the firm ownership structure over time by subsectors. Business services, and real estate and rental have a large presence of FDI firms, followed by hotel and restaurant, and transport and telecoms sectors. At the same time, the real estate and rental sector has the largest share of state-owned firms, followed by transport and telecommunication, and then by business services. Since the INS data are not a balanced panel, these changes of share of state ownership do not necessarily mean a group of the same firms changes their ownership structure but rather represent selected firms in each year and industry.

Table 3 provides the summary statistics of key variables for FDI and non-FDI firms.

There is a large difference in firm characteristics between FDI and non-FDI firms. FDI firms are larger than non-FDIs—have 4.47 times larger sales revenue, use 4.36 times the material inputs, and have 3.49 times the capital assets.

However, FDI firms hire only 2.57 times more employees, despite their large revenue size. This might imply that FDI firms are less labor-intensive sectors, or their workers are more efficient. In fact, FDI firms pay 2.17 times higher average wage than non-FDI

firms, which might suggest that FDI firms hire more skilled workers. FDI firms pay 4.84 times more tax than non-FDI firms, which is similar to their revenue size difference as compared to non-FDI firms. Interestingly, FDI firms receive much lower subsides and grants from the government than non-FDI firms, which might suggest that the government's subsidies and grants to domestic firms could be one barrier to foreign firms' entry in Tunisia.

Table 3. Comparison of Key Firm Characteristics between FDIs and Non-FDIs

	Non-FDI		FDI (full+partial)		Diff.	*T*-test
Variables	Obs.	Mean	Obs.	Mean	FDI/non	*p*-value
Firm age (years)	7,007	29	569	33	1.12	0.00
Revenue (TD)	8,939	7,629,803	649	34,100,000	4.47	0.00
Material inputs (TD)	8,939	1,009,895	649	4,413,636	4.37	0.00
Employment (persons)	8,939	104	649	268	2.57	0.00
Capital assets (TD)	8,939	9,878,576	649	34,500,000	3.49	0.00
Total tax (TD)	8,939	57,041	649	275,827	4.84	0.00
Subsidy/grants (D)	8,939	164,184	649	85,693	0.52	0.25
Average wage (TD)	8,939	6,491	649	14,074	2.17	0.00

Note: Revenue, material inputs, and other value terms (tax, subsidies, and average wage) are deflated by service price index. Capital assets are deflated by the capital price index provided by INS; TD = Tunisian dinar.

4. Estimating Service Firm Performance

4.1. Estimating TFP

As mentioned in the literature review section, researchers have relied on price indexes to deflate outputs and inputs and measure TFP (TFPR), as information on prices of every input and output in each firm is rarely available. The price deflator converts the value term to a quantity term, potentially taking out the differences of the quality component in the production function.

As in most other developing countries, there is no detailed price index available for service subsectors in Tunisia. INS provides one price deflator for the entire services

sector; however, applying the same price deflator for the entire sector could cause price bias across subsectors. I considered my own price index for subservice industries based on the available information, such as national accounts, but there are difficulties in doing so as this requires a number of weak assumptions.[69] Moreover, since the quantity measurement might not be feasible both for service inputs and outputs, I had to resort to using the aggregated service deflator.

As a mitigation measure, I measure TFP separately by subsectors, which allows the coefficient to vary across subsectors. Additionally, using firm-fixed effects (FE) will partially control heterogeneity across service firms within each subgroup, although it cannot capture time-variant heterogeneity. However, because INS data are weakly balanced, using firm-fixed effects could reduce the number of TFP estimations, thus raising the potential of a selection bias by narrowly focusing on firm observations showing multiple times in the data set. Therefore, in my TFP estimation, I provide the TFP with and without firm-fixed effects for a comparison.

Denote NACE two-digit codes by $j = 1, \ldots, J$

$$\ln Y_{ijt} = \beta_{0j} + \beta_a \ln K_{ijt} + \beta_b \ln L_{ijt} + \beta_c \ln M_{ijt} + \omega_{ijt} + \epsilon_{ijt} \qquad (1.2)$$

- Y_{ijt} : The real output of firm *i* operating in sector *j* at time *t,* which is calculated by the sales revenue deflated by the service price index.

69. Using an aggregated deflator will cause price differences within and across subindustries, which are embodied in productivity measures (omitted price bias). Given the large heterogeneity of services sectors, using the subservice sector price index of other countries could be considered. However, the service price index is very heterogeneous across countries even for those countries with similar income levels and geographical proximity, which disallows the use of the few available service price indexes from other countries, such as France. Moreover, to construct a set of deflators for subservice using the existing information, such as balance of payments and government expenditure, means having to make a number of unreasonable assumptions, such as homogenous prices among consumers, the government, and exporters, and that the change in government expenditure and export amounts are caused only by price change but not quantity change, which is not convincing.

- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by capital price index, from the National Account.
- L_{ijt} : Number of employees.
- M_{ijt}: The value of material inputs adjusted for changes in inventories, deflated by the service price index.

In the above production function, I decompose the residual into three components, β_{0j}, $\omega_{ijt,}$and ϵ_{ijt}.

ω_{ijt} is the transmitted component that influences firms' input decisions when firms know about their productivity level (simultaneity issue), ω_{ijt} is observable for firms, although it is not observable for researchers.

TFP consists of the predictable time- and producer-specific deviation (ω_{ijt}) from that mean efficiency level across firms within sector *j,* constant term (β_{0j}). In this paper, I include constant term (β_{0j}) in reporting TFP to capture the difference in productivity levels across subindustries. I take out the constant term if the main interest is the deviation from the mean in the subservice industry, rather than a cross-sectoral comparison.

ϵ_{ijt} is an unobservable and unanticipated shock to production (for example, exogenous circumstances and unanticipated delay) and i.i.d. shock, including measurement error. Firms do not observe ε_{ijt} when making optimal input decisions; therefore, it does not impact the firms' input decisions.

Dealing with the endogeneity of factor inputs with respect to production shocks

If productivity is correlated with the input choice, not controlling for unobserved productivity shocks would bias the estimated results (simultaneous bias). For instance, when there is external shock, if material is more easily adjustable than labor and capital, then material is more strongly correlated with the error term. Therefore, material could be upward-biased while other inputs might be downward-biased (Levinsohn and Petrin 2003). Effects of this unobserved productivity shocks might be larger in the services sector, which has larger heterogeneity across firms, than in the manufacturing sector.

Existing literature has extensively investigated methods to address this simultaneous bias and to obtain consistent estimates of productivity and the parameters β. Some papers relied on the use of instrumental variables (and more recently generalized method of moments [GMM]) and proxy approaches,[70] which solve for unobserved productivity as a function of observed firm-level decisions, such as investment and input demand, to deal with the endogeneity of inputs when estimating a production function.

I closely follow the methods suggested by De Loecker and Warzynski (2012), which are similar to proxy approaches suggested by Ackerberg, Caves, and Frazer (2006, henceforth ACF).[71]

No one method will be appropriate for all data sets, industries, and timeframes. Instead, the right method will depend on the details of the industry (data) being studied (Levinsohn and Petrin 2003). I compare the ACF with other econometric techniques to

70. They model unobserved productivity as a function of observed firm-level decision (for instance, firm's input demand) to deal with the endogeneity of input choices in a production function. Specifically, Olley and Pakes (1996, henceforth OP) proxy productivity by a function of investment and capital, and Levinsohn and Petrin (2003, henceforth LP) use a static input, such as material, to control for productivity.

71. The main difference between the ACF approach and OP/LP in the estimation process is that the ACF does not obtain the input coefficient in the first stage, while OP/LP obtain labor coefficient in the first stage (that is, $\ln Y_{it} = \beta_l \ln L_{it} + f_{it}(\ln M_{it}, \ln K_{it}) + \epsilon_{it}$) as they assume labor (how many workers to hire in year t) varies independently of the nonparametric function that is being estimated. Therefore, compared to OP and LP, the ACF approach has the advantages of i) dealing with the potential collinearity issues between labor (L_{it}) and the nonparametric terms (inverted material input demand function) (Ackerberg, Caves, and Frazer 2006), and ii) not having to revisit the underlying dynamic model of the original OP when dealing with additional state variables (De Loecker and Warzynksi 2012).

deal with simultaneity bias, and find that the ACF methods are quite suitable to service firms in the INS data set.[72]

To briefly summarize their methods, they proxy productivity by a function of material demand, assuming that a firm decides its material inputs based on knowledge of its productivity level and other inputs.

The material input demand function is defined as $\ln M_{ijt} = m_{tj}(\ln K_{ijt,}, \ln L_{ijt,}\, \omega_{ijt})$.

Assuming the monotonicity of intermediate inputs in productivity,[73] $\partial m / \partial \omega > 0$, conditional on the firm's capital stock and labor inputs, the above material input demand function can be inverted as $\omega_{ijt} = h_{jt}(\ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt})$.

Now the above production function (1.2) becomes

$\ln Y_{ijt} = \beta_{0_j} + \beta_a \ln K_{ijt} + \beta_b \ln L_{ijt} + \beta_c \ln M_{ijt} + h_{jt}(\ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt}) + \epsilon_{ijt}$

Denote $\phi_{ijt}(\ln M_{ijt,} \ln K_{ijt}, \ln L_{ijt})$

$= \beta_{0_j} + \beta_1 \ln K_{ijt} + \beta_b \ln L_{ijt} + \beta_c \ln M_{ijt} + h_{jt}(\ln M_{ijt,} \ln K_{ijt}, \ln L_{ijt})$

Which represents output net of the untransmitted shock.

$$\ln Y_{ijt} = \phi_{ijt}(\ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt}) + \epsilon_{ijt} \qquad (1.3)$$

72. As the role of material inputs in service production might be different from that of manufacturing (for example, material inputs for service could be difficult to define), I compare the ACF with other econometric techniques to deal with simultaneity bias and find that the ACF approach is suitable for service firms in the INS data set. For instance, my investment variables report too many zero values, which prevents me from using OP, as it requires a monotonicity assumption for investment and productivity. Also, GMM estimation results reveals that (i) the estimated coefficients are not in credible ranges, with very large coefficients on certain inputs but missing coefficients of other inputs; and (ii) the test results reject the null hypothesis that the differenced residuals are uncorrelated with previous year information and the instruments are exogenous. This is possibly because the GMM requires all input and output observations for a longer years than ACF, thus, losing more observations than ACF.

73. This monotonicity condition is preserved for a wide range of models of imperfect competition, such as Melitz and Levinsohn 2006; Levinsohn and Petrin 2003; and De Loecker and Warzynksi 2012.

Where I obtain estimates of expected output $\widehat{\phi_{ijt}}$ and an estimate for ϵ_{ijt} by approximating ϕ_{ijt}. Specifically, I use a fourth-order polynomial of all input variables to estimate $\phi_{ijt.}$

However, any consistent parametric or nonparametric estimator for each of these conditional means could be applied. For instance, in their proxy approaches, OP and ACF use a fourth-order polynomial, while LP uses a locally weighted quadratic least squares approximation in $\ln L_{ijt}$ $\ln M_{ijt,}$ $\ln K_{ijt}$ to approximate ϕ_{ijt}. I explain why this is the case below.

Similar to the exposition in Robinson (1988), I take the expectation of equation (1.3) conditional on $\ln M_{ijt,}$ $\ln K_{ijt}, \ln L_{ijt}$.

Because ϵ_{ijt} is mean independent of $\ln M_{ijt,}$ $\ln K_{ijt}$ and E
$[\phi_{ijt}(\ln M_{ijt,} \ln K_{ijt}, \ln L_{ijt}) | \ln M_{ijt,} \ln K_{ijt}, \ln L_{ijt}] = \phi_{ijt}\,(\ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt})$.

$$E\,[\ln Y_{ijt} | \ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt}] = \phi_{ijt}\,(\ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt}) \qquad (1.4)$$

Then subtracting (1.4) from (1.3), $\ln Y_{ijt} - E\,[\ln Y_{ijt} \,|\ln M_{ijt,}\, \ln K_{ijt}, \ln L_{ijt}] = \epsilon_{ijt}$

Therefore, without knowing the specific functional form of ϕ_{ijt}, ϵ_{ijt} can be removed in the first stage, above. Intuitively, this procedure allows the isolation and elimination of the portion of output determined by shocks unanticipated at t (for example, unanticipated weather shocks, defect rates, or machine breakdowns) or by measurement error, conditional on a firm's choice of material inputs.

The second stage provides estimates for all input coefficients by relying on the first-order Markov process for productivity (or law of motion for productivity), implying

productivity is a function of previous year productivity, given a firm′s information set and a productivity shock ξ_{it}.

A Markov process assumption is not unreasonable considering that TFP captures factors that have persistent influence on productivity (that is, absorption of techniques, modification of processes, and gains and losses due to changes in labor composition and management abilities), and thus represents all these influences over time (Doraszelski and Jaumandreu 2013).

For any $\boldsymbol{\beta}_j = (\beta_{aj}, \beta_{bj}, \beta_{cj})'$, $\omega_{ijt}(\beta) = g_{jt}(\omega_{ijt-1}(\beta)) + \xi_{ijt}(\beta)$

This simply decomposes ω_{it} into its conditional expectation at time t-1, and a deviation from that expectation, ξ_{ijt} , which is an innovation component of ω_{ijt} .

$\xi_{it}(\beta)$ is the residual obtained by nonparametrically regressing $\omega_{it}(\beta)$ on $(\omega_{it-1}[\beta])$.

And $\omega_{it}(\beta) = \widehat{\phi_{\iota jt}} - \widehat{\beta_{\mathrm{a}}} \ln K_{ijt} - \widehat{\beta_{\mathrm{b}}} \ln L_{ijt} - \widehat{\beta_{\mathrm{c}}} \ln M_{ijt}$.

The term $\xi_{ijt}(\beta)$ is by assumption uncorrelated with any lagged choice variables of the firm because the latter are in the firm′s information set. This forms the basis for identifying the input coefficients.

ACF (and De Loecker) assume that capital is decided a period ahead, and therefore, current year capital should not be correlated with shocks to the productivity process. Meanwhile, since labor is expected to react to shocks to productivity, ($E(\xi_{it} \ln L_{it})$ is nonzero), lagged labor is used to identify the coefficients of labor.
Also, it is assumed that all prices of production inputs vary across firms and are serially correlated. This assumption of serial correlation allows reliance on lagged input choices to identify the production coefficients. In fact, there is strong evidence of serial correlation of input variables (that is, current and past wages have a correlation of 0.92).

I can now form moments to obtain β estimates, relying on

$$E\left(\xi_{ijt}\left(\boldsymbol{\beta}_j\right)\begin{pmatrix}\ln L_{ijt-1}\\ \ln M_{ijt-1}\\ \ln K_{ijt}\end{pmatrix}\right)=0$$

A sample analogue to the above moment can be formed as

$\frac{1}{T}\frac{1}{N}\sum_t\sum_i \xi_{ijt}\left(\boldsymbol{\beta}_j\right)\begin{pmatrix}\ln L_{ijt-1}\\ \ln M_{ijt-1}\\ \ln K_{ijt}\end{pmatrix}$ and I find $\boldsymbol{\beta}_j$ that minimizes this sample analogue. Then, I rely on block bootstrapping for the standard errors.[74]

4.2. Estimating Markup

Using the labor coefficient, θ_{ijt^L}, estimated from the above Cobb-Douglas (CD) production function (1.2), I can now estimate markups as derived in (1.1). Because revenue term ($P_{ijt}Q_{ijt}$) includes ε_{ijt}, I remove ε_{ijt} by estimating revenue as $P_{ijt}Q_{ijt}/\widehat{\varepsilon_{ijt}}$. Thus, markup is estimated as $\mu_{ijt}=\theta_{ijt^L}\left(\frac{\omega_{ijt}L_{ijt}}{P_{ijt}Q_{ijt}}\right)^{-1}\exp\left(\widehat{\varepsilon_{ijt}}\right)$.

The correction of removing ε_{ijt} from revenue is important as it will eliminate any variation in expenditure shares that comes from output variation not related to variables impacting input demand including input prices, productivity, and technology parameters; and market characteristics, such as the elasticity of demand and income levels (De Loecker and Warzynski 2012).

While I closely follow the markups estimation proposed by De Loecker and Warzynski (2012), I go beyond their framework to ensure the firm-level markups would reflect the

74. OP provides the theoretical framework for computing asymptotic standard errors for their control function methods. However, instead of undertaking this difficult task, LP and ACF suggest using the bootstrap for inference, which samples empirical distribution of the observed data to construct new "bootstrapped" samples. The statistical value is computed for each of these samples and the distribution of estimates generated provides an approximation of the true sampling distribution of the statistic. I benefit from De Loecker and Warzinski (2012)'s code for estimating TFP with ACF and information provided by Sivadasan at http://webuser.bus.umich.edu/jagadees/other/acf_code.html.

differences in technology and production processes across service subsectors by estimating the production function by subsector *j* separately.

Because I estimate TFP by each subsector separately in the above CD production function, output elasticities of inputs (input coefficients) vary across subsectors, but are common within subsectors. However, estimated markups would still vary across firms even within subservice industries due to the different input cost and revenue for each firm.

However, restricting the output elasticities as independent of input use intensity may lead to potentially biased markup measures by attributing variation in technology to variation in markups.
In this regard, I estimate the markups with the translog production function, as my main estimation, to avoid the constant output elasticities of inputs in the case of Cobb-Douglas functions and to allow for heterogeneity in output elasticity across firms.[75]

Following De Loecker and Warzynski (2012), I approximate the translog production function by a second-order polynomial, where all (logged) inputs, (logged) inputs squared, and interaction terms between all (logged) inputs are included, as shown in equation 1.5.

While De Loecker and Warzynski used value-added production functions for their main specification, I use gross output productions, as they have several advantages. First, they provide multiple first-order conditions to recover markup. Second, they could potentially cancel out or reduce the price bias because price information is captured for both material input and output. Specifically, the price bias occurred due to using deflated revenue as a proxy of output quantity, but it would be canceled out by using deflated material cost as a proxy of deflated material input quantity in the right-hand side of the production function. Lastly, I can avoid imposing the Leontief technology assumption

75. Cobb-Douglas function is recovered when I drop higher-order and interaction terms.

(the fixed proportion assumption of materials input) in the value-added production functions.

I estimate the translog production function below by subservice industries *j* to allow for the production process; thus, output elasticities vary across subsectors.

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 (\ln K)^2_{ijt} + \beta_5 (\ln L)^2_{ijt} + \beta_6 (\ln M)^2_{ijt} + \beta_7 \ln K_{ijt} \ln L_{ijt} + \beta_8 \ln K_{ijt} \ln M_{ijt} + \beta_9 \ln L_{ijt} \ln M_{ijt} + \beta_{10} \ln K_{ijt} \ln L_{ijt} \ln M_{ijt} + \omega_{ijt} + \varepsilon_{ijt} \quad (1.5)$$

Again, not controlling for unobserved productivity shock biases, the estimate of the markup as productivity is potentially correlated with the input choice (simultaneity bias). For instance, if change of ownership impacts firm productivity, one needs to control for the productivity shock to measure the change in the markup due to the change in ownership. Therefore, I apply proxy methods to this translog function. The details are provided in appendix B.

Under a translog gross output function, the output elasticity for labor (θ_{it^L}) is given by[76]

$$\widehat{\theta_{ijt^L}} = \widehat{\beta_2} + 2\widehat{\beta_5} \ln L_{ijt} + \widehat{\beta_7} \ln K_{ijt} + \widehat{\beta_9} \ln M_{ijt} + \widehat{\beta_{10}} \ln K_{\text{ijt}} \ln M_{\text{ijt}} \quad (1.6)$$

θ_{ijt^L} is by definition independent of a firm's productivity level. Also, different from the output elasticity in Cobb-Douglas production function (β_b in equation 1.2), θ_{ijt^L} is firm-specific as the level of input $\ln L_{ijt}$, $\ln K_{ijt}$ and $\ln M_{ijt}$ varies across firms.

This firm- and time-specific markup, as opposed to an average markup for a set of producers, allows for an analysis of how markups are related to other firm-specific characteristics, such as ownership.

76. Please note that I recover the Cobb-Douglas (CD) production function by dropping higher-order and interaction terms.

Then I remove ε_{ijt} from revenue by estimating markup as $\mu_{ijt} = \theta_{ijt}^{L}(\frac{\omega_{ijt} L_{ijt}}{P_{ijt} Q_{ijt}})^{-1}\exp(\widehat{\varepsilon_{ijt}})$.

The suggested measurement, TFP and markup, can be used to understand firm performance trends and other firm characteristics that influence its performance, such as firm size, age, export, innovation, and ownership. Later in this paper, I investigate firm ownership's effect on service firm performance. Firm ownership could reflect market competition because, with high regulations and entry barriers, there seems to be less foreign but more state participation. The high protection and entry regulations are often cited as major constraints for Tunisian service firms; therefore, understanding how ownership influences firm performance could be crucial for services.

4.3. Understanding Ownership's Effect on Service Firm Performance

Using the above measured firm performance, TFP and markups, I investigate whether the variance of firm performance can be explained by foreign ownership.

$$Performance_{ijt} = \beta_1 FDI\ variables_{ijt} + \Psi_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt}, \text{ where} \quad (1.7)$$

- $\text{Performance}_{ijt} = \{\text{TFP}_{ijt}, \text{Markup}_{ijt}\}$
- $\text{FDI variables}_{ijt} = \{FDI_{Stat_{ijt}},\ FDI_{share_{ijt}},\ FDI_{Stat_{ijt-1}},\ FDI_{share_{ijt-1}}\}$

$$Performance_{ijt} = \beta_1 FDI_{stat_{ijt}} + \Psi_{ijt} + FDI_{stat_{ijt}} \Psi_{ijt} + \alpha_j + FDI_{stat_{ijt}} \alpha_j + \alpha_t + \varepsilon_{ijt} \quad (1.8)$$

Ψ_{ijt} is a vector of control variables, including firm size—measured by number of employees—and firm age, which are widely used to control for firm-specific characteristics (Huergo and Jaumandreu 2004; Balasubramanian and Lee 2008).

I also consider including additional control variables, such as subsidies and grants, and tax payments, because they could be the channels through which the government disproportionally supports or burdens targeted firms. As seen in the data section, FDI firms receive much smaller subsidies and grants, but pay more tax relative to their

revenue size, compared to non-FDI firms. However, those might be outcome variables of firm performance. For instance, the firm's level of tax payment could be decided proportionally to its revenue, which could raise a potential collinearity issue in the above specification. Therefore, I exclude those variables in the regression but use them for additional firm characteristics of FDI firms in the matching section below. Also, there is no information on exporting amount or quantity for the service firms in the INS data, probably due to difficulties in capturing exporting activities in services; therefore, I do not use an export variable as a control.

In equation (1.7), I investigate whether the variance of firm performance can be explained by foreign ownership. β_1 shows each ownership category's effect on firm performance relative to fully private firms.

Then, I add interaction terms between FDI_status and other control variables and subsector dummies, as seen in equation (1.8), to investigate whether firms' performance and the variation associated with foreign ownership change across subsectors.

Matching

Estimating equation (1.7) in ordinary least squares (OLS) would provide a biased result of foreign ownership's effect on firm performance, if firms with foreign ownership are systematically different from those without (selection bias). Given the small variations in FDI variables over time, the panel techniques to deal with such issues, including GMM, could not be applied.

Therefore, I apply a propensity score matching technique (Heckman, Ichimura, and Todd 1997; Rosenbaum and Rubin 1983) that reduces the selection bias that may be present in nonexperimental data by comparing units that do not participate in a program (non-FDI firms), but otherwise share similar characteristics as those units that have participated (FDI firms).

The propensity score matching technique allows me to find a control group of firms that are similar to FDI firms but do not have foreign ownership, by selecting firms that are as close as possible to the FDI firms in terms of their predicted probability to receive FDI. Specifically, I estimate the probability of receiving FDI with the observed key firm characteristics. I assume that all differences between FDI firms and the appropriate control group can be captured by a vector of observables. Then, I find the average differences in outcomes between the control and treatment groups (FDI firms).
In the first stage, I construct a control group of firms that have a comparable likelihood of FDI firms, but do not have foreign ownership. As seen in the logit model below, the propensity score is estimated as a function of key firm characteristics, such as firm size and firm age, which I used as controls in the above regression.

In addition, I include other firm characteristics, such as tax payment and subsidies received, as those could be the channels through which the government supports or burdens selected firms, and could influence firms' performance. For instance, as seen in the descriptive information, if the Tunisian government provides fewer subsidies and charges more tax for FDI firms than for domestic private firms or SOEs, subsidies and tax serve as additional barriers for foreign investors' entry into Tunisia; therefore, FDI firms would show lower TFP levels without controlling for tax payment and subsidies received. Furthermore, I include a full set of location and subsector dummies to control for common aggregated demand and supply shocks.

$$\text{logit}(FDI=1) = \phi\{\text{firm size, age, subsidy, tax, subsector dummy, location dummy}\} \quad (1.9)$$

For the robustness check, I add one more control, a firm's market share, which is measured as firm *i*'s revenue share in the total firm revenue in industry *j*. However, the INS data do not include all firms in Tunisia, thus, the suggested market share variable is not accurate, although it should be correlated with a firm's actual market share.

Then I use the nearest neighbour matching technique, which selects a non-FDI firm that has a propensity score closest to that of the FDI (Becker and Ichino 2002). This creates

a group of matched FDI firms and non-FDI firms, and allows an evaluation of the causal impact of foreign ownership on firm performance. Then I compare the average difference between the two groups (ATT).

I also consider employing difference-in-differences (DID) propensity score matching estimator to improve the quality of matching results by removing the initial differences between treated and control units (Blundell and Dias 2009) and by reflecting the difference in firm performance growth between new FDI firms and their matched controls, relative to the pre-FDI period (t-1). However, the number of firms that have reduced their foreign ownership during the period of data coverage is too small, which makes it difficult to rely on the DID methodology to examine the impact of changes of foreign share (or status) on performance over time.

5. Results

5.1. Service Firm Performance—TFP and Markups

Here I provide the estimation results of service firm performance, starting from TFP.

Table 4 Production Function Estimation by Subservice Sectors

Sector	Construction		45	Whole sale and reta		50	Whole sale and reta		51	Whole sale and reta		52	Hotel and restauran		55	ransport and teleco		60
ln_revenue	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF
ln_labor	0.300***	0.060**	0.181***	0.980***	0.343***	0.997***	0.896***	0.256***	0.851***	0.950***	0.404***	0.793***	0.635***	0.114***	0.372**	0.522***	0.263***	0.586***
	(0.017)	(0.019)	(0.043)	(0.046)	(0.060)	(0.198)	(0.024)	(0.030)	(0.130)	(0.031)	(0.050)	(0.201)	(0.019)	(0.019)	(0.198)	(0.037)	(0.044)	(0.195)
ln_capital	0.112***	-0.006	0.014	0.039**	0.035*	0.023	0.125***	0.026**	0.187**	0.060***	0.009	0.091	0.059***	0.015*	0.045	0.174***	0.021*	0.137**
	(0.008)	(0.009)	(0.054)	(0.014)	(0.014)	(0.033)	(0.011)	(0.010)	(0.095)	(0.014)	(0.014)	(0.092)	(0.005)	(0.006)	(0.044)	(0.017)	(0.010)	(0.127)
ln_intermed	0.508***	0.463***	0.663***	-0.035***	-0.000	-0.004	0.006	0.006*	0.003	0.006	0.004	0.009	0.318***	0.212***	0.706***	0.002	0.069***	0.004
	(0.011)	(0.014)	(0.039)	(0.009)	(0.005)	(0.012)	(0.005)	(0.003)	(0.006)	(0.008)	(0.005)	(0.012)	(0.012)	(0.010)	(0.149)	(0.015)	(0.013)	(0.053)
_cons	4.780***	7.602***	4.418***	11.484***	13.401***	11.531**	10.832***	14.210***	10.054***	10.555***	12.865***	10.578***	6.509***	10.846***	2.865***	9.765***	12.513***	10.123***
	(0.135)	(0.225)	(0.622)	(0.191)	(0.236)	(0.574)	(0.145)	(0.160)	(0.496)	(0.192)	(0.203)	(0.513)	(0.125)	(0.156)	(0.692)	(0.269)	(0.282)	(0.774)
N	1603	1603	1603	863	863	863	1792	1792	1792	843	843	843	1460	1460	1460	470	470	470
R2	0.820	0.522		0.485	0.179		0.683	0.145		0.717	0.161		0.884	0.461		0.694	0.288	
N_g		559			349			658			353			463			143	
rho		0.863			0.927			0.940			0.939			0.960			0.914	
Sum of coeff.	0.92	0.517	0.858	0.984	0.378	1.015	1.027	0.288	0.956	1.016	0.417	0.893	1.012	0.341	1.123	0.698	0.353	0.726

Sector	Transport and telec		63	eal estate and renta		70	eal estate and renta		71	Business services		72	Business services		74
ln_revenue	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF	OLS	FE	ACF
ln_labor	0.715***	0.501***	0.534***	0.740***	0.261	0.788**	0.645***	0.259	0.751*	0.547***	0.207	0.533**	0.438***	0.107***	0.554***
	(0.031)	(0.067)	(0.244)	(0.045)	(0.162)	(0.322)	(0.116)	(0.149)	(0.438)	(0.104)	(0.190)	(0.221)	(0.028)	(0.024)	(0.071)
ln_capital	0.153***	0.054**	0.072	0.075***	-0.018	0.063	0.089*	0.548**	0.089	0.295***	0.537**	0.248	0.137***	0.055***	0.170***
	(0.016)	(0.017)	(0.112)	(0.021)	(0.050)	(0.081)	(0.038)	(0.167)	(0.181)	(0.066)	(0.196)	(0.211)	(0.013)	(0.013)	(0.073)
ln_intermed	0.115***	0.066***	0.136***	0.038**	0.008	0.020	0.049*	-0.018	0.004	-0.012	0.028	-0.010	0.047***	0.046***	0.049***
	(0.010)	(0.010)	(0.029)	(0.012)	(0.012)	(0.015)	(0.019)	(0.018)	(0.053)	(0.019)	(0.025)	(0.039)	(0.008)	(0.008)	(0.018)
_cons	8.413***	10.950***	9.604***	10.901***	14.338***	11.094***	9.479***	6.206**	9.991***	8.196***	6.309**	8.830***	10.052***	12.273***	9.161***
	(0.192)	(0.341)	(0.722)	(0.355)	(0.788)	(0.572)	(0.543)	(2.090)	(0.817)	(0.712)	(1.972)	(0.640)	(0.195)	(0.191)	(0.751)
N	561	561	561	332	332	332	118	118	118	105	105	105	792	792	792
R2	0.862	0.388		0.606	0.058		0.494	0.318		0.721	0.660		0.505	0.347	
N_g		193			84			49			54			346	
rho		0.890			0.831			0.966			0.882			0.925	
Sum of coeff.	0.983	0.621	0.742	0.853	0.251	0.871	0.783	0.789	0.844	0.83	0.772	0.771	0.622	0.208	0.774

Note: Standard errors are provided in parentheses. Year and industry dummies were included but not reported. Rho reports that fraction of variance is due to u_i for FE estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$.

Table 4 reports mean input elasticities and efficiency level across firms within sector *j*, which is (β_{0_j}) obtained from the Cobb-Douglas production function shown in (1.2).

I use ACF as a main method to deal with the potential simultaneity issues between factor inputs and productivity. I also provide, for comparison purposes, additional estimation results using OLS and FE methods. While the direction of the simultaneity biases is difficult to anticipate, particularly in a gross production function, generally, the coefficient of more easily adjustable inputs (for example, labour and material) tend to be upward-biased in OLS, as the decision to use those inputs would respond to the productivity level. Input elasticities estimated from ACF range between OLS and FE estimation results for most sectors. Mean efficiency levels are similar when different methods are used.

There is large heterogeneity in output elasticities of inputs across subsectors. The construction sector shows a relatively large output elasticity of intermediate material input; wholesale and retail, and transport and telecom show large elasticities of labor, relative to other sectors. Sums of coefficients are close to 1 or smaller than 1 in most sectors (implying constant or diminishing returns to scale).

Table 5. Log TFP Estimations by Subservice Sectors

Subsector	Obs.	Mean	Median	S.D.	[5%,	95%]
Construction, 45	1,603	4.42	4.37	0.62	3.85	5.00
Wholesale and retail, 50	863	11.53	11.56	0.57	10.58	12.41
Wholesale and retail, 51	1,792	10.05	9.99	0.50	9.55	10.90
Wholesale and retail, 52	843	10.58	10.54	0.51	9.87	11.39
Hotel and restaurant, 55	1,460	2.87	2.73	0.69	2.51	3.44
Transport and telecom, 60	470	10.12	9.96	0.77	9.29	11.54
Transport and telecom, 63	561	9.60	9.54	0.72	8.48	10.99
Real estate and rental, 70	332	11.09	11.11	0.57	10.10	11.97
Real estate and rental, 71	118	9.99	9.86	0.82	8.94	11.60
Business services, 72	105	8.83	8.83	0.64	7.79	9.94
Business services, 74	792	9.16	9.01	0.75	8.27	10.63

Note: TFP=Total factor productivity; S.D.= Standard deviation.

Table 5 reports summary statistics of firm-specific TFP estimation from the CD production function in equation 1.2, using the ACF technique.

As explained above, I include constant term (β_{0_j}) in reporting TFP to capture productivity differences across subsectors. Therefore, table 5 reports firm-specific TFP that consists of the predictable time- and firm-specific deviation (ω_{ijt}) from that mean efficiency within sector j (β_{0_j}). If the production process varies across subsectors, comparison of absolute level of TFP across subsectors might be less informative, but relative ranks of productivity levels among subsectors still provide useful information.

I do not report TFP estimation results from different methods here, but note that they are highly correlated with each other. For instance, the TFP estimates from the CD production function using OLS and ACF have a correlation of 0.93.

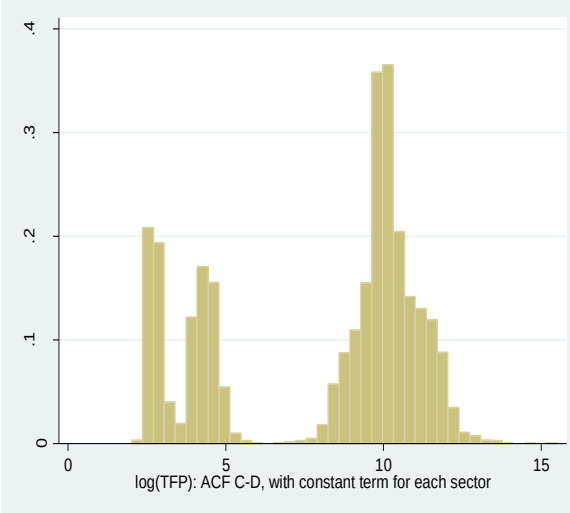
In terms of subsector means, construction, and hotel and restaurant sectors show low levels of TFP (low productivity group), but all other sectors show higher TFP levels (high productivity group). Graph 1 confirms that Tunisian service firms cluster into two groups: the more productive and the less productive.

Though I expected large heterogeneity in TFP levels among subservice sectors, estimated TFP results seem to be similar among several subsectors, particularly for those in the high productivity group. Graph 2 shows that TFP distributions are very close to each other among subsectors in the high productivity group although not exactly the same.[77] For the construction, and the hotel and restaurant sectors, TFP levels are distributed on the left side of the distribution charts. Most sectors show log normal distributions of TFP.

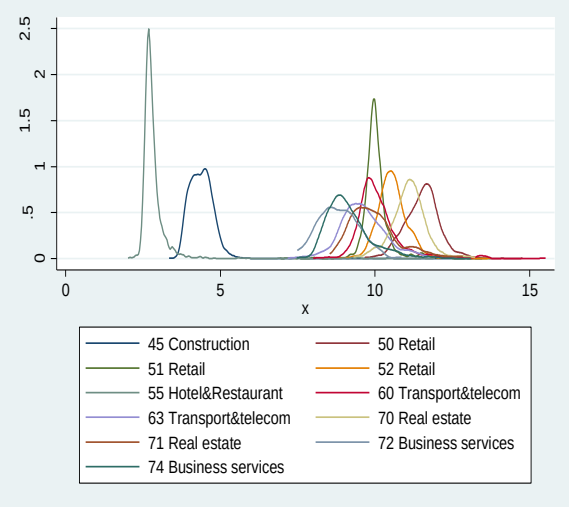
77. *F*-test results fail to reject the null hypothesis that there is no significant difference in mean TFP level across subservice sectors, excluding construction, and hotel and restaurant.

Meanwhile, as seen in graph3, TFP distribution without the constant term is log normal, similar to that of manufacturing firms in the INS data, which confirms that TFP can be used as an estimate of service firm performance.

Graph 1. TFP Distribution, All Firms

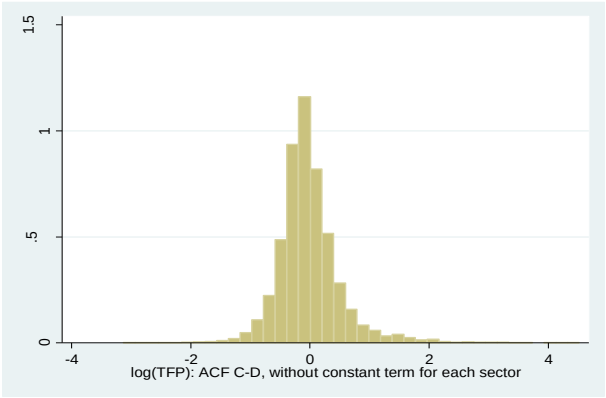


Graph 2. TFP Distribution by Subsectors



Note: Graph 1 provides TFP distribution of all service firms. Graph 2 provides TFP distributions by subservice sectors.

Graph 3. TFP Distribution, excluding Constant Term



Note: Graph 3 provides TFP distribution of all service firms without the constant term.

The above findings—the existence of more productive and less productive subsectors within the services sector, and similar TFP levels across subsectors within the high productivity group—are useful for understanding service firms' performance and pose further questions that could provide policy implications: Why were Tunisian subservice

sectors clustered around two different productivity levels? Have those subsectors in a low productivity group been reducing their size, while those in a high productivity group have been expanding? What are the barriers or regulatory obstacles that keep those subsectors in a low productivity group? Also, the findings may suggest that TFP can be used as a performance measure in the services sector as well.

Table 6. Markups by Subservice Sector

		(Log) markups				
Subsector	Obs.	Mean	Median	S.D.	Intervals [5%, 95%]	
Construction, 45	1,603	-0.32	-0.21	1.02	-0.85	0.31
Wholesale and retail, 50	863	3.33	3.38	0.73	2.11	4.40
Wholesale and retail, 51	1,792	3.28	3.30	0.70	2.18	4.35
Wholesale and retail, 52	843	2.47	2.46	0.66	1.46	3.56
Hotel and restaurant, 55	1,460	-1.83	-1.97	1.51	-4.49	0.64
Transport and telecom, 60	470	0.94	0.89	1.22	-0.79	2.50
Transport and telecom, 63	561	0.27	0.34	0.70	-1.04	1.37
Real estate and rental, 70	332	2.68	2.54	0.91	1.57	4.04
Real estate and rental, 71	118	1.59	1.75	1.20	-1.69	3.01
Business services, 72	105	-0.20	-0.01	1.25	-2.47	1.30
Business services, 74	792	-0.28	-0.10	1.28	-2.97	1.57

Note: S.D. = Standard deviation. Labour elasticities based on estimations from the translog production function using the ACF method.

Here I provide the estimated markups by subsector. Specifically, table 6 reports estimated markups using labor input elasticities from the translog production function using the ACF method.

As described in the estimation section, to allow firm-level variance in input elasticity and, thus, markup estimation, I estimate labor input elasticity from the translog production function and use ACF methods to deal with the potential simultaneity bias of input choice with productivity. I report markups in log to be consistent with the TFP results and with my further analysis, in which I use log markups to observe the effect of

firm ownership on firm performance. The negative log markups (unlogged markups between 0 and 1) imply that firms have a lower selling price than marginal cost (see unlogged markups in annex C).

There is large heterogeneity in markups across subsectors. Construction, hotel and restaurant, and business services sectors report negative median log markups (unlogged markups are less than 1), implying that many firms in those sectors face higher marginal costs than selling prices.[78] At the same time, firms in the wholesale and retail sector and some firms in the real estate and rental sector (NACE 70) report large markups. These markups are very large compared to the findings of De Loecker and Warzynski (2012), who report median markups were around 1 for Slovenian manufacturing firms from 1994 to 2000.

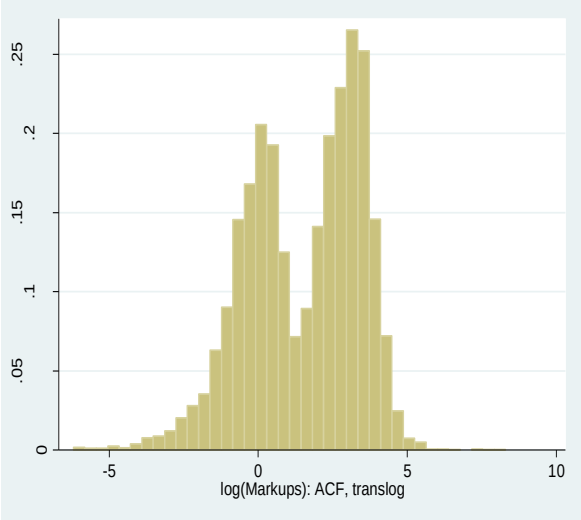
Moreover, there is large heterogeneity in markups within subsectors. In terms of variance within subsectors, the standard deviation is relatively large (average is around twice as large as the standard deviation of TFP) in each subsector with the smallest in the hotel and restaurant subsector, at 0.5. Sectors with high markups also show large standard deviation of markups.

For a comparison, I provide markups estimated with different methods in appendix C, table C.2. The markups estimated with different methods provide different magnitudes, but consistent relative magnitudes (ranks) across subsectors, and are correlated with each other. For instance, markups estimated from labor elasticities obtained from the CD production function (CD markups) show smaller magnitudes than the above translog markups, but show consistent relative magnitudes (ranks) across subsectors. Moreover, markups estimated with elasticities from different econometric techniques, such as OLS

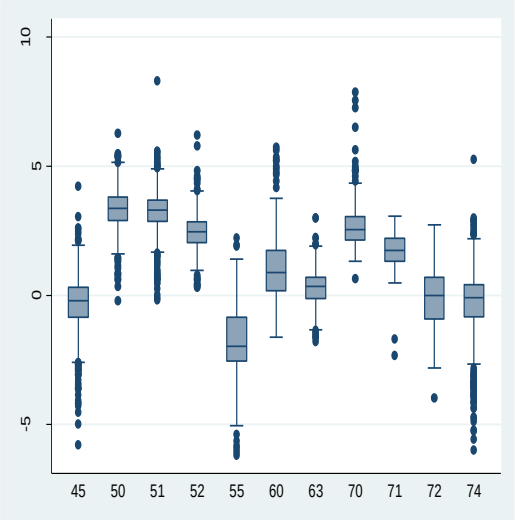
78. Please note that some firm observations were dropped while estimating markups in translog in the NACE 55, 71, and 72 sectors. However, those observations were kept when using the CD production function to estimate markups in those sectors. Compared to the translog production function estimated markups, using the CD function provides higher markups for NACE 55 (mean 0.05) and 72 (mean 0.31), but similar markups for NACE 71.

and FE; from the different production functions, CD and translog; as well as estimated with the elasticities of material input from ACF translog function; show consistent relative magnitude, such as rank of markup level across subsectors and are correlated with each other.

Graph 4. Markup Distribution for All Firms



Graph 5. Markup by Subsectors



Note: Graph 4 provides log markup distributions of all service firms. Graph 5 shows the box plot distribution of markups by subsector. The box shows the markup distribution between the 25th percentile (lower hinge) and the 75th percentile (upper hinge). The bar in the middle is the median value.

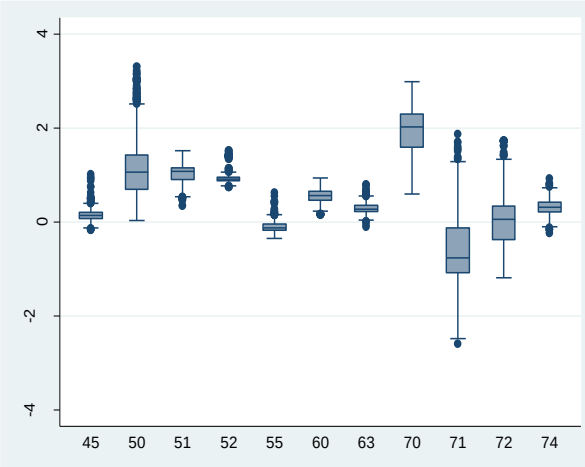
As seen in graph 4, the markup distribution also has two peaks as the TFP distribution does, although sectors in the high productivity group are not the same sectors in the high (or low) markup groups. For instance, sectors with low TFP, such as construction, and hotel and restaurant, likewise show low markups. However, business services show relatively high TFP but low markups.

The distributions of no logged markups are provided in appendix C, graphs C.1 and C.2, and show that markups are distributed around 1, but with many firms showing less than 1 or very high markups. Those confirm large heterogeneity of markup distribution across and within subsectors, with large outliers.

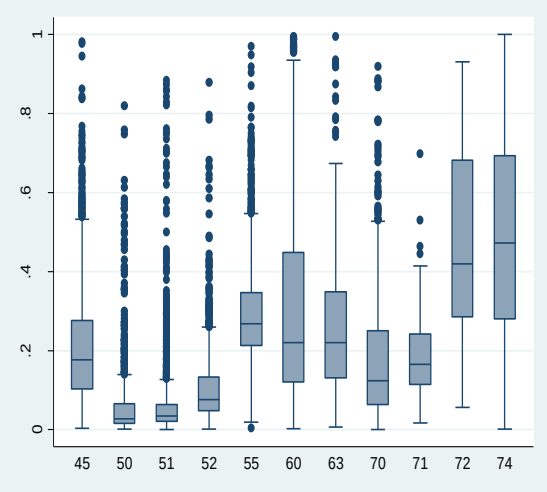
Graph 5 confirms the large heterogeneity of the distribution of markups across subindustries. Considering the distribution itself, wholesale and retail show very large markups. Meanwhile, markup distribution is more concentrated in some sectors (for example, NACE 60, 63, 71, 72), but dispersed in others (for example, NACE 45, 74).

Why are markups so large in the wholesale and retail sector? To investigate, I look at (1) markups' decomposition, and (2) literature on these sectors in Tunisia. First, I decompose markups in (1.2), into two components; θ_{ijt}^{L} and $\frac{L_{ijt}w_{ijt}}{P_{ijt}Q_{ijt}}$, and provide their distribution in below graphs 6 and 7 below.

Graph.6. Labor Input Elasticities(θ_{jt}^{L})



Graph 7. Labor Cost Share in the Revenue



Note: Graph 6 provides the distribution of labor input elasticities (θ_{ijt}^{L}). Graph 7 provides the distribution of labor cost share in revenue.

Graph 6 shows that the distribution of labor input elasticities (θ_{ijt}^{L}) varies greatly among subsectors and is relatively high in wholesale and retail (NACE 50, 51, 52), and very high for the real estate and rental sector (NACE 70). Labor input elasticities are particularly small and even negative for firms in real estate and rental (NACE 71). However, the

negative elasticity in NACE 71 was the result of the nonlinearity of the translog production estimation. All the input elasticities are positive in the CD function.

Graph 7 shows that wholesale and retail (NACE 50, 51, 52) report a particularly low labor cost share, which could be driven by the fact that Tunisian wholesale and retail firms (1) employ a small number of workers, or (2) pay low wages to their workers. In fact, the INS data show that the wholesale and retail sector hires a small number of employees for its size of revenue, which could be related to the education level of workers in this sector. According to INS, the wholesale and retail sector (commerce) employs the highest number of highly educated workers in Tunisia,[79] which might allow firms to keep the small number of workers if they are more skilled and more productive. At the same time, wholesale and retail firms do not pay higher average wages than other sectors to their workers (see appendix C, graphs C.3 and C.4, which further decompose the labor cost ratio in revenue into the share of workers and average wage).

Therefore, the high markups in the wholesale and retail sectors are explained by the combination of relatively high labor input elasticities and very low labor input cost shares, driven by the fact that firms in those subsectors hire a small number of workers with low wages.

However, as explained in the estimation section, the markups measure should be the same, regardless of which input elasticities are used in estimating markups. In fact, as seen in appendix C, table C.2, markups estimated with material input elasticities for these in the wholesale and retail sectors are likewise very large.

Another more intuitive explanation for these very large markups for the wholesale and retail sector is the lack of competition in these sectors, which allows firms to keep their

79. According to INS, the wholesale and retail sector employs more than 50 percent of highly educated workers in Tunisia, while the transport and telecom sector employs fewer than 8 percent, and the construction sector employs fewer than 1 percent.

high markups. In fact, some retail subsectors, such as automobile distribution, are affected by exclusive-distributor laws that not only require foreign suppliers to appoint only Tunisian citizens as local agents, but also ban parallel imports. This situation grants monopoly power to local agents and substantially raises consumer prices (Maskus and Lahouel 2000).

Moreover, the Foreign Commercial Activities Law of 1961 (Decree Law Number 61-14) requires non-Tunisians to obtain a trader's permit, *carte de commercant*, to engage in any form of commercial activity. This permit, granted on a discretionary basis, has effectively precluded foreign participation in most wholesale and retail markets. In fact, the INS data set reveals that there is a small number of large-size SOE in this sector, which could support the lack of competition therein. For instance, in NACE 51, wholesale and commission trade, a small number of SOE firms have large market shares (SOEs are only 3.6 percent of total observations but have a market share of around 49.0 percent of total revenue). Details of market share information are provided in appendix C, table C.5.

Also, those SOE firms receive very large subsidies from the government—with an average of TD 10.6 million, compared to the domestic private sector, which received average subsidies of TD 8,833; and FDI firms, TD 2,444 during that period. At the same time, FDI firms pay higher tax than SOEs despite the larger revenue of SOEs (FDI firms pay an average TD 597,000, while SOE firms pay TD 492,000), which demonstrates the high protection this sector receives from foreign participation and competition.

Services sector firm performance over time

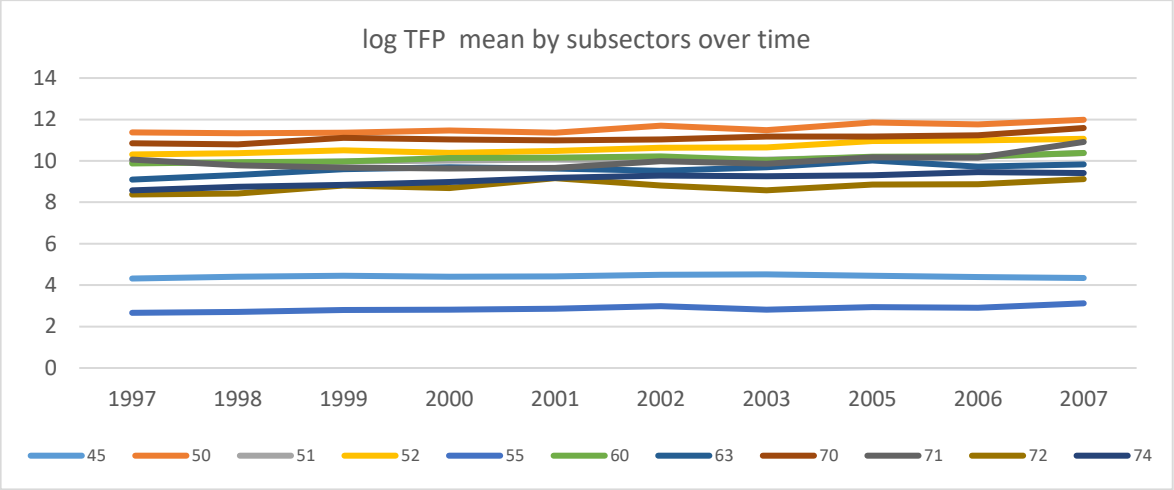
Here I provide the changes in service firm's TFP and markups over time.

Graph 8 shows that the TFP level seems to remain almost the same in most subsectors. There has been a very small increase in the TFP level in NACE 50, 52, 55, 71, and 72 since 2003. As seen in the TFP distribution figure above, there are two distinctive groups of

industries—high and low TFP—and those groups are fixed over time, as relative TFP across subsectors seems to be stagnant.

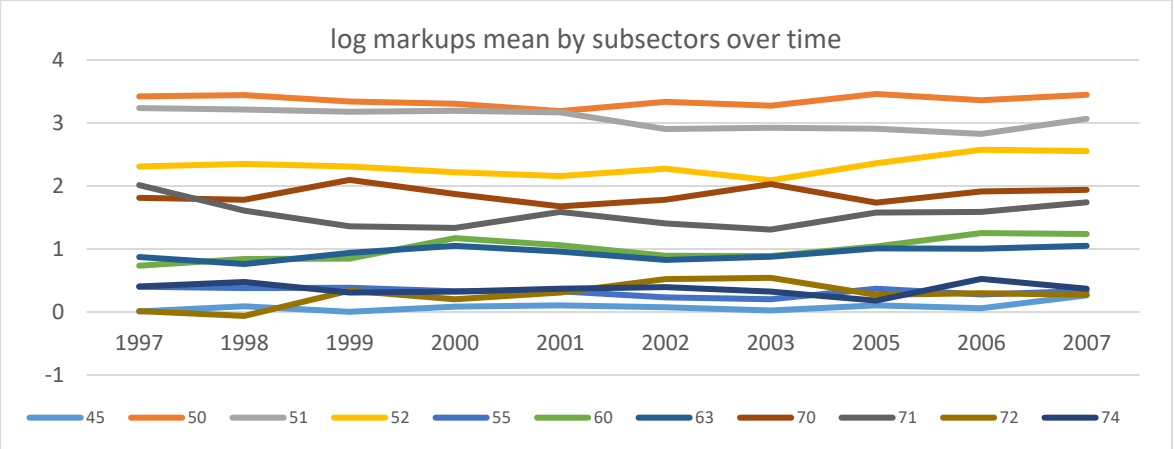
Graph 9 shows that there is more variation in markups than in TFP. NACE 52, 50, and 60 sectors show slight increases in markups since 2003, while NACE 51 and 72 markups seem to decrease slightly during that time. However, there are no common patterns of markup trends between subsectors.

Graph 8. Log TFP Mean by Subsectors



Note: Graph 8 shows the subsector mean TFP trend over time.

Graph 9. Log Markups Mean by Subsectors



Note: Graph 9 shows the subsector mean markups time trend.

The relationship between TFP and markups

The estimated TFP and markups are correlated, at 0.68. However, does this correlation make sense? In my view, the direction of the correlation between TFP and markups can go either way, as markups reflect both selling price and marginal cost. For instance, efficient firms with high TFP could reduce their costs, and thus have higher markups. At the same time, increased TFP could lead to decreases in prices, and thus in markups.

Also, there seems to be no clear pattern to the relationship between TFP and markups, as shown in the existing literature. For instance, some existing literature anticipates positive correlation between TFP and markups. Specifically, industrial organization and managerial science literature considers markup as a firm's ability to use inputs efficiently and to produce differentiated and high-quality products. For instance, in the UK retail sector, "better-run stores are the ones that generate better margins and better customer satisfaction" (Reynolds et al. 2005). Indicators in a competitive market, such as relative profits of firms, provide a sufficient statistical foundation for evaluating manager performance (Holmstrom and Tirole 1989). Also, macroeconomics literature on business cycles expects a positive correlation between TFP and markups, as a countercyclical markup (of price over marginal cost) is the transmission mechanism for demand shocks in the new Keynesian models.

However, other literature anticipates negative correlations. For instance, trade literature expects negative correlations between TFP and markups through increased competition and reduced misallocation. Through exporting, firms gain exposure to larger markets and increased competition, and hence exhibit higher productivity and lower markups (Melitz and Ottaviano 2008). Increased competition through trade reduces markup distortions, and thus lowers productivity losses due to misallocation (Edmond, Midrigan, and Xu 2015). Also, business formation is procyclical, and hence correlated with aggregate economic activity measured as TFP, but leads to endogenous countercyclical variations in markups (Jaimovich 2007).

Additionally, the measurement issue in TFPR makes this pattern unclear. For instance, increased productivity could lead to decreases in price; thus, physical productivity is negatively correlated with establishment-level prices, while TFPR is positively correlated with prices (Foster, Haltiwanger, and Syverson 2005).

Meanwhile, most of the studies on markups are conducted on the industry level and focus largely on the manufacturing sector and on industry-level correlation between TFP and markups. Estimating firm-level markups from production data is relatively new, and has not been widely applied. Moreover, to my knowledge, almost no literature investigates the relationship between service firms' TFP and markups.

The findings of this section confirm that TFP and markups could be used as performance measures of service firms.

For instance, TFP estimates for service firms are not very different from TFP estimates for manufacturing firms. Without the constant term, service firms have log normal TFP distribution, which is very similar to that of manufacturing firms. One unique characteristic of the Tunisian services sector is that there are two groups of TFP—high and low productivity groups—which leads to larger variance across subsectors. Also, the standard deviations of firm-level TFP are relatively high within subsectors, implying higher TFP variance within subsectors. Over time, TFP of service firms and subsectors seems to remain stable. These findings confirm that, despite these differences between service and manufacturing, TFP is still a useful measure of firm performance, even in services.

Moreover, there is large variance of markups across subsectors, which is consistent with the expectation of large heterogeneity of product quality and subsector characteristics, such as competition and ownership, in the services sector. The large variation in markups was driven by the large number of outlier firms in services, reflecting the high protectionism and complex entry regulations in the Tunisian

services sectors, which allows some firms to maintain high markups. Also, sectors with high markups show a particularly low number of employees but not a higher average wage. This measure of markups is particularly useful in services, where detailed output and input price information is limited, and where it is sometimes not even possible to separate price and quantity from revenue. Also, markups are particularly useful as they provide information about firms' market power, given high protectionism in the services sectors.

5.2. Foreign Ownership and Firm Performance

Here I investigate whether variations in TFP and markups can be explained by firms' foreign ownership, obtained by FDI. Previous literature suggests that foreign ownership serves as a channel of knowledge transfer from foreign investors. Additionally, foreign participation results in a more competitive market, thus lowering firm markups in the sectors with a greater FDI presence.

Table 7 provides the estimation results of regression 1.7 on TFP using OLS. Using firm-fixed effect could remove time-invariant unobservable firm characteristics (for example, firm location and work culture); however, the variation among FDI variables is too small in the data coverage, thus preventing application of the fixed effect.

The estimation results show that FDI firms are more productive than other firms. Coefficients of FDI variables are positive and statistically significant for all columns. This result is consistent when different FDI variables are used, such as FDI share and the previous year variable, and it is consistent when holding constant other firm characteristics, such as firm size and age.

Table 7. Different FDI Variables and TFP

	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP	(7) TFP	(8) TFP
FDI_stat	0.2150***	0.1684***						
	(0.000)	(0.000)						
FDI_share			0.0033***	0.0027***				
			(0.000)	(0.000)				
FDI_stat_lag					0.2800***	0.2409***		
					(0.000)	(0.000)		
FDI_share_lag							0.0041***	0.0037***
							(0.000)	(0.000)
firmsize		0.0001***		0.0001***		0.0001***		0.0001***
		(0.000)		(0.000)		(0.000)		(0.000)
firmage		0.0029***		0.0031***		0.0036***		0.0038***
		(0.000)		(0.000)		(0.000)		(0.000)
N	8939	7033	8939	7033	5766	5250	5766	5250
R^2	0.965	0.965	0.965	0.965	0.971	0.972	0.971	0.972

Note: FDI_stat is a dummy variable that shows if a firm has any foreign ownership. FDI_share shows share of foreign ownership. TFP=Total factor productivity, industry (NACE two-digit level), and year dummies are included to control industry-specific characteristics; and time dummies are included to control time-variant unobservable characteristics (for example, time trends), but they are not reported. NACE 45 and year 1997 are used as basis; *p*-values are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As shown in column (1), having foreign ownership is associated with log 0.215 higher TFP level than for other firms, holding industry and year constant. When controlling firm size and age, the coefficient gets smaller but is still large and significant, as shown in column (2). Also, the higher the foreign share in firms, the higher the TFP level. As seen in columns (3) and (4), 1.0 percent increase of SOE share is associated with 0.3 percent increase in the current and next year TFP levels. The coefficient of lagged FDI variables becomes even larger, as seen in columns (5) to (8), implying association between foreign share and larger TFP levels for the next year. Meanwhile, older firms have slightly higher TFPs, but the coefficient of firm size is close to zero.

This finding of more productive FDI firms in the service sector is consistent with the previous literature that finds FDI to be an important vehicle for productivity gains in the services sector, as foreign services are best transferred through personal contact between the service provider and client (Arnold, Javorcik, and Mattoo 2011; Markusen, Rutherford, and Tarr 2005; Griffith, Redding, and Simpson 2004; Dehejia and Wahba 2002).

Firm age has a positive and significant effect on the TFP level in column (8). The coefficient of firm size is close to zero.

Table 8 provides the estimation results of regression 1.7 on markups using OLS.

Table 8. Different FDI Variables and Markups

Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (MKs)	MKs	MKs	MKs	MKs	MKs	MKs	MKs	MKs
FDI_stat	-0.2526***	-0.2276***						
	(0.000)	(0.000)						
FDI_share			-0.0036***	-0.0037***				
			(0.000)	(0.000)				
FDI_stat_lag					-0.1147*	-0.0856		
					(0.037)	(0.133)		
FDI_share_lag							-0.0022**	-0.0022**
							(0.008)	(0.008)
firmsize		-0.0003***		-0.0003***		-0.0003***		-0.0003***
		(0.000)		(0.000)		(0.000)		(0.000)
firmage		-0.0033***		-0.0035***		-0.0036***		-0.0036***
		(0.000)		(0.000)		(0.000)		(0.000)
N	7380	5780	7380	5780	4695	4264	4695	4264
R^2	0.767	0.757	0.767	0.757	0.771	0.771	0.771	0.771

Note: MKs=Markups. Industry (NACE two-digit level), and year dummies are included to control industry-specific characteristics, and time dummies are included to control time-variant unobservable characteristics (for example, time trends), but not reported. NACE 45 and year 1997 are used as basis; *p*-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

FDI firms have lower markups than other firms. Specifically, in column (1), FDI firms have log 0.253 lower markup than other firms controlling industry and year dummies. In column (2), the coefficient of the FDI variable becomes slightly smaller but is still large and significant when also holding firm size and age constant. Moreover, the higher the foreign share of firms, the lower the markups. As seen in columns (3) and (4), 1.0 percent increase of SOE share is associated with 0.4 percent decrease in current and next year markups.

Columns (5) to (8) show estimation results using the previous year FDI variables based on the assumption that it might take time for foreign ownership to influence firm performance. The results remain consistent with columns (1) to (4) when the current year FDI variables are used. The coefficient of lagged FDI variables gets smaller but is still significant, except for column (6). Older firms charge slightly less markup on average; however, the coefficient of firm size is close to zero. The results of FDI firms' lower markups compared to other firms are consistent when I use different markup variables, such as markups estimated from the CD production function.

Then why do FDI firms have lower markups than other firms? One possible explanation might be that competition is high in a sector where foreign firms are allowed to enter; this reduces the firms' market power (markups). Although I control two-digit–level industry dummies, the most disaggregated level in the INS data—the competition level—might vary more in disaggregated subsectors. Given the large markups for Tunisian service firms, more competition could reduce the markup level. Those sectors with large FDI firms' market share show low SOE firms' market share, which might suggest that sectors with large FDI participation are more open to competition. FDI's market share, estimated as the sum of FDI firms' revenue, divided by the sum of all firms' revenue within sector *j,* is negatively correlated with SOE market share at 0.81.

This explanation is similar to the previous findings from the trade literature that explains the negative correlations between TFP and markups through increased

competition and reduced misallocation. Through exporting, firms gain exposure to larger markets, which increase competition and reduce distortions, and hence exhibit higher productivity and lower markups (Melitz and Ottaviano 2008; Edmond, Midrigan, and Xu 2015). However, FDI firms' performance could vary across subsectors, given the large heterogeneity of service subsectors. Therefore, I further investigate this sectoral variance, as reported below.

Sectoral analysis on foreign ownership's effect on firm performance

Table 9 demonstrates the FDI effect on firm performance, TFP, and markup, with additional interaction terms between FDI and other variables, thus providing sectoral variation for FDI effects on firm performance.

Table 9. FDI Effect on TFP and Markups

	(1) TFP	(2) TFP	(3) MKs	(4) MKs
FDI_stat	0.1684***	0.0797	-0.2276***	-1.3912***
	(0.000)	(0.380)	(0.000)	(0.000)
Firm size	0.0001***	0.0001***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm age	0.0029***	0.0018**	-0.0033***	-0.0051***
	(0.000)	(0.001)	(0.000)	(0.000)
Sec 50	7.1192***	7.1276***	3.6308***	3.5592***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 51	5.6273***	5.6216***	3.5864***	3.5551***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 52	6.1983***	6.1995***	2.8144***	2.8055***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 55	-1.5996***	-1.5555***	-1.4593***	-1.4984***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 60	5.6694***	5.6509***	1.3521***	1.3164***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 63	5.1982***	5.1980***	0.6511***	0.6284***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 70	6.6627***	6.6988***	3.0355***	3.0381***
	(0.000)	(0.000)	(0.000)	(0.000)

Sec 71	5.5509***	5.4182***	1.8252***	1.7803***
	(0.000)	(0.000)	(0.000)	(0.000)
Sec 72	4.3386***	4.3358***	0.1057	0.0671
	(0.000)	(0.000)	(0.432)	(0.635)
Sec 74	4.7270***	4.7231***	0.0420	-0.0452
	(0.000)	(0.000)	(0.365)	(0.347)
FDI_statXsize		-0.0002**		0.0009***
		(0.003)		(0.000)
FDI_statXage		0.0060***		0.0102***
		(0.001)		(0.000)
FDI_statXsec50		-0.2272		1.2311***
		(0.123)		(0.000)
FDI_statXsec51		0.1273		0.7842***
		(0.217)		(0.000)
FDI_statXsec52		0.0053		0.1261
		(0.968)		(0.549)
FDI_statXsec55		-0.3662***		2.0096*
		(0.000)		(0.033)
FDI_statXsec60		0.2164		1.0596***
		(0.278)		(0.001)
FDI_statXsec63		-0.0409		0.6501**
		(0.752)		(0.002)
FDI_statXsec70		-0.3778**		0.5010*
		(0.009)		(0.029)
FDI_statXsec71		1.5112***		0.0000
		(0.000)		(.)
FDI_statXsec72		0.0093		0.9226*
		(0.959)		(0.030)
FDI_statXsec74		-0.0224		1.1797***
		(0.832)		(0.000)
_cons	4.5924***	4.6154***	-0.1633***	-0.0887
	(0.000)	(0.000)	(0.000)	(0.060)
N	7033	7033	5780	5780
R^2	0.965	0.966	0.757	0.762

Note: TFP=Total factor productivity. MKs=Markups. Year dummies are included but not reported. Dependent variables are log TFP for columns (1) to (2) and log markups for columns (3) to (4); *p*-values in parentheses: * p < 0.05, ** p < 0.01, *** p < 0.001. The coefficient of FDI_statXsec71 is dropped due to the small number of FDI firm observations in this sector (10 FDI firms out of 118 firms in this sector).

Column (1) of table 9 is the same as column (2) in table 7, but reports coefficients of subsector dummies, which show the difference of TFP levels with the NACE 45—a basis sector with mean TFP of log 4.592 (constant term). For instance, firms in sector 50 have average log 7.119 larger TFP than firms in sector 45, basis sector. Most sectors have average log 4.3 to 7.2 higher TFP levels than sector 45. The only exception is sector 55, where firms have average log 1.6 lower TFP than sector 45.

In column (2), where I add interaction terms between FDI status and other variables, the coefficient of FDI becomes insignificant, implying that there is no significant difference in TFP levels between FDI and non-FDI firms in sector 45, the construction sector, which is the basis sector. Similarly, in many sectors, there is no significant difference in TFP level between FDI and non-FDI firms, as the coefficient of interaction terms between FDI status and sectors is insignificant in NACE 50, 51, 52, 60, 63, 72, and 74 sectors. Meanwhile, in NACE 55 and 70 sectors, FDI firms have lower TFP levels than non-FDI firms. Only NACE 71 sector has a significant and positive coefficient for the sector's interaction term with FDI. However, the results of column (2) require a careful interpretation because adding the interaction terms could potentially raise a multicollinearity issue.

Large firms do not have higher TFP levels, regardless of having foreign ownership, as the coefficient of firm size and its interaction term with FDI is still zero. At the same time, older firms have larger TFP levels, and older firms that have FDI have even larger TFP levels.

Column (3) shows that FDI firms have log 0.163 lower markups than non-FDI firms on average, holding firm age, size, subsectors, and years constant. It also shows that there is large variation in markups across subsectors. Markups are very large in the NACE 50, 51, 52, and 70 sectors, and large in the NACE 60, 63, and 71 sectors. Markups are negative for the NACE 45 and even lower for the NACE 55.

In column (4), FDI firms have average log 1.391 lower markups than non-FDI firms in NACE 45 sector, which is a large difference. In most sectors, FDI firms have lower markups than non-FDI firms, but the difference in markups between FDI and non-FDI firms is smaller than that of sector 45. For example, in the NACE 50, FDI firms have slightly lower markups than non-FDIs (-1.391 + 1.231 = -0.160). However, in NACE 55 sector, FDI firms have even higher markups than non-FDIs (-1.391 + 2.010 = 0.619). Interestingly, the coefficient of the interaction terms between FDI_stat and subsectors are quite different among the subsectors in wholesale and retail (NACE 50, 51, 52) although those sectors show similarly large markup levels.

For foreign firms, larger and older firms have higher markups, although for nonforeign firms, size does not matter.

The above findings show that there are large sectoral variations in FDI's effect on firm performance, TFP, and markups. Therefore, foreign ownership's effect on firm performance would need to be investigated at the sectoral level.

At the sectoral level, FDI's effect on TFP and markup are less obvious, although FDI firms generally have higher TFP levels and lower markups. This implies that sectors where FDI has higher TFP can have either lower or higher markups; for instance, in sector 55, FDI firms have lower TFP and higher markups than other firms.

However, the above results are not the causal effect of foreign ownership on firm performance in the case of other firm characteristics affecting both firm foreign ownership and performance. One way to deal with such omitted variable bias would be to use the firm-fixed effect to remove time-invariant unobservable firm characteristics (for example, firm location and work culture); however, as described in the data section, the variation among FDI variables is too small in the data coverage, thus preventing application of the firm-fixed effect here, as FDI's effect on performance would be

removed as a time-invariant unobservable.[80] Also, INS data are a weakly balanced panel, so using panel techniques would eliminate a number of observations. Therefore, I use propensity score matching.

Table 10 provides the estimation results of the first-stage logit model, which is equation (1.9).

The dependent variable is the FDI dummy on the current year (0/1). Firms with larger tax payments and older firms are more likely to have foreign ownership, controlling for subsectors and locations. Unexpectedly, receiving subsidies does not have a significant effect on the probability of FDI. Being large, firms have a statistically significant effect on the probability of obtaining foreign ownership, but the coefficient is very small, close to zero.

Table 10. First-Stage Logit Model

FDI_stat	Coeff.	S.E.	*z*	*P>z*	[95% Conf.	Interval]
Firm size	0.0004	0.000	3.07	0.001	0.0002	0.0006
Firm age	0.0119	0.004	3.03	0.003	0.0042	0.0196
Subsidy	0.0051	0.023	-0.10	0.828	-0.0404	0.0505
Tax	0.0344	0.017	2.17	0.037	0.0021	0.0667

Note: S.E.=Standard errors. Industry and location dummies are included but not reported.

Next, I select non-FDI firms in the comparison group that are comparable to FDI firms, using the nearest neighbour matching technique suggested by Becker and Ichino (2002), and select a subset of comparison units similar to the treatment units based on the above

80. In FE estimation, all coefficients become insignificant except for current year FDI status variable, which is negative and significant. However, when additional control variables are added, coefficients get close to zero and no longer significant.

logit model, which describes FDI firms' characteristics. Then I compare the average difference between the two groups (ATT).

Table 11 provides the estimation results using propensity score matching.

Table 11. Propensity Score Matching Results

Variable	Sample	Treated	Controls	Diff.	S.E.	*T*-stat	*P*-value
TFP	Unmatched	9.3706	8.8856	0.4850	0.207	2.34	0.01
	ATT	9.3706	8.8126	0.5380	0.205	2.73	0.00
Markups	Unmatched	1.0706	1.3008	-0.2302	0.148	-1.56	0.06
	ATT	1.0706	1.0793	-0.0087	0.166	-0.05	0.44

Note: S.E.=Standard errors. TFP is logged value, estimated with Cobb-Douglas production function using ACF. Markups are logged value, estimated in translog production function using ACF. ATT= The average difference between the control group (non-FDI firms) and the treatment group (FDI firms).

The results in table 11 confirm the regression-based results that FDI firms have higher TFP levels but lower markups than others in general. When matched with the above firm characteristics, the difference in TFP levels between the two groups becomes even larger and statistically significant; the average TFP level of the control group (non-FDI firms) becomes even larger than of the treatment group (FDI firms).

However, when matched, the difference in markups becomes much smaller between control and treatment groups, and becomes statistically insignificant. Firm characteristics, such as firm size, age, amount of subsidies received, and tax payment, are the factors that affect the firms' likelihood of having foreign ownership and firms' markup levels; thus, FDI firms do not have lower markups compared to non-FDI firms with similar characteristics.

The above matching results are consistent when I have different sets of control variables by removing some of the currently suggested control variables or adding additional controls, such as a firm's market share, measured as a proxy of competition, as described in the estimation section.

6. Conclusion

Developing countries such as Tunisia should give more attention to services. Service is the largest sector in the global economy, representing 70 percent of the world's added value, and over half of global employment. As countries develop, their share of services in GDP and in employment rises. As services become more tradable, service-led growth becomes more important even for developing countries (Fontagne et al. 2011; Marel 2010; OECD and WTO 2013).

This effort can be strengthened by understanding the characteristics and performance of the services sector. However, despite its importance, we know little about this sector, largely because of conceptual and empirical problems in measuring its performance.

In this paper, I investigate the measurement of service firm performance and suggest two different aspects of the performance measure for services—total factor productivity (TFP) and markups. Using these performance measures, I offer an analysis of the performance of service firms in Tunisia, where the services sector contributes 60 percent of GDP, but still faces high protection and low competition. Lastly, I investigate whether variations in these measures of performance can be explained in terms of foreign participation in Tunisian service firms.

TFP provides important information on a firm's production process (that is, input intensities and returns to scale), and can be applied to both services and to manufacturing. Possible methodological concerns in estimating TFP in the services, such as the constant quality of outputs assumption, are common even in estimating TFP in manufacturing, although those concerns could be greater in the services sector, given that it tends to have larger heterogeneity in quality and influence of market demand on production than does the manufacturing sector.

To improve TFP estimation in services, I propose that one should decompose the quality and market demand factors from revenue information, if possible, or estimate the revenue-based TFP (TFPR), while estimating and comparing TFP within a disaggregated-level, as price information for each firm is rarely available, and the measurement of quantity is not feasible. However, TFPR requires careful interpretation, as it captures quality and market power information, reflected in prices.

An alternative measure for service firm performance is markup derived from the production function, suggested by De Loecker (2011). This markup measure provides the percentage difference between the marginal cost and the selling price; however, contrast to the other methods, it does not require a demand function and information on price and quantity. In my view, the proposed markups are particularly useful for measuring service firm performance where detailed price and quantity information is limited. Moreover, the proposed markup measure reflects the firm's market power—its ability to charge prices above marginal costs—an important aspect of the services sector, which tends to have complex entry regulations and a low level of competition.

While I closely follow the markups estimation proposed by De Loecker, I go beyond his framework to ensure the firm-level markups reflect the large heterogeneity in technology and production processes across service subsectors, by using input elasticities estimated from the translog production function by each subsector.

Using these performance measures, I analyze service firm performance in Tunisia and discover the following relevant facts:

First, there is large heterogeneity in the production processes across subservice sectors, measured by output elasticities of inputs. For instance, the construction sector shows a relatively large output elasticity of intermediate material input; wholesale and retail, and transport and telecom show large elasticities of labor, relative to other sectors.

Second, in terms of TFP, Tunisian service firms cluster into two groups: the more productive and the less productive. The construction, and hotel and restaurant sectors have low levels of TFPs (low productivity group), but all other sectors show high levels of TFPs (high productivity group). Interestingly, although I expected the large heterogeneity in TFP levels among subservice sectors, the estimated levels of TFP are actually very similar among subsectors in the high productivity group.

Third, TFP distribution of all service firms, without the constant term, is log normal, as is the case for manufacturing firms in the INS data, which confirms that estimating TFP for service firms is not very different than for manufacturing firms; thus, TFP can be used as a service firm performance measure.

Fourth, there is large heterogeneity in markups across and within subservice sectors, which is consistent with the expectation of large heterogeneity in service product quality and subsector characteristics, such as competition and ownership. Overall, the markups are distributed around 1, but there are many outliers. For variation within subsectors, the standard deviation of markups in each subsector is no less than 0.5, and on average twice that of TFP. Meanwhile, the markups estimated with different methods provide consistent relative magnitudes (ranks) across subsectors and are correlated with each other.

Fifth, the particularly high markups in the wholesale and retail sectors are explained by the relatively high labor input elasticities, and very low number of workers with low wages. A lack of competition in these sectors seems to allow firms to keep such high markups. For instance, these sectors have precluded foreign participation and maintained large SOEs through exclusive-distributor laws and the Foreign Commercial Activities Law. From the INS data, I find that a few SOEs in this sector represent almost half of the sector's revenue. Also, those SOEs receive larger subsidies but pay less tax relative to private and FDI firms.

Finally, in terms of time trends, TFP levels are stagnant across subsectors and over time. There is more variation in markup trends than in TFP; however, no common pattern of such trends exists.

TFP and markups are correlated at 0.68, which is consistent with previous literature that considers markup as a firm's ability to use inputs efficiently and to produce differentiated and high-quality products (Reynolds et al. 2005; Holmstrom and Tirole 1989). However, most of the studies on markups are conducted at the industry level and focus on the manufacturing sector. Information on the relationship between TFP and markups in services is, at best, limited, and to my knowledge, does not exist. Moreover, in my view, the direction of such correlation can probably go either way as markups reflect marginal cost, which would be negatively correlated with physical TFP and selling prices, which would be positively correlated with revenue-based TFP.

The above findings—relatively similar TFP levels across several subsectors, high variances of markups across and within subsectors, as well as large markups in sectors with low levels of competition—are important in understanding service firm performance, and suggest that TFP and markups can be used as service firm performance measures. In fact, the suggested measurement can be used to understand firm characteristics—such as firm size, age, export capacity, innovation, and ownership—which may influence its performance.

I also investigate whether variations in these performance measures can be explained by foreign ownership in Tunisia, where the services sector is particularly important (at 60 percent of GDP) but faces high protection and complex entry regulations, such as a variety of investment regulations, exchange controls, and limits on movement of foreign personnel. As a result, there is little foreign participation but large SOE presence in key subservice sectors.

Earlier literature projected potential performance gains by enhancing foreign ownership in these sectors, assuming higher performance of foreign-owned firms. However, evidence of more efficient FDI than other firms is mixed, and especially rare in the services sector. This paper is one of the first attempts to provide such an analysis.

On the basis of this analysis, I have made a number of important findings:

First, FDI firms are more productive than non-FDIs. Having foreign ownership is associated with log 0.215 higher TFP level than for other firms, holding industry and year constant. Further, 1.0 percent increase of FDI share is associated with 0.3 percent increase in the current and next year TFP levels. The coefficient of lagged FDI variables becomes even larger. This result is consistent when different FDI variables are used and when other firm characteristics are held constant.

The finding of FDI firms' higher TFP than local firms is consistent with the previous literature that considered FDI to be a vehicle for productivity gains in the services sector, as foreign services are best transferred through personal contact between the service provider and client (Arnold, Javorcik, and Mattoo 2011; Markusen, Rutherford, and Tarr 2005; Griffith, Redding, and Simpson 2004; Dehejia and Wahba 2002).

However, evidence of FDI's positive effect on the service firm is still rare. Most studies focus on foreign ownership's impact on downstream manufacturing, instead of on services sector performance itself. Existing studies that focus on FDI's effect on the services sector are few and conducted largely at the aggregated level, such as at the industry level, and find mixed effects of FDI in the services sector (Alfaro 2003; Kumbhakar and Sarkar 2003; Inklaar, Timmer, and Van Ark 2008). This is one of the first studies that investigates foreign ownership's effect on service firm performance.

Second, FDI firms have lower markups than local firms. Specifically, having foreign ownership is associated with log 0.253 lower markup. Further, 1.0 percent increase of

SOE share is associated with 0.4 percent decrease in current and next year markups. The finding of FDI firms' lower markups than local firms' markups is consistent when I use lagged FDI variables and when other firm characteristics are held constant.

FDI firms' lower markups might be explained by the fact that foreign participation could bring more competition, thus, maintaining firms' lower markups. As seen above, markups are particularly high for many Tunisian services sectors with low levels of competition. Meanwhile, those sectors with a large FDI presence have low SOEs, which may also suggest that FDI presence is associated with higher competition.

Third, firm performance associated with foreign ownership varies significantly across subsectors, which may suggest that analysis on the services sector, such as foreign ownership's effect on firm performance, would require a careful investigation on sectoral variation.

When I add interaction terms between FDI status and other control variables, the coefficients of FDI on TFP are no longer significant in many subsectors. In the hotel and restaurant, and some business services (NACE 70) sectors, FDI firms have even lower TFP than non-FDI firms, while in some real estate and rental (NACE 71) sectors, FDI firms have higher TFP than others. Moreover, FDI firms' relative markup to local firms also varies significantly across subsectors. In the construction sector, FDI firms have much lower markup than local firms (log 1.391 lower, on average), while this difference gets smaller in other sectors except for the hotel and restaurant sector, where FDI firms have higher markup than non-FDIs. Meanwhile, at the sectoral level, a systematic pattern for the relationship between foreign ownership and firm performance is less obvious, although FDI firms have higher TFP and lower markups in general.

Finally, when matching techniques are applied, the average difference between FDI and non-FDI firms gets larger for TFP but smaller (and statistically insignificant) for markups. The regression-based results do not necessarily suggest causal effect if there

are other factors that influence both the firms' probability of having foreign ownership and their performance. Therefore, to further investigate foreign ownership's effect on performance, I use matching to control firm-specific characteristics.

When matched with the observed firm characteristics above, the average TFP level of the control group (non-FDI firms) becomes even larger than of the treatment group (FDI firms), confirming the regression-based estimation results above. However, when matched, the difference in markups becomes much smaller between control and treatment groups, and statistically insignificant, implying that these observed firm characteristics affect firms' likelihood of having foreign ownership as well as firms' markup levels.

The findings of this paper will contribute to the literature on ownership's effect on firm performance. This paper differs from previous studies on service firm ownership, which predominantly focus on the effect of service firm ownership on other sectors' performance, instead of on the services sector itself.

References

Ackerberg, D., K. Caves, and G. Frazer. 2006. "Structural Identification of Production Functions." *MPRA Paper*, University Library of Munich, Germany.

Alfaro, L. 2003. "Foreign Direct Investment and Growth: Does the Sector Matter?" Boston: Harvard Business School.

Ang, J. S., R. A. Cole, and J. W. Lin. 2000. "Agency Costs and Ownership Structure." *The Journal of Finance* 55 (1): 81–106.

Arnold, J. M., B. S. Javorcik, and A. Mattoo. 2011. "Does Services Liberalization Benefit Manufacturing Firms? Evidence from the Czech Republic." *Journal of International Economics* 85 (1): 136–46.

Arnold, J. M., A. Mattoo, and G. Narciso. 2008. "Services Inputs and Firm Productivity in Sub-Saharan Africa: Evidence from Firm-Level Data." *Journal of African Economies* 17 (4): 578–99.

Arvis, J. F., Y. Duval, B. Shepherd, C. Utoktham, and A. Raj. 2016. "Trade Costs in the Developing World: 1996–2010." *World Trade Review* 15 (03): 451–74.

Balasubramanian, N., and Lee, J. 2008. "Firm Age and Innovation," *Industrial and Corporate Change* 17 (5): 1019–47.

Baumol, W. J. 1967. "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crises." *American Economic Review* 57 (June): 415–26.

Baumol, W. J. 2001. "Paradox of the Services: Exploding Costs, Persistent Demand." In *The Growth of Service Industries: The Paradox of Exploding Costs and Persistent Demand,* ed. T. Ten-Raa and R. Schettkat, 3–28. Cheltenham, UK, and Northampton, MA: Edward Elgar.

Baumol, W. J. 2002. "Services as Leaders and the Leader of the Services." In *Productivity, Innovation and Knowledge in Services*, edited by J. Gadrey and F. Gallouj, 147–63. Cheltenham, UK: Edward Elgar.

Baumol, W. J., S. Blackman, and E. Wolff. 1985. "Unbalanced Growth Revisited: Asymptotic Stagnancy and New Evidence." *American Economic Review* 75: 806–16.

Blundell, R., and Dias, M. C. 2009. "Alternative Approaches to Evaluation in Empirical Microeconomics." *Journal of Human Resources*, 44 (3): 565–640.

Boardman, A. E., and A. R. Vining. 1989. "Ownership and Performance in Competitive Environments: A Comparison of the Performance of Private, Mixed, and State-Owned Enterprises." *The Journal of Law and Economics* 32 (1): 1–33.

Boycko, M., A. Shleifer, and R. W. Vishny. 1996. "A Theory of Privatisation." *The Economic Journal* 106 (435): 309–19.

Branstetter, L. 2006. "Is Foreign Direct Investment a Channel of Knowledge Spillovers? Evidence from Japan's FDI in the United States." *Journal of International Economics* 68 (2): 325–44.

Budiman, A., D. Lin, and S. Singham. 2009. "Improving Performance at State-Owned Enterprises." *McKinsey Quarterly,* (May).

Cainelli, G., R., Evangelista, and M. Savona. 2006. "Innovation and Economic Performance in Services: A Firm Level Analysis." *Cambridge Journal of Economics* 30: 435–58.

Choi, J., R. Hausmann, S. Bustos, K. Abderrahim, and J., Kim. 2012. "Comparative Study on Export Policies in Egypt, Morocco, Tunisia and South Korea," African Development Bank, Tunis.

Ciarli, T., and M. Valente. 2005. "Firms' Interaction and Industrial Development: A Simulation Model." In *Clusters Facing Competition: The Importance of External Linkages,* ed. E. Giuliani, R. Rabellotti, and M. P. Van Dijk, 259–90. Hampshire, UK: Aldershot Ashgate.

Clark, C. 1940. *The Conditions of Economic Progress.* London: Macmillan.

Cohen, S., and J. Zysman. 1987. *Manufacturing Matters: The Myth of the Post Industrial Economy*. New York: Basic Books.

Corden, W. M., and J. P. Neary. 1982. "Booming Sector and De-Industrialisation in a Small Open Economy." *The Economic Journal* 92 (368): 825–48.

De Loecker, J. 2011. "Recovering Markups from Production Data." *International Journal of Industrial Organization* 29 (3): 350–55.

De Loecker, J., and F. Warzynski. 2012. “Markups and Firm-Level Export Status.” *American Economic Review* 102 (6): 2437–71.

Dehejia, R. H., and S. Wahba. 2002. “Propensity Score-Matching Methods for Nonexperimental Causal Studies.” *Review of Economics and Statistics* 84 (1): 151–61.

Dewenter, K. L., and P. H. Malatesta. 2001. “State-Owned and Privately Owned Firms: An Empirical Analysis of Profitability, Leverage, and Labor Intensity.” *American Economic Review* 320–34.

Doraszelski, U., and Jaumandreu, J. 2013. “R&D and Productivity: Estimating Endogenous Productivity.” *Review of Economic Studies* 80 (4): 1338–83.

Edmond, C., V. Midrigan, and D. Y. Xu. 2015. “Competition, Markups, and the Gains from International Trade.” *American Economic Review* 105 (10): 3183–221.

Ehrlich, I., G. Gallais-Hamonno, Z. Liu, and R. Lutter. 1994. “Productivity Growth and Firm Ownership: An Analytical and Empirical Investigation.” *Journal of Political Economy* 102 (5): 1006–38.

Eschenbach, F., and B. Hoekman. 2006. “Services Policy Reform and Economic Growth in Transition Economies.” *Review of World Economics* 142 (4): 746–64.

Evangelista, R., and M. Savona. 2003. “Innovation, Employment and Skills in Services. Firm and Sectoral Evidence.” *Structural Change and Economic Dynamics* 14: 449–74.

Feenstra, R., and J. Romalis. 2014, “International Prices and Endogenous Quality.” *Quarterly Journal of Economics* 129 (May): 477–527.

Fernandes, A. M., and C. Paunov. 2012. “Foreign Direct Investment in Services and Manufacturing Productivity: Evidence for Chile.” *Journal of Development Economics* 97 (2): 305–21.

Fixler, D. J., and D. Siegel. 1999, “Outsourcing and Productivity Growth in Services.” *Structural Change and Economic Dynamics* 10 (2): 177–94.

Fontagné, L., A. Guillin, and C. Mitaritonna. 2011. “Estimations of Tariff Equivalents for the Services Sector,” CEPII Working Papers no. 2011–24. Centre d’Etudes Prospectives et d’Informations Internationales, Paris.

Foster, L., J. Haltiwanger, and C. Syverson. 2005. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" NBER Working Paper no. w11555, National Bureau of Economic Research, Cambridge, MA.

Fourastié, J. 1949. *Le Grand Espoir du XX Siècle.* Paris : Presse Universitaire de France.

Francois, J., and J. Woerz. 2008. "Producer Services, Manufacturing Linkages, and Trade." *Journal of Industry, Competition and Trade* 8 (3–4): 199–229.

Freund, C. L., and D. Weinhold. 2004. "The Effect of the Internet on International Trade." *Journal of International Economics* 62 (1): 171–89.

Fu, X., B. Helmers, and C., Zhang. 2012. "The Two Faces of Foreign Management Capabilities: FDI and Productive Efficiency in the UK Retail Sector." *International Business Review* 21 (1): 71–88.

Fu, X., and R. Hoyes. 2003. "The Role of Management Practices in Closing the Productivity Gap: A Literature Review." Cambridge, UK: University of Cambridge, Centre for Business Research.

Fuchs, V. R. 1968. "Front Matter, The Service Economy." *The Service Economy*, National Bureau of Economic Research, Cambridge, MA.

Fuchs, V. R. 1977. "The Service Industries and US Economic Growth since World War II." NBER Working Paper, no. 211. National Bureau of Economic Research, Cambridge, MA.

Gallouj, F., and M. Savona. 2009. "Innovation in Services: A Review of the Debate and a Research Agenda." *Journal of Evolutionary Economics* 19: 149–72. doi:10.1007/s00191-008-0126-4.

Girma, S., A. Greenaway, and R. Kneller. 2004. "Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms." *Review of International Economics* 12 (5): 855–66.

Griffith, R., S. Redding, and H. Simpson. 2004. "Foreign Ownership and Productivity: New Evidence from the Service Sector and the R&D Lab." *Oxford Review of Economic Policy* 20 (3): 440–56.

Griliches, Z., ed. 1971. *Price Indexes and Quality Change*. Cambridge, MA: Harvard University Press.

Griliches, Z., ed. 1992. *Output Measurement in the Service Sector.* Chicago: University of Chicago Press.

Grönroos, C., and K. Ojasalo. 2004. "Service Productivity: Towards a Conceptualization of the Transformation of Inputs into Economic Results in Services." *Journal of Business Research* 57 (4): 414–23.

Grossman, G., and E. Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring." *American Economic Review* 98: 1978–97.

Grossman, S. J., and O. D. Hart. 1986. "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration. *Journal of Political Economy* 94 (4): 691–719.

Guerrieri, P., and V. Meliciani. 2005. "Technology and International Competitiveness: The Interdependence between Manufacturing and Producer Services." *Structural Change and Economic Dynamics* 16 (4): 489–502.

Gupta, N. 2005. "Partial Privatization and Firm Performance." *The Journal of Finance* 60 (2): 987–1015.

Hall, R. 1988. "The Relation between Price and Marginal Cost in U.S. Industry." *Journal of Political Economy* 96 (5): 921–47.

Hallak, J. C., and P. Schott. 2011, "Estimating Cross-Country Differences in Product Quality." *Quarterly Journal of Economics* 126: 417–74.

Harik, I., D. Sullivan, and M. J. Patton. 1992. *Privatization and Liberalization in the Middle East.* Bloomington: Indiana University Press.

Heckman, J. J., H. Ichimura, and P. E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Review of Economic Studies*, 64 (4): 605–54.

Henn, C., C. Papageorgiou, and N. Spatafora. 2015. "Export Quality in Advanced and Developing Economies: Evidence from a New Dataset." WTO Staff Working Paper no. ERSD-2015-02, World Trade Organization, Geneva.

Hoekman, B., and C. A. P. Braga. 1997. "Protection and Trade in Services: A Survey." *Open Economies Review* 8 (3): 285–308.

Hoekman, B., and M. Kostecki. 2009. *The Political Economy of World Trading System,* 3rd ed. Oxford, UK: Oxford University Press.

Holmstrom, B. R., and J. Tirole. 1989. "The Theory of the Firm." *Handbook of Industrial Organization* 1: 61–133.

Hottman, C., S. Redding, and D. Weinstein. 2014. "What Is 'Firm Heterogeneity' in Trade Models? The Role of Quality, Scope, Markups, and Cost." NBER Working Paper no. 20436, National Bureau of Economic Research, Cambridge, MA.

Hsieh, C. T., and P. J. Klenow. 2007. "Misallocation and Manufacturing TFP in China and India." NBER Working Paper no. w13290, National Bureau of Economic Research, Cambridge, MA.

Huergo, E., and J. Jaumandreu. 2004. "Firms' Age, Process Innovation and Productivity Growth." *International Journal of Industrial Organization* 22 (4): 541–59.

Hummels, D., and P. Klenow. 2005. "The Variety and Quality of a Nation's Exports." *American Economic Review* 95: 704–23.

Hwang, J. 2007, "Introduction of New Goods, Convergence and Growth," Job Market Paper, Department of Economics, Harvard University, Cambridge, MA.

Iacovone, L., A. Mattoo, and A. Zahler. 2013. "Trade and Innovation in Services: Evidence from a Developing Economy." World Bank Policy Research Working Paper 6520, Washington, DC.

Inklaar, R., M. P. Timmer, and B. Van Ark. 2008. "Market Services Productivity across Europe and the US." *Economic Policy* 23 (53): 140–94.

Jaimovich, N. 2007. "Firm Dynamics and Markup Variations: Implications for Sunspot Equilibria and Endogenous Economic Fluctuations." *Journal of Economic Theory* 137 (1): 300–25.

Jensen, J. B. 2011. *Global Trade in Services: Fear, Facts, and Offshoring.* Washington, DC: Peterson Institute for International Economics.

Katayama, H., S. Lu, and J. Tybout. 2009. "Why Plant-Level Productivity Studies Are Often Misleading, and an Alternative Approach to Inference." *International Journal of Industrial Organization* 27 (3): 403–13.

Kee, H. L. 2002. "Markup, Returns to Scale, and Productivity: A Case Study of Singapore's Manufacturing Sector." World Bank Policy Research Working Paper no. 2857, Washington, DC.

Khandelwal, A. 2010. "The Long and Short (of) Quality Ladders." *Review of Economic Studies* 77: 1450–76.

Kikeri, S., J. Nellis, and M. Shirley. 1994. "Privatization: Lessons from Market Economies." *The World Bank Research Observer* 9 (2): 241–72.

Klette, J. 1999. "Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data." *Journal of Industrial Economics* 47 (4): 451–76.

Konan, D. E., and K. E. Maskus. 2006. "Quantifying the Impact of Services Liberalization in a Developing Country." *Journal of Development Economics* 81 (1): 142–62.

Kumbhakar, S. C., and S. Sarkar. 2003. "Deregulation, Ownership, and Productivity Growth in the Banking Industry: Evidence from India." *Journal of Money, Credit and Banking* 35 (3): 403–24.

Levinsohn, J., and A. Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies* 70 (2): 317–41.

Lin, J. Y., F. Cai, and Z. Li. 1998. "Competition, Policy Burdens, and State-Owned Enterprise Reform." *American Economic Review* 88 (2): 422–27.

Liu, X., P. Siler, C. Wang, and Y. Wei. 2000. "Productivity Spillovers from Foreign Direct Investment: Evidence from UK Industry Level Panel Data." *Journal of International Business Studies* 31 (3): 407–25.

Love, J., and M. Mansury. 2007. "External Linkages, R&D and Innovation Performance in US Business Services." *Industry and Innovation* 14 (5): 477–96.

Love, J., and M. Mansury. 2009. "Exporting and Productivity in Business Services: Evidence from the United States." *International Business Review* 18 (6): 630–42.

Marel, E. 2010. "What Determines Services TFP Growth: Services Trade or Services—Trade Regulation?" *MIMEO, Forum for Research in Empirical International Trade.*

Markusen, J., T. F. Rutherford, and D. Tarr. 2005. "Trade and Direct Investment in Producer Services and the Domestic Market for Expertise." *Canadian Journal of Economics/Revue Canadienne d'Économique* 38 (3): 758–77.

Maskus, K., and M. Lahouel. 2000. "Competition Policy and Intellectual Property Rights in Developing Countries: Interests in Unilateral Initiatives and a WTO Agreement." *The World Economy* 23: 595–611.

Megginson, W. L., and J. M. Netter. 2001. "From State to Market: A Survey of Empirical Studies on Privatization." *Journal of Economic Literature* 39 (2): 321–89.

Melitz, M. J., and J. Levinsohn. 2006. *Productivity in a Differentiated Products Market Equilibrium.* Princeton, NJ: Princeton University Press.

Melitz, M. J., and G. I. Ottaviano. 2008. "Market Size, Trade, and Productivity." *Review of Economic Studies* 75 (1): 295–316.

Neil, G., S. Nollen, and S. Tenev. 2009. *New Industries from New Places: The Emergence of the Hardware and Software Industries in China and India.* Redwood City, CA: Stanford University Press, and Washington, DC: World Bank.

Nekarda, C. J., and V. A. Ramey. 2013. "The Cyclical Behavior of the Price-Cost Markup." NBER Working Paper no. w19099, National Bureau of Economic Research, Cambridge, MA.

Nellis, J. R. 1999. *Time to Rethink Privatization in Transition Economies?* International Finance Corporation Discussion Paper 38, World Bank Group, Washington, DC..

Nicoletti, G., and S. Scarpetta. 2003. "Regulation, Productivity and Growth: OECD Evidence." *Economic Policy* 18 (36): 9–72.

Nucifora, A., D. Doemeland, and B. Rijkers. 2014. *Barriers to the Creation of Good-Quality Jobs in Tunisia: Economic Stagnation and Private Sector Paralysis.* Washington, DC: World Bank.

OECD and WTO (Organisation for Economic Co-operation and Development and World Trade Organization). 2013. "OECD-WTO Database on Trade in Value Added First Estimates." Paris: OECD.

Olley, G. S., and A. Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6): 1263–97.

Ostrom, A. L., M. J. Bitner, S. W. Brown, K. A. Burkhard, M. Goul, V. Smith-Daniels, H. Demirkan, and E. Rabinovich. 2010. "Moving Forward and Making a Difference: Research Priorities for the Science of Service." *Journal of Service Research* 213 (1): 4–36.

Ostrom, A. L., A. Parasuraman, D. E. Bowen, L. Patrício, C. A. Voss, and K. Lemon. 2015. "Service Research Priorities in a Rapidly Changing Context." *Journal of Service Research* 18 (2): 127–59.

Oulton, N. 2001. "Must the Growth Rate Decline? Baumol's Unbalanced Growth Revisited." *Oxford Economic Papers* 53 (4): 605–27.

Parasuraman, A., V. A. Zeithaml, and L. L. Berry. 1985. "A Conceptual Model of Service Quality and Its Implications for Future Research." *Journal of Marketing* 49 (4): 41–50.

Pires, C. P., S. Sarkar, and L. Carvalho. 2008. "Innovation in Services—How Different from Manufacturing?" *The Service Industries Journal* 28 (10): 1339–56.

Reynolds, J., E. Howard, D. Dragun, B. Rosewell, and P. Ormerod. 2005. "Assessing the Productivity of the UK Retail Sector." *The International Review of Retail, Distribution and Consumer Research* 15 (3): 237–80.

Robinson, P. 1988, "Root-N-Consistent Semiparametric Regression." *Econometrica: Journal of the Econometric Society* 56 (4): 931–54.

Roodman, D. 2006. "How to Do xtabond2: An Introduction to Difference and System GMM in Stata." Working Paper 103, Center for Global Development, Washington, DC.

Rosenbaum, P., and D. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrica* 70 (1): 41–55.

Sáez, S. 2014. *Valuing Services in Trade: A Toolkit for Competitiveness Diagnostics*. Washington, DC: World Bank Publications.

Saghir, J. 1993. *Privatization in Tunisia*. Washington, DC: World Bank Publications.

Sasser, W. E., and S. P. Arbeit. 1976. "Selling Jobs in the Service Sector." *Business Horizons* 19 (3): 61–65.

Savona, M. 2004. "Structural Change and Macro-economic Performance. The Structural Bonus Hypothesis for Services." Paper presented at the XIV International Conference of RESER, IUT Castres and Toulouse, France, September 23–25.

Savona, M., and A. Lorentz. 2005. "Demand and Technology Contribution to Structural Change and Tertiarisation: An Input-Output Structural Decomposition Analysis." LEM Working Paper Series, 2005/25. http://www.lem.sssup.it/WPLem/files/2005–25.pdf.

Schott, P. 2004, “Across-Product versus Within-Product Specialization in International Trade.” *Quarterly Journal of Economics* 119: 646–77.

Shleifer, A. 1998. “State versus Private Ownership.” NBER Working Paper no. w6665, National Bureau of Economic Research, Cambridge, MA.

Shleifer, A., and R. W. Vishny. 1997. “A Survey of Corporate Governance.” *The Journal of Finance* 52 (2): 737–83.

Sutton, J., and D. Trefler. 2011, “Deductions from the Export Basket: Capabilities, Wealth and Trade.” NBER Working Paper no. 16834, National Bureau of Economic Research, Cambridge, MA.

Triplett, J. E., and B. Bosworth. 2003. “Productivity Measurement Issues in Services Industries: Baumol's Disease Has Been Cured.” *Economic Policy Review* 9 (3).

Van Beveren, I. 2012. “Total Factor Productivity Estimation: A Practical Review.” *Journal of Economic Surveys* 26 (1): 98–128.

Vandenbussche, J., P. Aghion, and C. Meghir. 2006. “Growth, Distance to Frontier and Composition of Human Capital.” *Journal of Economic Growth* 11 (2): 97–127.

Varoudakis, A., and C. M. Rossotto. 2004. “Regulatory Reform and Performance in Telecommunications: Unrealized Potential in the MENA Countries.” *Telecommunications Policy* 28 (1): 59–78.

Vickers, J., and G. Yarrow. 1991. “Economic Perspectives on Privatization.” *Journal of Economic Perspectives* 5 (2): 111–32.

Vuorinen, I., R. Järvinen,, and U., Lehtinen. 1998. “Content and Measurement of Productivity in the Service Sector: A Conceptual Analysis with an Illustrative Case from the Insurance Business.” *International Journal of Service Industry Management* 9 (4): 377–96.

World Bank. 2010. *Tunisia—Development Policy Review: Towards Innovation-Driven Growth*. Washington, DC: World Bank. https://openknowledge.worldbank.org/handle/10986/2955.

Appendix A. Services Sector in Tunisia and Descriptive Information from the INS Data

Service is the largest sector in Tunisia, its value-added contributes around 60 percent of GDP. It made up one-third of household consumption (Konan and Maskus 2006) and 18 percent of intermediate demand, according to Tunisian input-output table 1994 from INS.

The structural transformation from agriculture to the services sector has been relatively slow. As shown in table 1A.1, while agriculture's value-added share of GDP decreased by 3.0 percent, services' value-added has increased by only around 1.7 percent from 1998 to 2009. Meanwhile, nonmanufacturing industry, such as mining, has absorbed the reduced portion from the agriculture sector.

This speed of structural transformation is much slower than in other emerging economies or developed countries. For instance, in China, there has been a rapid shift from agriculture to services during the period (agriculture's share decreased from 17.2 percent to 9.9 percent, while services' share increased from 37.1 percent to 44.4 percent). In the case of France, Tunisia's largest trade partner, there has been a gradual shift from industry to services (industry's share was reduced from 23.6 percent to 20.0 percent, while services' share has been increased from 73.7 percent to 78.5 percent from 1998 to 2009).[81]

Meanwhile, trade in services has slowly increased during the period and is larger than in other benchmark economies. Trade in services increased from 18.5 percent of GDP in 2005, the earliest year when the data were available, to 20.0 percent in 2009 (WDI data[82]). The 2011 revolution has negatively affected service exports, particularly tourism, due to turmoil in the political economy; however, trade in services is still around 17 percent, which is much higher than North African countries' average, 8

81. Data source: World development indicator (WDI).

82. Trade in services is the sum of service exports and imports divided by the value of GDP, all in current US dollars.

percent of GDP and higher than France and China (13.7 percent, and 6.0 percent, respectively, WDI data).

However, trade in service, outside of tourism, is below potential. Tourism has been the largest service export, followed by transport and computer-related services, as shown in figure 1A.1. Tourism represents over 15 percent of total imports, including goods and services, and more than 19 percent of total exports (Konan and Maskus 2006).

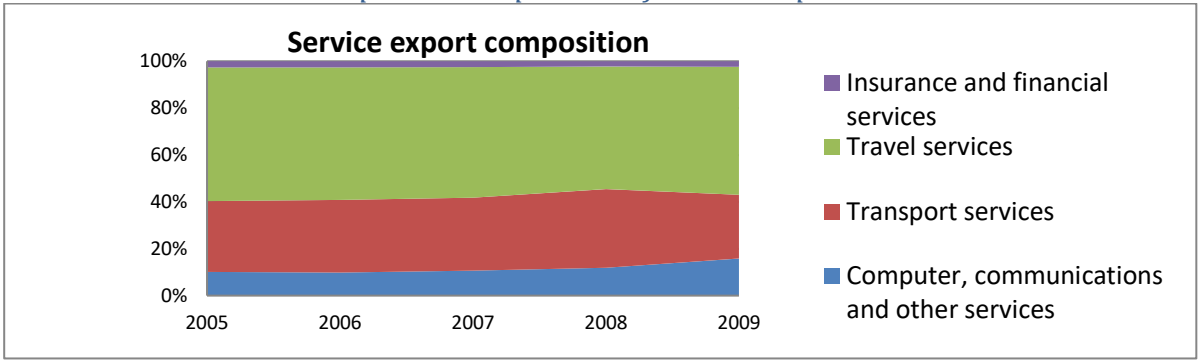
The sight increase of computer, communication, and other services since 2008 was attributed to the increase in Tunisian exports of professional services to Europe in recent years (Sáez et al. 2014). However, excluding travel services, trade in services is quite low, partially due to the restraints on services trade involving both cross-border supply (tariff-equivalent price wedges) and on foreign ownership (monopoly-rent distortions and inefficiency costs) (Konan and Maskus 2006).

Table A.1. Tunisian Economic Structure Over Time

% of GDP	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Agriculture, VA	12.0	12.0	11.3	10.7	9.3	10.4	11.0	10.1	10.2	9.4	8.5	9.1
Industry, VA	29.1	29.4	30.4	30.0	29.9	28.6	28.4	29.2	29.7	31.4	33.8	30.3
(Manufacturing, VA)	*18.8*	*18.6*	*18.5*	*18.8*	*18.6*	*18.0*	*17.5*	*17.3*	*17.7*	*18.3*	*19.5*	*18.4*
Services, etc., VA	58.9	58.6	58.3	59.4	60.8	61.1	60.6	60.7	60.1	59.2	57.7	60.6

Source: World Development Indicators,
Note: Industry corresponds to ISIC divisions 10–45 and includes manufacturing (ISIC divisions 15–37). It comprises value-added (VA) in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas. Value-added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. *Note:* VA =Value-added.

Graph A.1. Composition of Service Exports



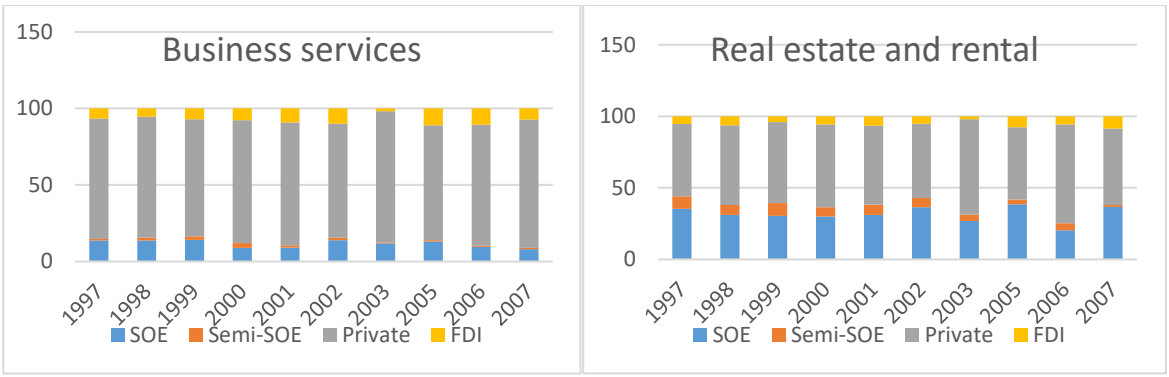
Source: Tunisian Central Bank and World Bank 2016,

Note: Unlike balance of payment data, which are the source of trade in services in the World Development Indicator (WDI), there is no tourism as a subservice industry in NACE. However, there are detailed categories on what tourists will consume, such as hotels and restaurants.

Ownership variables

Graph A. 2. Graph A.7 Ownership Structure by Subservice Sectors





Note: Figure 1A.2 to figure 1A.7 show how the ownership of firms has changed over time for each subservice industry. There is small variation in ownership structure in each industry. As mentioned above, the INS data are not a balanced panel. Therefore, these changes do not mean a group of the same firms change their ownership structure but show instead the ownership share of selected firms in each year in each industry.

Appendix B. Additional Methods

Estimating output elasticities using proxy methods from the translog production function

In the first stage, I obtain estimates of expected output ($\widehat{lnY_{it}}$), as below, and an estimate for ϵ_{ijt}. By subtracting (1.5) from (1.4).

$$\widehat{lnY_{it}} = \widehat{\beta_1}\ln K_{ijt} + \widehat{\beta_2}\ln L_{ijt} + \widehat{\beta_3}\ln M_{ijt} + \widehat{\beta_4}\,(\ln K_{ijt})^2{}_{\text{ijt}} + \widehat{\beta_5}\,(\ln M_{ijt})^2{}_{\text{ijt}} + \widehat{\beta_6}\,(\ln L_{ijt})^2{}_{ijt} + \widehat{\beta_7}\ln L_{ijt}\ln K_{ijt} + \widehat{\beta_8}\ln M_{ijt}\ln K_{ijt} + \widehat{\beta_9}\ln L_{ijt}\ln M_{ijt} + \widehat{\beta_{10}}\ln K_{ijt}\ln L_{ijt}\ln M_{ijt} + h_{jt}(\ln M_{ijt,}\ln K_{ijt}) \quad (1.5)$$

In the second stage, for any $\boldsymbol{\beta}_j = (\beta_{1j}, \beta_{2j}, \beta_{3j})'$,

$$\omega_{\text{it}}(\beta) = \widehat{\phi_{ijt}} - \widehat{\beta_1}\ln K_{ijt} - \widehat{\beta_2}\ln L_{ijt} - \widehat{\beta_3}\ln M_{ijt} - \beta_4(\ln K)^2{}_{ijt} - \beta_5(\ln L)^2{}_{ijt} - \beta_6(\ln M)^2{}_{ijt} - \beta_7\ln K_{ijt}\ln L_{ijt} - \beta_8\ln K_{ijt}\ln M_{ijt} - \beta_9\ln L_{ijt}\ln M_{ijt} - \beta_{10}\ln K_{ijt}\ln L_{ijt}\ln M_{ijt}$$

Nonparametrically regressing $\omega_{it}(\beta)$ on its lag, $(\omega_{it-1}(\beta))$, I recover the innovation to productivity given $\boldsymbol{\beta}_j$, $\xi_{ijt}(\beta)$. I can form moments to obtain β estimates as below and estimate $\xi_{it}(\beta)$ by minimizing a sample analogue to the moment.

$$E\left[\xi_{\text{ijt}}(\beta)\begin{pmatrix}\ln L_{ijt-1}\\ \ln M_{ijt-1}\\ \ln K_{ijt}\\ \ln L^2{}_{ijt-1}\\ \ln M^2{}_{ijt-1}\\ \ln K^2{}_{ijt}\\ \ln K_{ijt}\ln L_{ijt-1}\\ \ln K_{ijt}\ln M_{ijt-1}\\ \ln L_{ijt-1}\ln M_{ijt-1}\\ \ln K_{ijt}\ln L_{ijt-1}\ln M_{ijt-1}\end{pmatrix}\right] = 0$$

Appendix C. Service Firm Performance

Table C.1. ACF-CD Markup by Subservice Sector

		(log) *L*-markups				
Subsector	Obs.	Mean	Median	S.D.	Intervals [5%, 95%]	
Construction, 45	1,603	0.09	0.04	0.84	-1.28	1.51
Wholesale and retail, 50	863	3.36	3.37	0.70	2.16	4.41
Wholesale and retail, 51	1,792	3.11	3.15	0.66	2.08	4.08
Wholesale and retail, 52	843	2.32	2.32	0.65	1.32	3.33
Hotel and restaurant, 55	1,460	0.33	0.31	0.50	-0.38	1.16
Transport and telecom, 60	470	1.02	0.93	1.01	-0.28	2.36
Transport and telecom, 63	561	0.94	1.01	0.81	-0.43	2.22
Real estate and rental, 70	332	1.87	1.67	0.87	0.83	3.21
Real estate and rental, 71	118	1.53	1.51	0.56	0.68	2.50
Business services, 72	105	0.31	0.23	0.70	-0.59	1.55
Business services, 74	792	0.37	0.33	1.15	-1.51	2.34

Note: S.D.= Standard deviation. Markups are estimated using input elasticities estimated from the Cobb-Douglas production function, using ACF methods.

Table C.1 reports estimated markups in log, using equation (1.1) by subsectors. The labor input elasticity was estimated from the Cobb-Douglas production function using ACF methods. I report these markup results in log to be consistent with the reporting of TFP results and of results in later tables.

There is high variance of markups across and within subsectors. The construction, hotel and restaurant, and business services sectors have median markup range between 0.04 and 0.33 (which is around 1), close to a perfectly competitive market. Meanwhile, estimated markups are extremely large for the wholesale and retail sector. Markups are also large for some of the real estate and rental sector. In terms of variance within subsectors, the standard deviation is relatively large in each subsector, with the least at 0.5 in hotel and restaurant. Those sectors with high markups also show large standard deviation of markups.

Within-industry variance from the translog estimation is even larger than the CD function, due to the additional firm-level variance in the input elasticities. Real estimate and rental (NACE 70), and wholesale and retail show large variance.

Table C.2. Different Markup Estimation

Subsector	Obs.	Markups	(1) OLS_CD	(2) OLS_TL	(3) FE_CD	(4) FE_TL	(5) ACF_CD	(6) ACF_TL	(7) ACF_TL_M
Construction, 45	1,603	Mean	0.591	-0.423	-0.957	-1.102	0.086	-0.316	0.214
		S.D.	0.737	0.950	0.737	1.144	0.839	1.015	0.250
Wholesale and retail, 50	863	Mean	3.345	2.335	2.428	2.423	3.362	3.328	3.729
		S.D.	1.040	1.235	1.040	1.118	0.701	0.729	2.355
Wholesale and retail, 51	1,792	Mean	3.158	2.748	1.965	1.854	3.107	3.280	3.800
		S.D.	0.924	0.989	0.924	1.017	0.659	0.696	1.907
Wholesale and retail, 52	843	Mean	2.499	2.126	1.621	1.426	2.318	2.473	1.851
		S.D.	0.844	0.896	0.844	0.911	0.645	0.662	1.481
Hotel and restaurant, 55	1,460	Mean	0.865	-0.200	-1.127	-2.043	0.330	-1.829	0.961
		S.D.	0.468	0.507	0.468	1.291	0.500	1.506	0.418
Transport and telecom, 60	470	Mean	0.906	-0.044	0.211	-0.292	1.020	0.939	-1.644
		S.D.	1.024	1.665	1.024	1.176	1.008	1.216	2.379
Transport and telecom, 63	561	Mean	1.231	0.746	0.966	0.214	0.940	0.271	0.483
		S.D.	0.743	0.671	0.743	0.809	0.813	0.696	0.944
Real estate and rental, 70	332	Mean	1.807	1.833	0.733	0.476	1.871	2.685	2.648
		S.D.	1.083	1.034	1.083	1.115	0.871	0.905	0.894
Real estate and rental, 71	118	Mean	1.382	1.177	-0.461	-0.554	1.535	1.591	3.776
		S.D.	0.593	0.864	0.593	0.876	0.562	1.196	1.545
Business services, 72	105	Mean	0.332	0.456	-0.420	-0.680	0.305	-0.197	2.164
		S.D.	0.590	0.846	0.590	1.370	0.696	1.246	1.582
Business services, 74	792	Mean	0.132	-0.395	-1.165	-1.639	0.368	-0.284	0.827
		S.D.	0.831	1.033	0.831	1.133	1.152	1.284	0.990

Note: OLS_CD=markups estimated from the CD production function, using OLS method. OLS_TL = markups estimated from the translog production function, using OLS method. FE_CD (and FE_TL) = markups estimated from the CD (translog) production function, using firm-fixed effects. ACF_CD (and ACF_TL) = markups estimated from the CD (translog) production function, using ACF method. ACF_TL_M= markups estimated using material input elasticities estimated from the translog production function, using ACF method. S.D.=Standard deviation.

Table C.2 provides, as a comparison, markups estimated with elasticities from different econometric techniques, such as OLS, FE, and ACF, applied to different production functions, such as CD and translog.

ACF estimated markups and their standard deviation (in columns 5 and 6) are larger than markups estimated with OLS and FE (in columns 1 to 4).

However, the relative magnitude, such as ranks of markup level across subsectors, is consistent across different techniques used. For instance, markups calculated using different labor input elasticities estimated from the CD; and translog production functions using different econometric techniques, such as OLS and FE; as well as markups estimated using material input elasticities all show similar ranks across subsectors.

Also, the above markup measures are correlated with each other. For instance, correlation of markups estimated using the CD production function, using OLS and ACF markups is 0.91. Correlation of markups estimated from ACF, CD, and ACF translog production function is 0.81.

Markup measures using labor input elasticities (l markup) and material input elasticities (m markup) from the same ACF translog function are correlated (columns 6 and 7), with the correlation of around 0.3, as explained in the estimation section above, markups estimated using either labor input or material input should provide the same results in principal. While the relative markups across subsectors are mostly consistent between markups estimated labor elasticities and material elasticities, there are exceptions; m markups get higher than l markups for NACE 55, 71, 72, and 72. Markups (m) get smaller for NACE 60.

These differences between two markups measures could be caused by the different adjustment cost of inputs, for instance, hiring and firing cost for labor input and difficulties in managing inventory for material input. The wedge between the firms' output elasticity of labor (or material) and its revenue share contains the expected stream of costs and revenues, and adjustment costs, in addition to the current markups

(De Locker and Warzynski 2012). These could also result from the different roles of material input in producing services, compared to their role in manufacturing.

The results above of similar markup estimations from different econometric techniques and production functions suggest that estimated markups are consistent.

Table C.3. Unlogged Markup by Subservice Sector—Estimated by the CD Production Function Using ACF Methods

ACF-CD	*L*-markups					
Subsector	Obs.	Mean	Median	S.D.	Intervals [5%, 95%]	
Construction, 45	1,603	1.61	1.04	2.50	0.28	4.55
Wholesale and retail, 50	863	37.19	29.10	39.11	8.71	82.33
Wholesale and retail, 51	1,792	28.82	23.22	70.84	7.98	58.99
Wholesale and retail, 52	843	12.87	10.19	16.15	3.73	27.96
Hotel and restaurant, 55	1,460	1.65	1.37	2.50	0.68	3.18
Transport and telecom, 60	470	6.42	2.54	20.21	0.75	10.61
Transport and telecom, 63	561	3.75	2.75	6.98	0.65	9.18
Real estate and rental, 70	332	15.98	5.30	74.25	2.30	24.81
Real estate and rental, 71	118	5.61	4.51	5.09	1.97	12.17
Business services, 72	105	1.80	1.26	1.84	0.56	4.73
Business services, 74	792	3.76	1.40	21.83	0.22	10.33

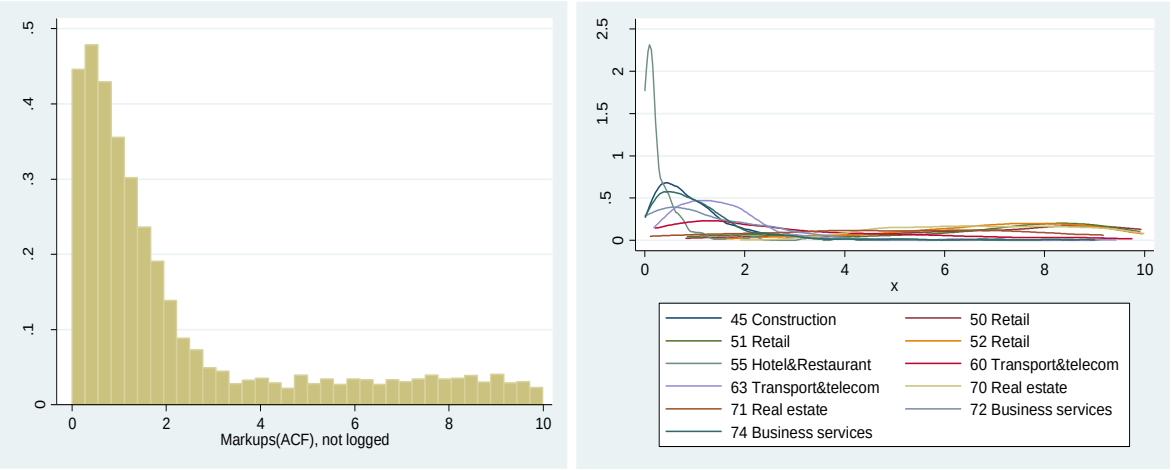
Table C.4.Unlogged Markup by Subservice Sector—Estimated by the Translog Production Function Using ACF Methods

ACF- translog	*L*-markups					
Subsector	Obs.	Mean	Median	S.D.	Intervals [5%, 95%]	
Construction, 45	1,603	1.02	0.73	2.20	-0.23	2.99
Wholesale and retail, 50	863	35.68	29.25	30.77	8.26	81.25
Wholesale and retail, 51	1,792	35.38	27.22	98.63	8.86	77.63
Wholesale and retail, 52	843	15.46	11.73	22.69	4.32	35.08
Hotel and restaurant, 55	1,460	0.44	0.42	0.80	-1.27	1.20
Transport and telecom, 60	470	7.61	2.43	27.18	0.45	12.10
Transport and telecom, 63	561	1.67	1.41	1.64	0.35	3.87
Real estate and rental, 70	332	39.35	12.67	195.92	4.79	56.69
Real estate and rental, 71	118	-4.33	-3.76	11.48	-9.17	11.52
Business services, 72	105	0.26	0.15	2.52	-2.28	3.14
Business services, 74	792	1.64	0.89	7.16	0.03	4.78

Note: ACF_CD = markups estimated from the CD production function, using ACF method. ACF_ translog = markups estimated from the translog production function, using ACF method. S. D. =Standard deviation.

In the translog estimation, some markup estimation shows negative values due to the negative input elasticities reported from the translog production function, which is not linear. These negative markups are dropped in reporting log markups and further analysis on ownership's effect on firms' markup.

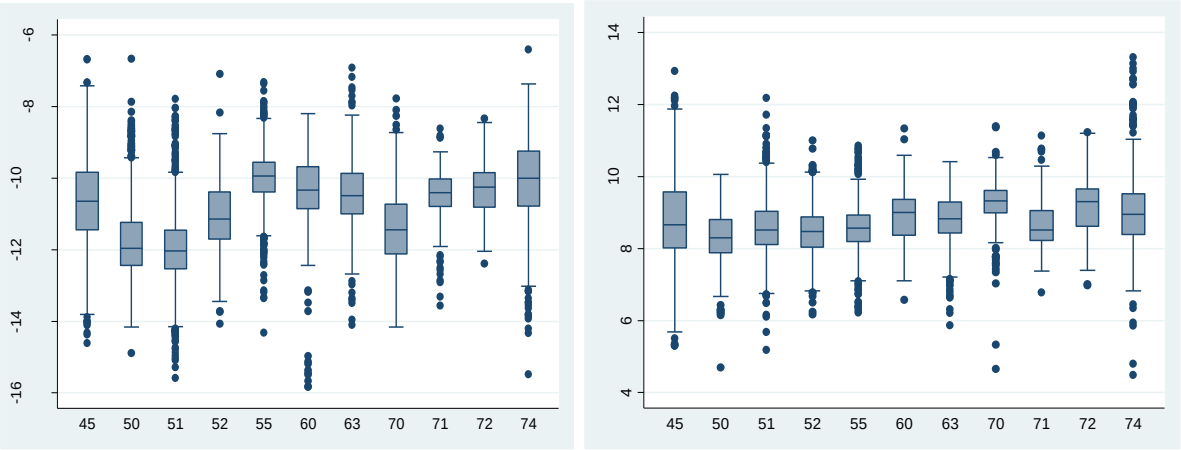
Graphs C.1 and C.2 Unlogged Markups Distribution for All Firms and by Subsectors



Note: Graph C.1 provides markup distribution of all firms. Graph C.2 shows the markup distribution by subsectors. The markups are estimated from the translog production function, using ACF technique, and no logged markup values are reported.

There is large heterogeneity of markups across subsectors. Markups are distributed around 1 (implying perfect competition), but there are many outliers. Significant number of firms in the hotel and restaurant, construction, and business services sectors show markups less than 1, implying that for those firms, marginal cost of production is higher than selling prices. A greater number of firms report markups greater than 1, implying that a large number of firms have very high markups.

Graphs C.3. and C.4. Box Plot—Workers and Average Wage



Labor input intensities vary across subsectors. Wholesale and retail show a relatively low number of workers, while their average wage is not higher than in other sectors.

Table C.5. FDI and SOE's Market Power by Sector

NACE	Obs.	FDI obs. (%)	FDI revenue (%)	SOE obs. (%)	SOE revenue (%)	TFP	Diff FDI	Diff SOE	markups	Diff FDI	Diff SOE
45	1,603	4.7	14.2	1.9	12.8	4.4	0.3	-0.9	-0.3	-5.5	-0.8
50	863	4.5	32.5	0.6	1.3	11.5	0.3	-8.7	3.3	0.4	-0.5
51	1,792	5.3	19.1	3.6	48.5	10.1	0.4	-6.7	3.3	-0.2	0.0
52	843	4.9	24.3	1.5	1.2	10.6	0.2	-8.4	2.5	-0.7	-0.3
55	1,460	9.7	29.5	1.2	6.6	2.9	-0.1	-2.9	-1.8	N/A	N/A
60	470	3.4	2.0	22.6	72.6	10.1	0.4	-10.6	0.9	0.2	-1.4
63	561	6.8	8.2	13.2	66.2	9.6	0.2	-9.3	0.3	-0.2	0.0
70	332	8.7	9.8	50.6	83.7	11.1	-0.1	-8.6	2.7	-0.5	-0.2
71	118	8.5	33.4	0.0	0.0	10.0	1.7	N/A	1.6	N/A	N/A
72	105	17.1	13.0	16.2	36.7	8.8	0.1	-9.2	-0.2	-0.3	-0.2
74	792	11.2	26.5	10.6	35.6	9.2	0.2	-9.1	-0.3	0.1	0.4
	8,939										

Note: N/A=not applicable;

V. Conclusions

The underlying question explored in this thesis is the following: "What are the determinants of productivity in firms in developing countries that would lead the firms to grow and catch up with more productive firms, and, hence, lead the aggregated economy of the developing nations to reach the level of advanced economies?" Using Tunisian annual firm surveys from 1997 to 2007, which have never been explored as extensively, this overarching question was investigated in the three empirical chapters; each of the chapters can also be read separately as a stand-alone paper.

The first chapter, "Productivity Convergence and Learning by Exporting," evaluates the role of technology distance and exports in explaining productivity growth of manufacturing firms in Tunisia from 1997 to 2007. The chapter generates three main results. First, there is strong evidence of convergence in productivity at the firm level, both unconditionally and conditionally. Second, while the differentially higher productivity among exporters compared to non-exporters is explained by self-selection rather than learning by exporting, the evidence suggests that the further away a firm is from the technology frontier, the more likely it is to obtain technology through exporting, and the higher its rate of productivity growth. Third, FDI enhances technology spillovers—especially for exporters that are far behind the technology frontier—but innovation does not.

The findings of this chapter fill a gap in the literature by documenting the evidence of unconditional convergence at the firm level. While growth theories predict that there is a force that promotes convergence in levels of income and productivity, empirical findings are not consistent. Moreover, existing evidence is mostly from macro-level data in advanced countries that typically do not indicate what causes convergence to happen. To my knowledge, this paper is one of the first to empirically substantiate firm-level convergence from a developing country, and to examine the role of exporting as a driver of productivity convergence.

The second chapter, "'Create' or 'Buy'? Internal vs. External Sources of Innovation and Firm Productivity," studies the effect of innovation outsourcing on productivity using manufacturing firms in Tunisia. It finds that innovation has an overall positive effect on output productivity, but that different types of innovation have different effects. The external source of innovation (buying) has a positive effect on productivity; whereas internal innovation (creating) does not, which might imply that Tunisian firms do not invest sufficiently in "creating," or that "creating" is more difficult for Tunisian firms because they might be too far from the technology frontier.

There is no synergy from using both sources of innovation simultaneously—a finding that counters all the literature suggesting that "creating" could enhance firms' absorptive capacity. I consider the possibility that "creating" and "buying" are substitutes for each other when a certain amount of investment is required before innovation can impact output productivity. The estimation result using the Tobit model supports the assumption that a minimum innovation investment is required. The findings of this chapter contribute to our knowledge of the heterogeneous effect of different sources of innovation on firm productivity, and provide micro-level evidence that is consistent with the prediction of the Schumpeterian model that followers would gain more from buying.

The last chapter, "Measurement and Performance of Service Firms and Foreign Ownership," tackles the difficult issue of measuring performance of service sector firms. This is examined by using two related measures: the first, a conventional total factor productivity (TFP) measure, and the second, a measure based on the price markup over marginal cost. Using these performance measures, I find less variance for TFP but more variance for markups across and within subservice sectors, which suggests that factors besides productivity influence a firm's markup level. Meanwhile, firms in sectors that have high barriers for foreign firms show particularly high markups, which may imply that reducing barriers for FDI and improving competition could lower markups.

Foreign-owned firms are found to have higher TFP but lower markups than local firms, as FDI serves as a channel of knowledge transfer and brings more competition into the market. When propensity score matching is applied, the difference in TFP between foreign-owned and local firms becomes even larger, but is insignificant for markups, implying that other firm characteristics may affect firms' likelihood of acquiring FDI and impact their markup level. Meanwhile, there are large sectoral variations in firm performance and foreign ownership premiums. This chapter pushes the frontier of knowledge on the measurement and determinants of performance in service firms, and is one of the first attempts to investigate the effect of service firm ownership on firm performance in the services sector itself.

The findings of all three chapters are consistent with each other. All three chapters find that economic openness is a major driver of productivity for Tunisian firms. Specifically, exporting, outsourcing innovation, and acquiring foreign ownership facilitate knowledge transfer from more advanced foreign firms. Moreover, the chapters find that the further away a firm is from the technology frontier, the faster this knowledge transfer occurs through exporting (chapter 1) and through innovation outsourcing (chapter 2), thus, the faster the firm's productivity will grow. The above findings support the predictions of endogenous growth theory. Therefore, the three chapters are closely linked to each other.

The aforementioned findings provide practical implications for growth, trade, innovation, and industrial policies.

The strong (unconditional) convergence pattern at the firm level that I find in the first chapter, despite little evidence of it at the macro-level, suggests that identifying and removing certain barriers that prevent micro-level convergence aggregating up to the macro-level could help increase aggregate productivity. For instance, industry growth consists of existing firm growth and reallocation of firms (the entry and exit of more and less productive firms). An unfavourable regulatory environment for establishing (that

is, bureaucratic red tape and difficult access to finance) and closing firms (that is, bankruptcy procedures), as well as a lack of mobility of factor inputs from less productive to more productive firms (that is, difficulties of firing or retraining workers) may result in suboptimal rates of reallocation. Therefore, growth and industrial policies in Tunisia could emphasize efficiency of reallocation, rather than conventional support for existing firm growth. Lastly, my results document that exports play a significant role in productivity convergence, and thus, growth, confirming the value of conventional export promotion policies. The finding that the firms' distance from the frontier is directly correlated to potential for technologies to be transferred through exporting suggests that export promotion programs could target those firms with greater potential for technology upgrading.

The second chapter provides insights for innovation policy design. In many countries, the government's innovation policy—such as tax benefits and subsidies to conduct R&D—focuses too narrowly on promoting internal innovation, without considering the level of a country's technological advancement. This chapter suggests that innovation policy in Tunisia should emphasize technology adoption over technology creation. In a developing country like Tunisia, where firms are constrained by limited resources and skill level, it is important to understand which sources of innovation are more efficient at improving final output. To encourage firms' investment in "buying," the government can promote exports and workers' skills, whereas incentives that encourage firms to hire more technicians, or that promote FDI, are not efficient ways to encourage firms' investment in innovation. Moreover, the fact that there is a minimum requirement (threshold) for innovation investment suggests that policies that aim to reduce this threshold or to support firms around this threshold could catalyze investment in innovation. Such policies could include government's cofinancing or risk-sharing of firms' innovation investment (that is, through governments' matching grants or guarantee schemes) and tax benefits for target firms around this threshold. Lastly, the finding that so-called "high-tech" industries are not the most innovative industries in Tunisia suggests that these should not be the main focus of innovation policy.

The last chapter provides valuable information on the Tunisian services sector. Developing countries like Tunisia should pay more attention to services, the largest sector in the global economy. This effort can be strengthened by understanding the characteristics and performance of the services sector. The findings of this chapter suggest that reducing entry barriers for foreign investors and improving competition could enhance the performance of service firms. Also, the large sectoral variations that I find in firm performance and foreign ownership premiums may suggest that policies that aim to attract FDI could benefit from carefully investigating its impact at the sectoral level, rather than at the economy-wide one. That markups are distributed around 1 but with many outliers suggests that market inefficiencies (for example, absence of insolvency practices or high social and monetary costs of closing businesses) may have kept loss-bearing firms in the market, and that complex entry regulations and distortionary supports to state-owned enterprises keep markups high in certain sectors (for example, the wholesale and retail sectors).

I would like to conclude this section by suggesting areas for further research.

The foremost direction for further research is to link the findings of the first chapter with macro-level convergence evidence. Since INS data are not firm census data, they do not have information on which firms enter into and exit from the market—which is necessary for comparing the intensive margin (firm productivity growth within industry) and extensive margin (reallocation of resources from less to more productive sectors). With other sources of data that include firm entry and exit information, or a panel of industry-level data, one could compare the strong evidence of firm-level convergence with the industry- and macro-level convergence pattern, to investigate the extent to which micro-level convergence adds up to the macro-level. This extension could elicit new questions on the specific factors that prevent firm-level convergence patterns to aggregate at the macro-level, and on how efficiently input factors can move from less productive (or closed) firms to more productive (or new) firms in Tunisia.

The second chapter raises a number of questions regarding innovation policies. For instance, given my findings that internal innovation has an insignificant effect on firms in Tunisia, it would be interesting to investigate why Tunisian firms continue to invest in internal innovation, and how they can make these investments more impactful on their output productivity. Further, though I find that policies to reduce the innovation threshold or support firms around it could catalyze innovation investment, methods for identifying this threshold and the firms around it must still be developed. This finding could suggest practical policy implications; for instance, many governments provide support to firms through matching grants or subsidies for innovation, but do not use systematic mechanisms for identifying target firms that could maximize the effects of their support. Lastly, if the effect of innovation on productivity varies according to a firm's position relative to the technology frontier, what is the threshold level of technological advancement that determines whether it will benefit more from "creating" or "buying" innovation? The same question applies at the country level in innovation policy design.

Further research is required to fully understand the measurement and determinants of the performance of service firms. The performance measurement I suggest in this thesis only scratches the surface, in large measure due to limitations in the data. Moreover, it is important to investigate the determinants of service firm productivity besides foreign ownership, as well as whether the determinants of productivity in the manufacturing sector apply to services as well. Similarly, more investigation on markups is required; for instance, What determines firms' markup levels in the services sector; What are the implications of markup variances within and across subsectors; and What are the broader implications of having firms with very low or very high markups? Lastly, the findings that Tunisian service firms cluster into two groups, a more productive and a less productive one, and the TFP level of each sector does not change much over time, raise the question of why resources do not move from low-productivity sectors to high-productivity sectors in Tunisia.

Finally, further improvements are needed in identifying the determinants of firm performance and methods for its measurement. Many studies use revenue-based TFP (TFPR) to measure firm performance, which, along with efficiency, reflects information internalized by the market price, such as product quality and market power. As we typically do not have detailed price information, how can we improve the measurement of TFPR? Is there any way to decompose TFPR into the different effects it captures, and thus make it a better tool for measuring firm efficiency? The three chapters, along with existing literature, raise concerns about the simultaneity issue that arises between firm performance measures and independent variables. As an example, in the second chapter, if exporting firms know that they will have higher growth, and a firm's propensity to export is correlated with unobserved characteristics other than its initial productivity level, it would be difficult to convincingly isolate the causal effect of exporting on firm productivity growth. I apply various econometric techniques to work around this bias, but finding new external instrumental variables that can be applied to firm-level analysis could further improve my estimations. One idea worth exploring is to use satellite images to identify firms' physical distance from ports, markets, and other firms, as well as to use variables for firm electricity usage.