China, AI, Robots, Taxation:

Essays in Applied Microeconomics

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A thesis submitted for the degree of

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This thesis consists of four self-contained essays in applied microeconomics. The first exploits China's accession to the WTO to investigate the impact on Indian manufacturing firms of improved access to intermediate inputs, and finds a persistent quality-upgrading effect which ripples out across the production network. The second examines the impact of artificial intelligence on hiring and wages in the Indian service sector, using a novel dataset of 15 million online vacancy posts, and finds evidence of direct negative effects within incumbent firms. The third paper explores the impacts on developing countries of robot adoption at home and abroad, drawing on industry- and firm-level robot data from a wide range of countries, and outlines the groups most likely to benefit – and those most likely to lose out. Finally, the fourth paper investigates the sources of observed heterogeneity in VAT pass-through, using reforms across 14 Eurozone countries between 1999 and 2013, and finds important roles for product market regulation and product quality.

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When I was considering embarking on a doctorate, my father – who has overseen many – warned that "50% of PhDs are a nightmare". Relaying this to my prospective supervisor, I was greeted with the wry response that "well, 50% of lives are a nightmare". The fact that the last few years have been some of the best of my life are testament to both of their guidance, and to the support of many more family, friends and colleagues.

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Introduction

This thesis consists of four self-contained essays in applied microeconomics. The first three are loosely connected, investigating the impacts of three interrelated global 'megatrends': the (re-)rise of China, advances in artificial intelligence, and the proliferation of industrial robots.[1] Chapter 1 considers the impact of China's accession to the WTO on the Indian manufacturing sector, then Chapter 2 considers the implications of recent improvements in machine learning for employment in the Indian services sector. Chapter 3 returns to the manufacturing sector but broadens the geographic scope, examining how various robotisation scenarios – including Chinese subsidies to stimulate further automation – affect workers across all developing countries. Finally, Chapter 4 uses similar theoretical and empirical methods to analyse a distinct topic – namely the share of a given value-added tax change that is passed onto consumers by firms, and how this is affected by changes in market structure.

The first two papers pick up from my undergraduate interest in demography, as a social science with rare predictive power.[2] India is projected to surpass China as the world's most populous country by 2030, with around 200 million young people ageing into the labour market over the next ten years (United Nations 2019). At the same time, globalisation and technological advances are

[1] Megatrends are 'important shifts in the evolution of society, ... which tend to persist over the long term' (The Oxford Martin Commission for Future Generations 2013).

[2] In contrast to the complex dynamics of many economic and political systems, which we struggle to predict within a timeframe of days, months or years, we can in theory place a *certain* upper bound on the number of people aged 30+ in 2050, or 80+ in 2100 – because, by definition, they have already been born. Central and lower bound demographic projections also have a relatively strong track record (see, for instance, O'Neill et al. 2001, section 6.4).

driving radical upheaval in the world economy, such that previous development paths from agriculture to manufacturing to services may no longer be available (Baldwin 2019, Baldwin & Forslid 2020). What does this mean for India's rising generation? Will there be jobs available, and if so, where? Chapter 1 seeks to shed light on the globalisation aspect, by examining the impacts on Indian manufacturing firms of China's rapid export expansion in the 2000s, while Chapter 2 investigates the impacts of advances in artificial intelligence on employment in the Indian services sector.

Specifically, Chapter 1 exploits China's accession to the WTO to investigate the consequences of this external supply shock across the Indian production network. In contrast to the focus on negative import competition effects in developed countries (e.g. Autor et al. 2013), I find an important beneficial effect through the improved supply of intermediate inputs. Consistent with a model of multi-product manufacturers gaining access to higher-quality components, a fall in input tariffs raises revenue, quality and prices whilst lowering quality-adjusted prices and the probability of product exit. This upgrading effect persists for at least ten years; at the peak in 2010, products with a 10% higher pre-accession input tariff, and hence a larger post-accession fall in tariffs, have 5.3% higher quality. This in turn raises quality further down the supply chain, with input-output linkages amplifying the one-step effect by up to 75%. Contrary to the fear that Chinese manufacturing would inhibit Indian expansion in the sector, these results suggest that it was complementary for large Indian firms – and that improved input access in fact caused beneficial ripples of upgrading across the broader Indian production network.

Chapter 2 (jointly with Ashley Pople at Oxford and Katherine Stapleton at the World Bank) turns to the Indian white-collar services sector, to investigate fears of substitution by artificial intelligence (AI) systems – for example, chat-bots replacing call centre operators. We leverage a novel dataset of 15 million vacancy posts from India's largest jobs website, and identify AI-related hiring from the text of job descriptions and skills requirements. We first document a rapid rise in demand for AI skills since 2016, particularly in the IT, finance and professional services industries. Vacancies demanding AI skills list substantially higher wages, but require more education and are highly concentrated in the largest firms and a small number of high-tech clusters. Exploiting plausibly exogenous variation in exposure to advances in AI technologies, we then examine the impacts of establishment demand for AI skills, as a proxy for AI adoption. We find that growth in AI demand has a direct negative impact on the growth of non-AI and total job posts by incumbent firms, and reduces the growth of wage offers across the distribution. This chapter thus presents less sanguine implications for Indian employment than the first. However, future research is required to see if the aforementioned reductions in hiring by large existing firms are outweighed by the creation of new tasks, jobs and firms elsewhere in the economy.

While such questions of trade and technology are particularly acute in India, they have far broader relevance. Chapter 3 (jointly with Erhan Artuc, Paulo Bastos and Bob Rijkers at the World Bank) examines the implications for all developing countries of a third megatrend, the proliferation of industrial robots. There is substantial media debate about whether robots will destroy jobs, and also more specifically whether developed-country robots will cut developing countries out of global production networks. Yet while increasingly sophisticated industrial robots reduce the demand for low-skilled labour in some tasks, there remain many goods whose production is hard to automate. These could provide valuable room for developing countries to specialise their remaining low-skilled manufacturing capacity. Drawing on the Ricardian framework of Artuc et al. (2018), we explore these dynamics and test them with industry- and firm-level robotisation data from a wide range of countries.

We present four main results. First, robot adoption in advanced economies can ultimately benefit workers in developing countries through lower prices and increased demand for intermediate inputs – though there may be adverse effects in the short run, particularly for the least mobile workers. Second, continued

Chinese subsidisation of robots is likely to reduce China's trade with OECD countries, while increasing that with developing countries – as China's profile of comparative advantage increasingly aligns with the former. Third, larger and more globally-connected firms in developing countries are more likely to adopt robots, aligning with findings in developed countries, as they can afford the fixed costs of upgrading, and value the resulting precision more highly. Fourth, these firms expand post-adoption, increasing the competitive pressure on the smaller, less international firms in which those workers most vulnerable to replacement by robots are also more likely to work. Overall, this paper illuminates the complexity of the interactions between technological progress and patterns of international production, and highlights some potential areas where policy could improve the distribution of the gains that result.

Chapter 4 (jointly with Matthieu Bellon at the International Monetary Fund) considers a less closely-related topic, but uses similar theoretical and empirical methods. When a government raises value-added tax (VAT) rates, firms choose how much of this change to pass onto consumers through higher prices. Previous work has found substantial variation in this 'pass-through' parameter (e.g. Benedek et al. 2020). Understanding the sources of this heterogeneity is therefore critical for policymakers, who want to understand which of consumers or producers would face the brunt of a reform across different settings. To fill this lacuna, I again adopt a firm-level perspective, modelling firms' pricing decisions in a variety of market structures, and again use product-level data to test the frameworks. Supply chains, and the transmission of shocks along them, turn out to play a central role in this paper, as in Chapters 1 and 3.

Specifically, in the paper we first extend existing theory to characterise the roles of imperfect competition and product differentiation, then we investigate these relationships empirically using a panel of 14 Eurozone countries between 1999 and 2013. We find important roles for product market regulation and product quality, and little impact of advance announcement of reforms. Together our results imply that market structure should be an important consideration when reforming VAT. For a government seeking to mobilise revenue through raising VAT (e.g. Saudi Arabia in May 2020), a greater share of the burden of higher taxes will fall on consumers relative to firms for products with higher upstream competition or for products characterised by a wider quality range. For a government using a VAT cut to stimulate consumption (e.g. Germany in June 2020), or to support firm profits, the effects are the inverse. Firms will retain more of the VAT cut in higher markups, and consumers will experience smaller price reductions, the less competitive the upstream sector or the narrower the range of product quality. These results are also significant in a historical context: liberalising reforms over the last thirty years have substantially increased the competition-friendliness of regulation in European product markets, so our findings imply that VAT cuts today will be passed on to consumers substantially more than in the past.

Contributions: The research in this thesis makes several contributions to literatures within international trade, development, labour and public economics. This main contribution of Chapter 1 is that the 'China shock' had significant and important benefits for Indian consumers through the 'supply-driven quality upgrading' mechanism, particularly when the amplifying role of the production network is taken into account. More than three billion people live in emerging economies that have developed large trade deficits with China since 2000, and no previous paper considers this channel in detail. Along the way, I make three main theoretical and methodological innovations. First, I extend the multi-product firm model of Manova & Yu (2017) to allow a new 'quality in, quality out' mechanism. Second, I characterise five channels through which the 'China shock' can affect a country – where previous studies consider only two or three – and model their impact on a range of firm-level observables. I also extend standard import tariff and import competition measures (Schott 2002, Bernard & Jensen 2002) to create analogous measures for each of the other four channels. Finally, I develop a novel method for tracing ripple effects across a network, and use it to provide the first evidence on the degree of quality propagation along a supply chain.

Chapter 2 makes two main contributions. First, we construct a large new dataset of job posts in India since 2010, and use this to offer the first comprehensive picture of the demand for AI skills in India's service sector. Our dataset contains detailed information on wages and the education and experience requirements for job candidates, so we can provide a more complete profile of these jobs than is possible with similar datasets in the UK and USA. Second, we offer one of the first attempts to evaluate the causal effects of establishment-level AI deployment on labour demand and wages, and the first for a developing country. Through our IV strategy, we isolate effects resulting directly from establishment AI adoption, improving upon an existing literature which focuses on the effects of AI exposure (e.g. Webb 2020, Acemoglu, Autor, Hazell & Restrepo 2020).

The primary aim of Chapter 3 is to structure and synthesise existing evidence on the impacts of industrial robotics on developing countries. Nonetheless, it also makes several novel contributions. It extends the model of Artuc et al. (2018) from three representative countries to four, allowing us to simulate the effects of increased Chinese robot subsidies on developed and emerging economies. We also move beyond a Ricardian framework and document non-price drivers of robot adoption in developing countries, drawing on new data on robot purchases in eleven developing countries. These data then allow us to provide the first multi-developing-country event study of firm-level robot adoption, illuminating potential consequences for the firm size distribution.

Chapter 4 makes significant theoretical and empirical contributions. It first uses four partial equilibrium models to extend existing theory and thus identify how supply and demand features can influence the degree of VAT pass-through under different market structures. On the empirical side, we extend the methodology of Benedek et al. (2020) to allow for this new heterogeneity, and test the models by combining their tax data with additional information on regulation, trade, quality and various other controls. We also match data on VAT changes to the Tax Policy Reform Database (Amaglobeli et al. 2018) to create the first cross-sector database of VAT reforms including announcement dates, and use it to provide the first systematic assessment of announcement effects across many product categories.

Chapter 1

Inputs, networks and quality-upgrading: Evidence from China in India*

This paper exploits China's accession to the WTO to investigate the propagation of a supply shock across the Indian production network. Consistent with a model of multi-product manufacturers gaining access to higher-quality components, a fall in input tariffs raises revenue, quality and prices whilst lowering quality-adjusted prices and the probability of product exit. Upgrading persists for at least ten years; at the peak in 2010, products with a 10% higher pre-accession input tariff, and hence a larger post-accession fall in tariffs, have 5.3% higher quality. This in turn raises quality further down the supply chain, with input-output linkages amplifying the one-step effect by up to 75%. In contrast to existing literature focused on negative demand effects of the 'China shock', these results highlight a potential beneficial impact in developing countries, namely supply-driven quality upgrading.

Keywords: *quality, production networks, international trade*
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1.1 Introduction

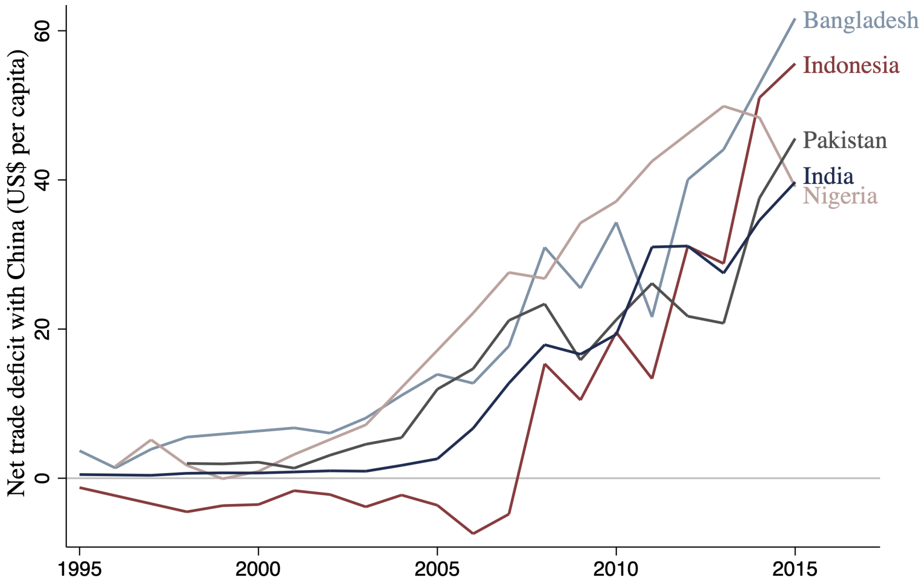
China's rapid industrial expansion since 2000 has had repercussions across global markets. The negative effects on manufacturing in the USA, among other developed countries, have been widely studied (e.g. Autor et al. 2013, Bloom et al. 2019). Yet the implications are far broader: more than three billion people live in emerging economies that have developed large trade deficits with China since 2000. Figure 1.1.1 shows the per capita bilateral deficit with China in the next five largest developing countries: the rapid takeoffs in these deficits are striking, and strikingly similar.[1] Moreover, the composition of the imports from China driving these deficits is markedly different from the US story (Figure 1.1.2). In the USA, the rise in Chinese imports is mostly capital and consumption goods. In contrast, in large developing countries it is imports of intermediate inputs – i.e. parts and components yet to be assembled into final products – that are dominant, and that grow the fastest.

How did this sudden flood of Chinese components affect manufacturing firms in developing countries? I address this question using firm-product-level data from India, by far the largest of these trade partners.[2] Given the lack of linked customs-firm data, the first challenge is to isolate the effect of these inputs from other impacts of China's expansion. Figure 1.1.3 provides an overview of the key channels, from the perspective of a single product, Good 0, embedded within a supply chain in India. New Chinese inputs compete with existing inputs, improving the price and/or quality of Good -1 available for use in Good 0. Yet Chinese imports may also compete directly with Good 0, as is the focus of import competition studies (e.g. Autor et al. 2013). In addition, such imports could reduce demand for Good 0 as a component, by

[1] I exclude Brazil, which – as a major commodity exporter to China – has a different pattern, examined in Costa et al. (2016).

[2] This scale is reflected in the size of the resulting trade deficit with China, which grew from less than \$1bn in 2000 to more than \$50bn in 2015.

Figure 1.1.1: Bilateral per capita trade deficits with China



Notes: This graph shows the annual net trade deficit with China, in US$ per capita, in the five largest developing countries (excluding China itself, and excluding Brazil – which is, in contrast, predominantly a commodity exporter to China, as examined in Costa et al. (2016)). *Source:* UN Comtrade.

competing with domestic producers of the final consumption good, Good 1.[3] Further competition occurs in export markets, as Indian producers face new Chinese competition when selling into the OECD, for example.[4] Lastly, Indian exporters can also export to the Chinese domestic market – although Indian exports to China are far smaller than the reverse, as already noted.[5][6]

To gauge the effects through each of these channels, I exploit China's

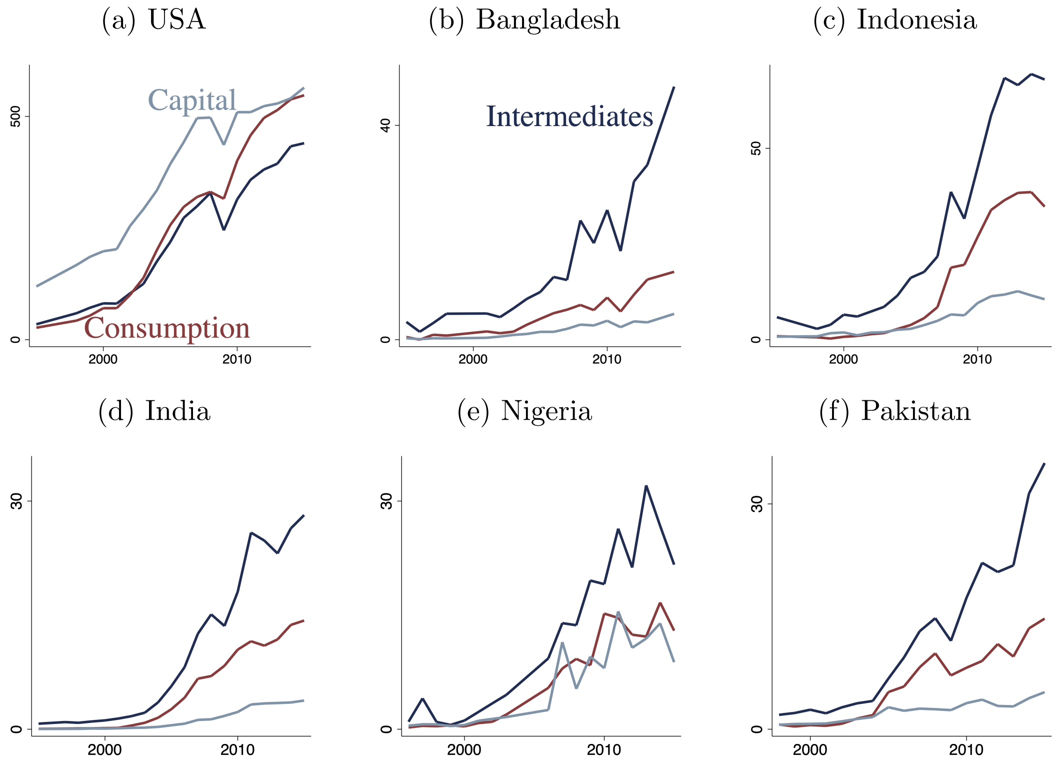
[3]Such 'upstream' spillovers of import competition, where shocks to customers affect those who supply them, are considered in Acemoglu, Akcigit & Kerr (2015) and Acemoglu, Autor, Dorn, Hanson & Price (2016). I label this the 'output channel' throughout this paper to avoid any ambiguity arising from the fact that, in Figure 1.1.3, Good 1 is the downstream good.

[4]Caselli et al. (2018) and Branstetter et al. (2019) find significant effects of Chinese competition through this indirect channel, for Mexican and Portuguese exporters respectively.

[5]Again, this channel is, in contrast, important for Brazil (Costa et al. 2016).

[6]The five channels shown in Figure 1.1.3 are clearly not exhaustive. For instance, there could be input or output effects related to channels (iv) or (v). I focus on import effects because these were important during India's tariff liberalisation in the early 1990s (e.g. Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*, Topalova & Khandelwal 2010, De Loecker et al. 2016), while goods exports (especially to China) are a relatively small share of India's GDP.

Figure 1.1.2: Total imports from China by type of good, US$ per capita

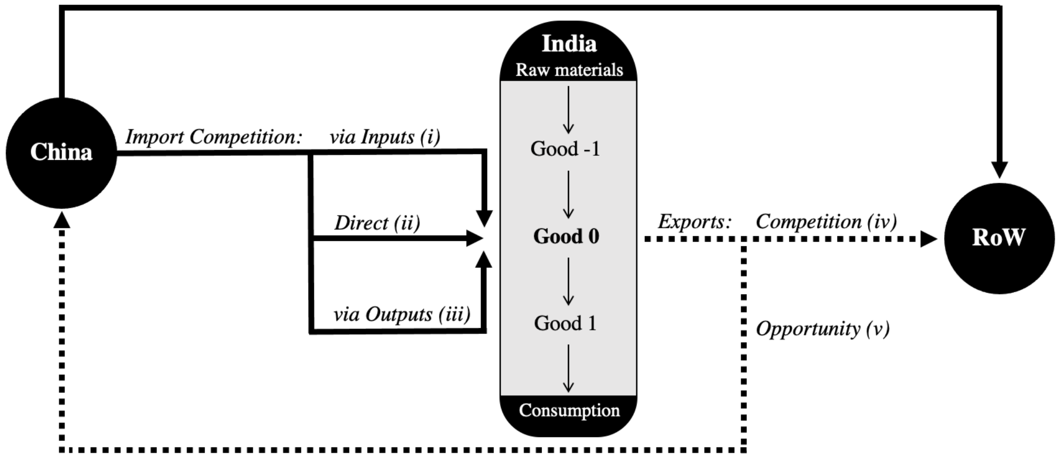


Notes: These graphs show countries' respective imports from China, in US$ per capita, split by end use. Goods are divided into three categories – specifically consumption goods, intermediate goods and capital goods – according to the UN's Broad Economic Categories classification (Revision 4). *Source:* UN Comtrade.

accession to the WTO in 2001 and the resulting changes in tariffs. For the input and output effects (channels (i) and (iii) in Figure 1.1.3), I use detailed input-output shares from the Indian Ministry of Statistics and Programme Implementation (MoSPI) to calculate the average reduction in Indian tariffs on relevant inputs and outputs respectively. I supplement this identification strategy with an alternative method, following Autor, Dorn and Hanson (2013, hereafter ADH) which uses changes in trade flows between China and a basket of Southeast Asian countries to isolate plausibly exogenous changes in Chinese import competition and export opportunities.

Guided by a simple model of multi-product manufacturers, I then assess the impact of improved access to intermediates from China on a range of firm outcomes. I find that a fall in the tariffs on a firm's inputs raises revenue,

Figure 1.1.3: China's growth & Indian manufacturing firms – five channels



Notes: This figure provides an overview of five channels through which China's accession to the WTO could affect Indian manufacturing firms. Thin lines depict the Indian manufacturing supply chain, thick lines represent China's exports, and dotted lines represent India's exports. China's expansion could affect a particular product, Good 0, by: (i) increasing competition in the market for inputs, i.e. Good -1; (ii) increasing competition directly in the domestic market for Good 0; (iii) increasing competition in the market for those final products Good 1 for which Good 0 is itself an intermediate input; (iv) increasing competition in the export market for Good 0; and/or (v) providing new demand or opportunities to export to the Chinese market.

quality and prices whilst lowering quality-adjusted prices and the probability of product exit, consistent with the theoretical predictions. In the main specification, following Lu & Yu (2015), a 10% higher average tariff on input industries in 2001, and hence a larger post-accession fall in tariffs, corresponds to a 2.4% rise in quality and a 1.9% rise in price in the post-accession period. This 'quality in, quality out' upgrading effect contrasts with previous 'demand-pull' (e.g. Verhoogen 2008) and 'escape competition' (Amiti & Khandelwal 2013) quality-upgrading mechanisms. It has a similar flavour to previous 'variety in, variety out' findings on product scope across India's trade liberalisation in the early 1990s (Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*, Goldberg, Khandelwal & Pavcnik 2010), but differs in focusing on the intensive rather than the extensive margin.[7]

[7] I find that fewer than 20% of manufacturing goods produced after 2001 are new products,

This supply-driven quality-upgrading result is robust to various alternative specifications. It holds both when estimating quality directly using the method of Khandelwal et al. (2013), and when inferring quality from observables (as in e.g. Verhoogen 2008, Kugler & Verhoogen 2012) or using standard firm-level measures of productivity (e.g. Ackerberg et al. 2015). Likewise I find similar results with the alternative identification mechanism inspired by ADH, and when using various combinations of controls and fixed effects. I also draw on the geographic collocation measure of Acemoglu, Akcigit & Kerr (2015) to confirm that the upgrading effect is indeed driven by production linkages *per se*, rather than simply proxying for the tendency of related industries to locate close to one another. Comparing the input channel to measures of the four others in Figure 1.1.3, I find that its effects are relatively significant and relatively important – as expected from the composition of Indian imports from China. Disaggregating, quality upgrading occurs only in medium and large firms, suggesting the presence of fixed costs to adapting procurement to take advantage of newly available higher-quality inputs.

I then consider spillovers of the supply-driven quality-upgrading effect in two dimensions. First, it persists over time. Upgrading continues for at least ten years; at the peak in 2010, products with a 10% higher pre-accession input tariff, and hence a larger post-accession fall in tariffs, have 5.3% higher quality. Second, upgrading spreads to other firms. I use a novel method to trace the propagation of the effect along the supply chain, and find a knock-on quality upgrade for the next product in line. In other words, access to better inputs (Good -1) raises quality not just of the product using them (Good 0), but also raises the quality of products for which Good 0 is itself a component (Good 1). When broadening the analysis to include all ripples throughout the input-output network, using coefficients of the Leontief inverse matrix, the peak upgrading effect is amplified by up to 75%. I thus find that the production network plays

at the seven-digit level, and that the quality-upgrading effect holds even when excluding new products.

a major role in spreading the effects of the Chinese supply shock to other firms and industries whose immediate inputs are not themselves directly affected.

In sum, this paper finds evidence that China's integration with Indian supply chains drove a persistent and widely spread rise in quality, even as quality-adjusted prices fell. I then note the robust findings elsewhere that: (i) firms producing higher quality goods pay higher wages to their workers (e.g. Verhoogen 2008, Kugler & Verhoogen 2012), and (ii) quality upgrading is strongly associated with long-run growth and development (e.g. Grossman & Helpman 1991, Kremer 1993, Hausmann & Rodrik 2003, Rodrik 2006, Hidalgo et al. 2007, Matsuyama 2008, Khandelwal 2010, Lane 2019, Verhoogen 2020). Altogether, this suggests that the Indian population received important direct and indirect gains from trade from China's resurgence through the supply-driven quality-upgrading mechanism. From a policy perspective, this also highlights an additional source of potential benefits forgone by the 2019 decision to withdraw India from the Regional Comprehensive Economic Partnership with other large Asian economies.

This paper's main contribution to the literature is that the 'China shock' may have had important benefits for other developing countries through the supply-driven quality-upgrading mechanism, particularly when the amplifying role of the production network is taken into account. More than three billion people live in developing economies which have grown large trade deficits with China since 2000, and no previous paper considers this mechanism in detail. Along the way, I make three main theoretical and methodological innovations. First, I extend the multi-product firm model of Manova & Yu (2017) to allow a new 'quality in, quality out' mechanism. Second, I characterise five channels through which the 'China shock' can affect a country – where previous studies consider only two or three – and model their impact on a range of firm-level observables. I also extend standard import tariff and import competition measures (Schott 2002, Bernard & Jensen 2002) to create analogous measures for each of the other four channels. Finally, I develop a novel method for tracing ripple effects across a network, and use it to provide the first evidence on the degree of quality propagation along a supply chain.

The rest of this paper proceeds as follows. Section 1.2 situates the paper within the literature, Section 1.3 describes the data, and Section 1.4 outlines the model. Section 1.5 then details the empirical specification, and Section 1.6 presents baseline results on the supply-driven quality-upgrading mechanism. Section 1.7 explores the spillovers of this effect, specifically persistence over time and propagation across the production network. Section 1.8 concludes.

1.2 Literature

A growing recent literature considers the role of production networks in propagating and amplifying microeconomic shocks to have macroeconomic implications (Carvalho 2008, Acemoglu et al. 2012, Acemoglu, Ozdaglar & Tahbaz-Salehi 2016, Carvalho et al. 2020, Acemoglu & Tahbaz-Salehi 2020). Acemoglu, Akcigit & Kerr (2015) and Acemoglu, Autor, Dorn, Hanson & Price (2016) use this framework to examine the China shock in the USA, while Liu (2019) and Lane (2019) use a network lens to evaluate development policy in China and South Korea. This paper is closest to Acemoglu, Autor, Dorn, Hanson & Price (2016), but the key difference in the Indian context is that the China shock has a supply as well as a demand element, and indeed I find that the former has larger spillovers than the latter.[8]

Other papers investigating the impact of China's increased role in global trade during the 1990s and 2000s have so far largely focused on developed countries (Autor, Dorn & Hanson 2013, 2016, Autor, Dorn, Hanson & Song 2014, Autor, Dorn, Hanson & Majlesi 2016, Bloom, Draca & Van Reenen 2016,

[8]Investigating the spillovers of import competition, Acemoglu et al. (2015) show theoretically that demand shocks will mainly propagate upstream, while supply shocks will mainly propagate downstream. In their main model with Cobb-Douglas preferences and technologies, demand shocks *only* travel upstream and supply shocks *only* travel downstream. Generalisations of the model (e.g. Acemoglu, Ozdaglar & Tahbaz-Salehi 2016) suggest only limited effects in the opposing directions, and their empirical results support the Cobb-Douglas version.

Pierce & Schott 2016, Amiti, Dai, Feenstra & Romalis 2017, Dauth, Findeisen & Suedekum 2017), with some work on China (Lu & Yu 2015, Brandt et al. 2017), Brazil (Costa et al. 2016), Mexico (Iacovone et al. 2013), Ecuador (Bas & Paunov 2020) and India (Barua 2015, 2016, Chai 2018). The paper by Costa et al. (2016) is closely related, in considering the upside of China's boom for a developing country. However, its focus on the export opportunity channel in Brazil is less applicable to India and other large developing countries, given that Bangladesh, India, Indonesia, Nigeria and Pakistan (the remainder of the largest eight countries in the world, after excluding China, the USA and Brazil) all have large trade deficits with China, unlike Brazil. My finding that access to imported inputs has especially large benefits for large firms echoes the results from Iacovone et al. (2013) in Mexico and Bas & Paunov (2020) in Ecuador, while the relative granularity of the Indian input-output table allows me to investigate the network aspects of the upgrading mechanism. On India, this paper builds upon Barua (2015, 2016) and Orr (2018) by disentangling the five channels, considering input and output quality, and examining network effects.

A series of studies have focused on the import competition and imported input channels during the Indian tariff liberalisation of the 1990s. Goldberg, Khandelwal, Pavcnik & Topalova (2010*a*) consider the impact of declines in input tariffs, Goldberg, Khandelwal, Pavcnik & Topalova (2010*b*) consider declines in output tariffs, and Topalova (2010), Topalova & Khandelwal (2010) and De Loecker et al. (2016) consider both together.[9] Similarly, studies investigating the impact of tariff changes in other countries (e.g. Amiti & Konings 2007, Halpern et al. 2015) have focused on examining the import channels.[10] Studies on India's liberalisation have considered a range of dependent variables, e.g. product scope (Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*,*b*),

[9]Purely domestic aspects of India's regulatory liberalisation, such as the elimination of small-scale industry promotion considered by Martin et al. (2017), are less relevant here.

[10]Investigations into declines in both input and output tariffs generally find that the former have larger effects. Muendler (2004) is an exception, while Schor (2004) and Brandt et al. (2017) find the two to have similar magnitude.

productivity (Krishna & Mitra 1998, Sivadasan 2009, Topalova & Khandelwal 2010), and poverty and employment (Hasan et al. 2007, Topalova 2007, 2010, Edmonds et al. 2010); none to date focus on quality and quality-adjusted prices as the main outcomes of interest.

Empirical studies usually deal with quality in four main ways. Those focusing on other dependent variables can use various controls to remove quality effects; e.g. De Loecker et al. (2016) proxy for input quality variation using output prices, market shares and other observable product and firm characteristics, utilising the 'O-Ring' assumption that production of high-quality goods requires high-quality inputs (Kremer 1993). Some studies have direct measures of quality, (e.g. Atkin et al. 2017, Bai, Gazze & Wang 2019, Bai, Barwick, Cao & Li 2019, Chen & Juvenal 2016, 2018, 2019, Hansman et al. 2017, Macchiavello & Miquel-Florensa 2017, 2019), but to date these are only available for a limited range of products, such as coffee, wines and rugs, so are not suitable for the type of large-scale sectoral effects considered here.[11] To investigate quality across the whole manufacturing sector, this paper primarily uses the approach of Khandelwal (2010) and Khandelwal et al. (2013). This imposes specific preferences, thus assuming that quantity and price have a certain relationship as given by the resulting demand function, then backs out quality as quantity conditional on price. Intuitively, a variety in which a higher quantity is consumed at the same price is judged to have a higher quality. Lastly, some studies (e.g. Verhoogen 2008, Kugler & Verhoogen 2012) use reduced-form relationships between price and other observables to argue indirectly for a quality mechanism, to avoid making the assumptions required for an explicit measure of quality. This paper also draws upon this approach: the results for revenue and prices, which are directly observable, support the quality-upgrading mechanism, even in models without the CES assumption, as in Appendix 1.A.

[11] These studies build on earlier work by Sutton (2000, 2004), Goldberg & Verboven (2001), Macchiavello (2010), Crozet et al. (2012) and Bai (2016), again with direct measures only in narrow markets, from machine tools to watermelons.

1.3 Data

This paper uses manufacturing data for the financial years 1998-99 to 2013-14 from the Indian Annual Survey of Industries (ASI), which contains all manufacturing plants larger than 100 workers and a representative sample of plants that either a) use electricity and employ more than 10 workers, or b) do not use electricity and employ more than 20 workers.[12][13] In the main specifications I focus on census firms to allow an examination of the product-exit margin, then in secondary results I also examine heterogeneity across the full firm-size distribution. Martin et al. (2017) examine the quality of the ASI panel data, e.g. by checking for consistency in opening and closing stock variables reported by the same establishment in consecutive years. They conclude that the data quality is consistent across state, industry, time and establishment size, and that the panel identifier correctly tracks each establishment across the years surveyed. Each plant in the ASI is asked to detail the product type, production quantity and net sale value for each of its top ten products, but incomplete data reporting means that product-level data are only available for a subset of factories, as shown in Table 1.3.1. Product type is reported at the five-digit ASI Commodities Code (ASICC) level prior to 2010, or at the seven-digit National Product Classification for Manufacturing Sector (NPCMS) thereafter.

I use annual bilateral tariffs from the UNCTAD Trade Analysis Information System (TRAINS), and annual bilateral trade flows from UN Comtrade. I use publicly available concordances to map the ASICC codes onto NPCMS, the first five digits of which are identical to the UN's Central Product Classification (CPC). I then match these CPC codes to Harmonized System (HS) tariffs and

[12]In the case of multi-plant firms, the ASI data does not record which plants belong to which firms; this paper therefore conducts the analysis at the level of plants and uses the terms 'plant' and 'firm' interchangeably.

[13]The ASI financial year runs from April to March; for convenience I label values for the 1998-99 financial year as 1998, and so on, throughout this paper.

Table 1.3.1: Comparison of subsets of data used

Mean		**Factory-level**	**Product-level**	**Trade-level**
Number of products		3.8	3.7	3.5
Fixed assets (INR million)		571	595	590
Working capital (INR million)		162	167	165
No. of employees		335	327	337
Ownership (%)	Private	92.2	91.9	93.4
	Joint	5.1	5.4	4.7
	Public	2.7	2.7	1.9
Location (%)	Urban	57.8	56.8	58.2
	Rural	42.2	43.2	41.8
Observations		546,913	353,383	215,287

import/export flows. Each of these mappings is imperfect, resulting in the smaller subset in the third column of Table 1.3.1. However, the table shows that firms which report product-level data, and whose product codes can be matched to trade data, are not substantially different from those only reporting factory-level data.[14]

Identifying variation comes from the fall in the tariffs on China's imports and exports following its accession to the WTO in 2001. India-China bilateral trade grew dramatically after 2001, shown in Figure 1.3.1 Panel (a), particularly Indian imports from China. Chinese exports to the OECD also grew dramatically, dwarfing those from India, as shown in Panel (b). Growing Chinese import competition over the period was predominantly concentrated in manufactures rather than primary commodities, as shown in Figure 1.3.2, with particular clusters in electronics, textiles and chemicals. The districts that most heavily used these products as inputs are clustered around urban centres in the north, west and south, as shown in Figure 1.3.3. These districts also

[14]The exact number of observations used in each regression in Section 1.6 varies with the particular dependent variable under consideration, as in each case the largest available dataset is used. For instance, the De Loecker et al. (2016) algorithm for calculating markups and marginal costs is particularly demanding, so there are fewer observations with sufficiently complete data to be included in the markup and marginal cost regressions.

saw the largest increases in quality (measured using the procedure outlined in Section 1.5.3), as shown in Figure 1.3.4.[15]

Examples of supply-driven quality upgrading: Anecdotally, supply-driven quality upgrading occurred in medium and large firms across industries.[16] Consider two examples: a young electric-vehicle startup, with only 30 production workers, and one of India's largest pharmaceutical firms, with 11,500 employees and more than half a billion USD in revenue.[17] The former produces swappable batteries for electric mopeds, autorickshaws and municipal buses. Each autorickshaw battery contains 14 lithium-ion cells, imported from China, which have fallen substantially in weight while improving in efficiency – allowing the assembled batteries to be lighter with a longer charge. The latter firm specialises in production of insulin for diabetes treatment, and imports many active ingredients and raw materials from China, primarily acids, alkalis, reagents and other basic chemical compounds. Since 2001, the price-adjusted rate of defects (e.g. the frequency of impurities or air bubbles in the chemicals, within any given price band) has fallen substantially – increasing safety, i.e. quality in this context.[18]

[15]Since the ASI dataset with panel identifiers does not include district locations, unlike the annual cross-sectional dataset, locations are identified using the method of Martin et al. (2017) – specifically, matching firms across the two datasets on those variables which are common to both. Similarly, I use the mapping from Martin et al. (2017) to convert the (time-varying) district codes onto the 1998 district boundaries. Currently I only have access to a limited number of annual cross-sections, hence the limited timespan in the maps.

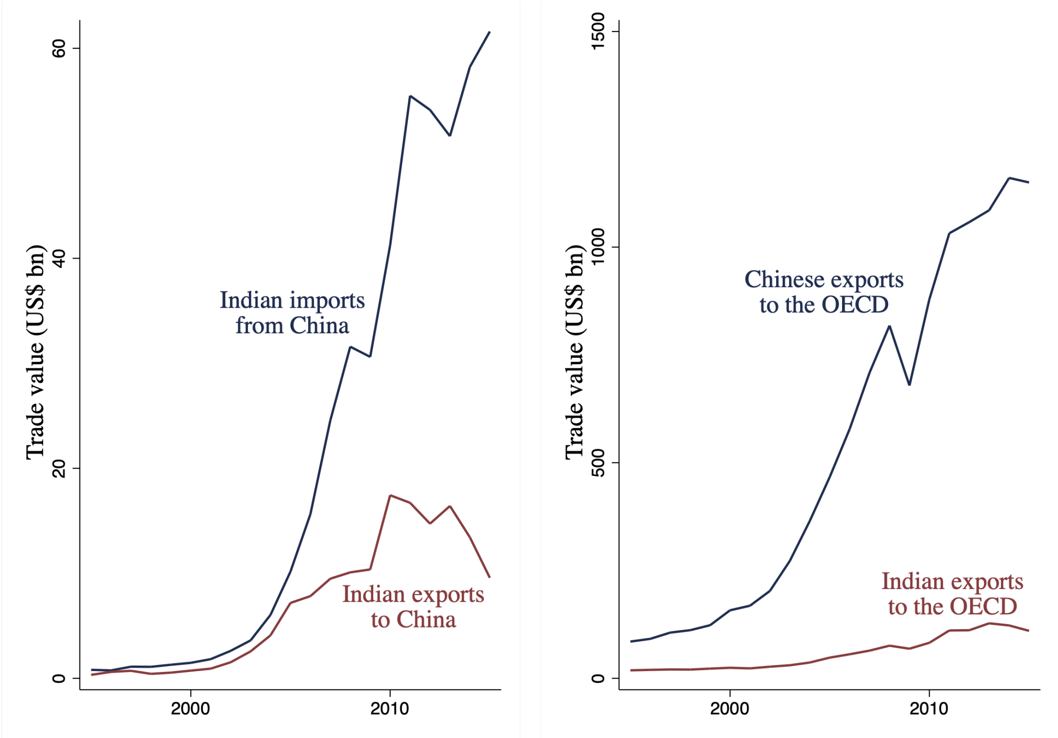
[16]The distribution of firms across sectors is shown in Table 1.B.7 in the Appendix, along with pictures from the two exemplar firms in Figures 1.B.1 and 1.B.2.

[17]Source: discussions with management in both companies, Bangalore and Delhi, January 2020.

[18]Indeed, Chinese pharmaceutical inputs were so successful that they would later raise concerns about supply chain risk during the Covid-19 pandemic: by 2020, one in every three pills taken by an American was a generic drug produced in India, which in turn purchased 66% of all ingredients from China (Zakaria 2020).

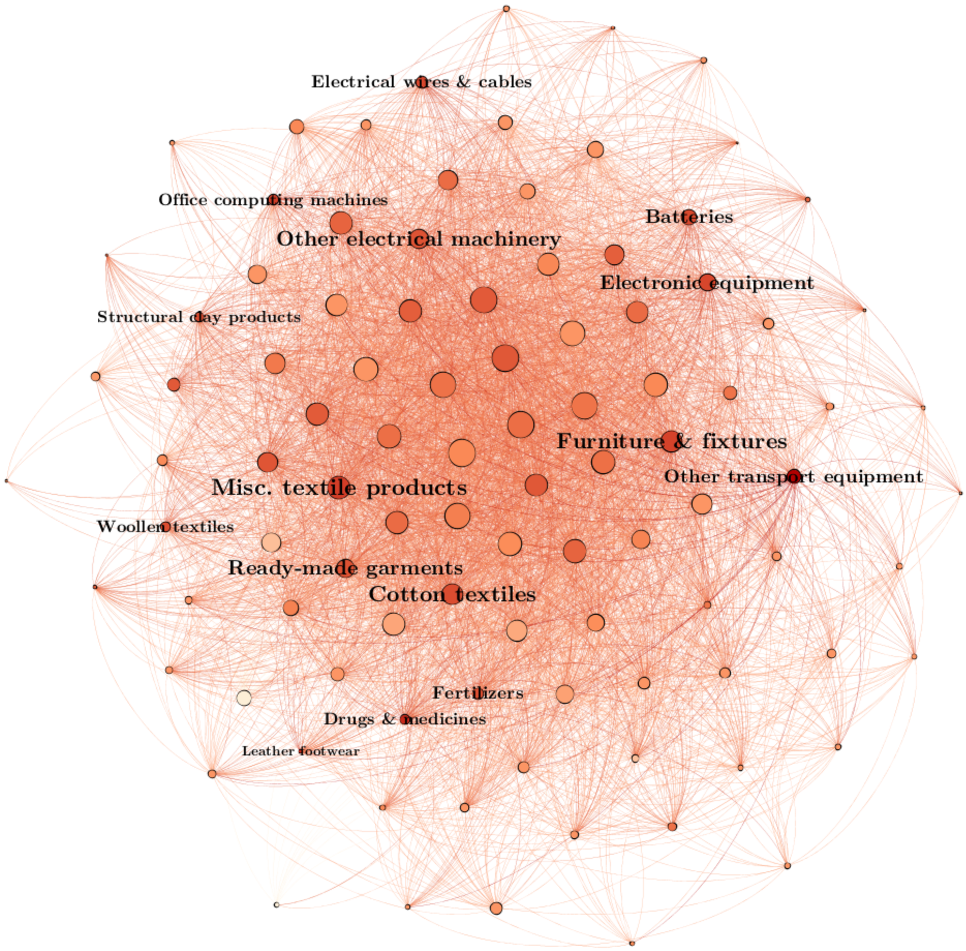
Figure 1.3.1: Goods trade between India, China and the OECD

(a) India & China bilateral trade (b) Indian & Chinese exports to OECD



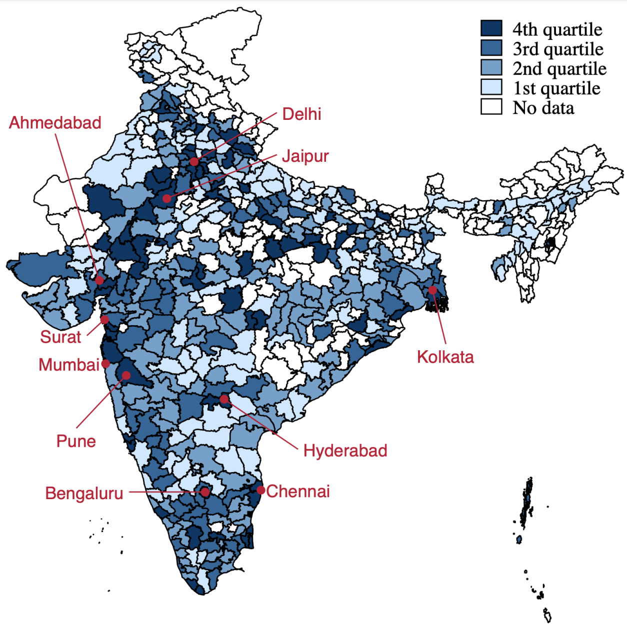
Notes: These graphs show total goods trade for four key relationships. Chinese imports into India have grown far faster than the reverse (highlighting channels (i)-(iii) from Figure 1.1.3 relative to channel (v)), while China has also greatly expanded its sales into the OECD market, where they compete with Indian exports (channel (iv)). *Source:* UN Comtrade.

Figure 1.3.2: Chinese import competition across the input-output network



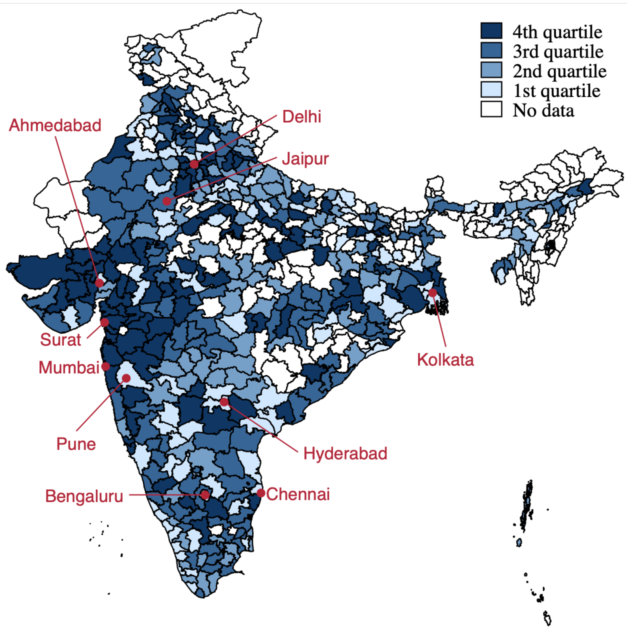
Notes: This graph shows the input-output connections between Indian primary and manufacturing industries in 1998. Nodes are scaled by number of downstream connections (out-degrees), and coloured darker the greater the increase in import competition between 1999 and 2013 – where import competition is measured by the share of Chinese imports in total Indian imports, as described in Section 1.5.2. Labels are shown for the top 15% of industries by increase in import competition.

Figure 1.3.3: Intensity of import competition among input industries by district



Notes: This map shows the change in the import competition faced by input industries between 2000 and 2008, by district, with darker shades reflecting larger increases. This measure is constructed as an average of the import competition faced by each input good, weighted by the value share of each in total input use, as in Section 1.5.2. The ten largest cities by population are labelled.

Figure 1.3.4: Quality upgrading by district



Notes: This map shows the change in the quality measure (described in Section 1.5.3) between 2000 and 2008, by district, with darker shades reflecting larger increases in quality. The ten largest cities by population are labelled.

1.4 Theory

This section outlines a simple model linking inputs and quality, then uses it to predict the impact of improved input supply, as well as the other four channels. The analysis focuses on firm behaviour in partial equilibrium for simplicity; it could also be extended to endogenise labour and input prices, but the results would not change qualitatively.

Consumers: Assume that consumers have constant elasticity of substitution (CES) preferences across horizontal varieties i. Define quality as the mean utility associated with consuming a product net of price (De Loecker et al. 2016), approximated by market share net of price following Berry (1994). Assume that vertical quality q_i enters multiplicatively with quantity x_i, such that a representative global consumer has utility:[19]

$$U = \left(\int_{i \in \Omega} (q_i x_i)^{\alpha} di \right)^{\frac{1}{\alpha}} \tag{1.4.1}$$

with elasticity of substitution $\sigma \equiv 1/(1-\alpha) > 1$ and $0 < \alpha < 1$. This gives demand $x_i = RP^{\sigma-1} q_i^{\sigma-1} p_i^{-\sigma}$ for product i, where R is total expenditure and $P = \left[\int_{i \in \Omega} \left(\frac{p_i}{q_i} \right)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$ is a quality-adjusted ideal price index.

Note that the CES assumption is not critical for the conclusions of this paper. I adopt it for simplicity of exposition and because it matches the Khandelwal et al. (2013) method of deriving a quality measure. If deviations from CES lead to constant over- or under-estimation of the *levels* of quality and quality-adjusted prices, then this will not impact the conclusions of this paper on the *direction* of the impact of Chinese components on quality. Furthermore, one common concern with CES preferences, that they imply constant markups, is not severe in this context: Figure 1.4.1 Panel (a) shows only a weak relation-

[19] This assumption of CES preferences with multiplicative quality is shared with other papers considering the interaction of inputs and quality, e.g. Kugler & Verhoogen (2012).

ship between quantity sold and markups, where markups are derived using the method of De Loecker et al. (2016), which requires only very general functional form assumptions. The major theoretical and empirical results of this paper are also robust to using linear demand, under which markups vary, as outlined in Appendix 1.A.

Firms: Let atomistic firms produce horizontally and vertically differentiated goods using (i) a numéraire labour input L with price $w = 1$, and (ii) raw materials with price m and quality q_m. Let firms draw two independent and identically distributed parameters taking values between zero and infinity: firm-wide ability ϕ_f and firm-product-specific expertise λ_{fi}. These determine marginal costs $c_{fi} = \phi_f \lambda_{fi} m$ and quality $q_{fi} = (\phi_f \lambda_{fi} q_m)^{\theta+1}$, where $\theta > -1$ is a parameter reflecting the potential for quality differentiation. This reduced-form cost and quality structure, following Manova & Yu (2017) and Baldwin & Harrigan (2011), is substantially simpler than models which endogenise the quality decision (e.g. Verhoogen 2008, Johnson 2012) while retaining the relevant qualitative predictions.[20] The assumed positive relationship between cost and quality is based on the previous literature (Verhoogen 2008, Kugler & Verhoogen 2012, Manova & Zhang 2012, Crozet et al. 2012, Iacovone & Javorcik 2010), and also matches the data, as shown in Figure 1.4.1 Panel (b) – where marginal costs are calculated using the method of De Loecker et al. (2016), which again requires few assumptions, and quality is calculated using the method of Khandelwal et al. (2013), described below.[21]

Assume also that firms must pay a fixed headquarter cost F_h to operate and a fixed management cost F_i for each active product line. Firms produce

[20] Following Manova & Yu (2017), the special case of $\theta = -1$ corresponds to the existing model of Bernard et al. (2010), while this case with linear demand (as outlined in Appendix 1.A), corresponds to Mayer et al. (2016).

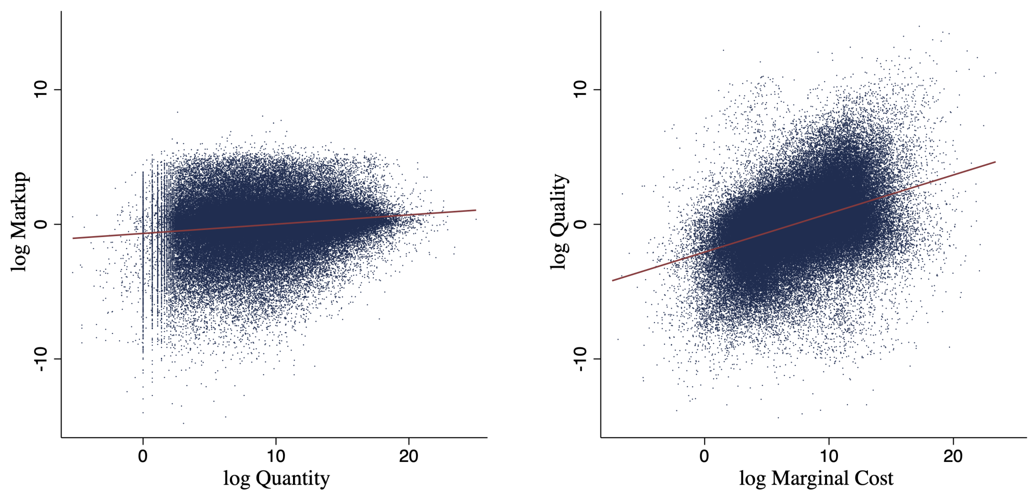
[21] This framework also abstracts from within-firm product interdependencies in production or consumption, e.g. 'flexible manufacturing' and 'cannibalisation' effects (Eckel & Neary 2010). This substantially simplifies the model, yet does not affect the product hierarchy in quality or production efficiency (Manova & Yu 2017) so does not change the main qualitative predictions.

those products for which they have sufficient ability and expertise to earn profits π_i greater than F_i, choosing prices and output to maximise $\pi_i(\phi_f, \lambda_{fi}) = p_i(\phi_f, \lambda_{fi})x_i(\phi_f, \lambda_{fi}) - x_i(\phi_f, \lambda_{fi})\phi_f\lambda_{fi}m - F_i$ subject to demand x_i, giving:

$$
\begin{aligned}
&\text{Price} && p_i(\phi_f, \lambda_{fi}) && = \frac{\phi_f\lambda_{fi}m}{\alpha} && (1.4.2)\\
&\text{QAP}^{22} && a_i(\phi_f, \lambda_{fi}) && = \alpha^{-1}q_m^{-(\theta+1)}m(\phi_f\lambda_{fi})^{-\theta} && (1.4.3)\\
&\text{Quantity} && x_i(\phi_f, \lambda_{fi}) && = \alpha^{\sigma}RP^{\sigma-1}q_m^{(\theta+1)(\sigma-1)}m^{-\sigma}(\phi_f\lambda_{fi})^{\theta(\sigma-1)-1} && (1.4.4)\\
&\text{Revenue} && r_i(\phi_f, \lambda_{fi}) && = \alpha^{\sigma-1}RP^{\sigma-1}q_m^{(\theta+1)(\sigma-1)}m^{1-\sigma}(\phi_f\lambda_{fi})^{\theta(\sigma-1)} && (1.4.5)\\
&\text{Mark-up} && \mu_i(\phi_f, \lambda_{fi}) && = \frac{1}{\alpha} && (1.4.6)\\
&\text{Profit} && \pi_i(\phi_f, \lambda_{fi}) && = \frac{r_i(\phi_f, \lambda_{fi})}{\sigma} - F_i && (1.4.7)
\end{aligned}
$$

Figure 1.4.1: Modelling assumptions and the data

(a) Quantity sold and markups (b) Marginal costs and quality



Notes: These graphs show the observed empirical relationship between important variables in the model. Markups and marginal costs are derived using the method of De Loecker et al. (2016), which requires only very general functional form assumptions. Quality is calculated using the method of Khandelwal et al. (2013), described in Section 1.5.3 below. Markups are almost constant across firm size, supporting the use of CES preferences, while there is a strong positive relationship between cost and quality, as assumed in the model.

[22] QAP = quality-adjusted prices, i.e. price over quality.

Cost- vs. quality-based competition: These results imply that firms engage in one of two types of competition, depending on the cost of producing higher quality goods. If $\theta \in (-1, 0)$, quality increases only slowly with costs, so firms with lower costs $\phi_f \lambda_{fi} m$ have higher revenue and profits – i.e. goods are relatively homogenous, so firms compete primarily on cost and price. In contrast, if $\theta > 0$ then quality increases faster than costs, so the higher prices received by firms with high ability ϕ_f and λ_{fi} outweigh the extra cost of producing high quality goods – i.e. when goods are relatively differentiated firms producing high quality goods have higher revenue and profits. This structure generates the testable propositions shown in Table 1.4.1.

Product scope: Firms produce those goods with $\pi_i > 0$, so the threshold expertise $\lambda^*(\phi_f)$ above which a firm will produce a good is defined by rearranging equation 1.4.7:

$$\lambda^*(\phi_f) = \phi_f^{-1} \left[\alpha^{1-\sigma} R^{-1} P^{1-\sigma} q_m^{(\theta+1)(1-\sigma)} m^{\sigma-1} \sigma F_i \right]^{\frac{1}{\theta(\sigma-1)}} \tag{1.4.8}$$

Thus the higher a firm's ability ϕ_f the lower the threshold and the larger the number of products N it will produce; noting the correlation between ability and costs c_i then gives Proposition 6 in Table 1.4.1.

Testing the framework: The regressions in Table 1.4.2 test each of the propositions of Table 1.4.1 in turn, and find strong correlational support for the key relationships predicted by the model. For instance, equations 1.4.2 and 1.4.5 imply that higher firm ability and expertise $\phi_f \lambda_{fi}$ correspond to (i) higher prices, and (ii) higher revenue the larger is θ. The first two columns in Table 1.4.2 test these predictions within and between firms, using the Rauch (1999) measure of product differentiability as a proxy for θ, and find strong support.[23] Columns (3)-(6) show similar tests for the remaining propositions,

[23]Specifically, I construct a 'homogenous' vs. 'differentiated' dummy as in Eckel et al.

Table 1.4.1: Observables for cost- vs. quality-based competition

Proposition		$\boldsymbol{\theta \in (-1, 0)}$		$\boldsymbol{\theta > 0}$
1. Price & Revenue across i within f:	$cov(p_i, r_i)$	< 0		> 0
2. Price & Revenue across f within i:	$cov(p_i, r_i)$	< 0		> 0
3. QAP & Revenue across i within f:	$cov(a_i, r_i)$	< 0	$\forall\, \theta > -1$	
4. QAP & Revenue across f within i:	$cov(a_i, r_i)$	< 0	$\forall\, \theta > -1$	
5. Quality & Cost across f within i:	$cov(q_i, c_i)$	> 0	$\forall\, \theta > -1$	
6. Scope & Cost across f within i:	$cov(N, c_i)$	> 0	$\forall\, \theta > -1$	

Notes: This table presents six propositions, derived from the model, which can be tested in the data. Each takes the form of a predicted covariance between two observable variables. In the first two cases, the expected relationship depends on the scope for quality differentiation, θ, unlike in the subsequent four. The propositions are tested in turn in Table 1.4.2.

considering quality-adjusted prices, marginal costs, quality and firm scope.[24] This evidence is entirely correlation-based, and is not intended to prove that the highly stylised framework presented above is a perfect description of the Indian manufacturing sector. The aim is merely to show that the model has empirical relevance, sufficient to serve as a useful guide for thinking about the impact of the China shock on Indian manufacturing, as outlined in the following section.

Modelling the five channels: I now use this framework to model the impact of China's WTO accession on Indian manufacturing firms, through each of the five channels in Figure 1.1.3. First, model the improved access to new components as a reduction in quality-adjusted input prices caused by an improvement in input quality relative to input prices. Specifically, model

(2015), using Rauch's 'liberal' classification with his 'reference-priced' and 'traded on an organised exchange' categories amalgamated into the 'homogenous' category.

[24] Note that the corresponding propositions in Table 1.4.1 do not depend on θ, so I do not include an interaction with the Rauch measure.

Table 1.4.2: Tests of cost- vs. quality-based competition

	(1) PriceDM	(2) Price	(3) QAP	(4) QAP	(5) Quality	(6) Scope
Revenue	0.0973***	0.102***	-0.168***	-0.367***		
	(14.34)	(52.47)	(-49.88)	(-1847.89)		
Revenue × Dfftd	0.0323***	0.0151***				
	(2.78)	(4.36)				
Marginal cost					0.496***	0.0331***
					(101.57)	(6.72)
Fixed effects	ft	it	ft	it	it	it
Observations	61553	629999	432705	628359	149671	149675

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Dfft* and *Scope*. *Dfftd* = dummy variable for differentiated product, using Rauch (1999) liberal classification. *PriceDM* = de-meaned prices, to allow cross-product comparisons on price; quality-adjusted prices are already standardised during construction. Firm-time FEs remove variation across firms in the relationship being considered, leaving within-firm across-product variation; product-time FEs remove variation across products, leaving only within-product variation across firms. Marginal costs are calculated using the method of De Loecker et al. (2016), which requires only very limited functional form assumptions, and quality is calculated using the method of Khandelwal et al. (2013), as described in section 1.5.3. All regressions including a *Dfft* interaction also include *Dfft* alone as a control. All relationships are also robust to clustering at the product level or firm-product level rather than the firm level.

increases in input quality Δq_m and input price Δm such that:

$$\frac{(\Delta q_m)^{\theta+1}}{\Delta m} > 1 \tag{1.4.9}$$

Under this condition, and when combined with equations 1.4.2 to 1.4.6, the firm responds by raising output quality more than prices, such that revenues rise even as quality-adjusted output prices fall. In other words, the improved access to components drives an increase in output quality, which is sufficiently attractive to consumers that revenues rise despite the downward pressure on demand from higher prices. The impact on the probability of product exit, Ex_i, then follows straightforwardly from profit in equation 1.4.7: higher product-wise revenue r_i raises the the probability of covering the product-specific fixed cost F_i, so lowers the probability that the firm drops the product. These impacts are shown in row (i) of Table 1.4.3, which summarises the predicted effects on variables which can be observed in or derived from the ASI data.[25]

The impacts on firms through the other remaining channels – shown in rows (ii) to (v) of Table 1.4.3 – follow similarly. Firstly, model direct import competition with Good 0 as an expansion in the set of varieties Ω available, which reduces residual demand, quantity and revenue for each good i via a fall in the price index term $P^{\sigma-1}$ in equations 1.4.4 and 1.4.5. Second, model import competition via outputs as a reduction in expenditure R – the 'consumers' of Good 0, namely those firms to which it is sold as a component, reduce their scale of input purchases in response to import competition for their product (Good 1 in Figure 1.1.3).[26] Third, model increased export competition in the same way as direct import competition – the forces are the same, merely occurring in export markets rather than the domestic market.[27] Lastly, model the increased demand from improved access to Chinese consumers as a rise in total consumer expenditure R, which raises quantity and revenue.

With these predictions in hand, I next turn back to the data and outline methods for testing them. Appendix 1.A derives equivalent predictions for the case of linear demand – all predictions remain qualitatively the same, except for some new price effects resulting from the concomitant variation in markups.

[25]The impact on output quantity x_i of improved access to inputs is not shown, as (a) it is not critical for the argument of this paper, and (b) the direction of the effect is not determined by the minimal assumption on the relative sizes of the input quality and input price rises specified in equation 1.4.9.

[26]I model these 'customer' firms as consumers for simplicity, to avoid requiring an extra layer of firms in the model. The model could be extended in this way, but the qualitative predictions in Table 1.4.3 would be unchanged.

[27]While the expected impacts on observables have the same pattern, these channels can still be identified independently as they are driven by variation in different bilateral tariffs and different import/export flows.

Table 1.4.3: Predicted impacts of the China shock on observables

			Channel	***Shock***	$\boldsymbol{c_i}$	$\boldsymbol{q_i}$	$\boldsymbol{p_i}$	$\boldsymbol{a_i}$	$\boldsymbol{x_i}$	$\boldsymbol{r_i}$	$\boldsymbol{Ex_i}$
Import	Competition:	(i)	via Inputs	$\uparrow q_m > \uparrow m$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\sim$	$\uparrow$	$\downarrow$
		(ii)	Direct	$\uparrow \Omega \rightarrow \downarrow P^{1-\sigma}$	–	–	–	–	$\downarrow$	$\downarrow$	$\uparrow$
		(iii)	via Outputs	$\downarrow R$	–	–	–	–	$\downarrow$	$\downarrow$	$\uparrow$
Exports:		(iv)	Competition	$\uparrow \Omega \rightarrow \downarrow P^{1-\sigma}$	–	–	–	–	$\downarrow$	$\downarrow$	$\uparrow$
		(v)	Opportunity	$\uparrow R$	–	–	–	–	$\uparrow$	$\uparrow$	$\downarrow$

Notes: This table summarises, for each channel, the predicted effects on variables which can be observed in or derived from the ASI data. From left to right, the outcome variables are: c_i – marginal cost; q_i – quality; p_i – price; a_i – quality-adjusted price; x_i – quantity; r_i – revenue; Ex_i – probability of dropping the product next period.

1.5 Empirics

In this section, I outline two complementary methods for identifying effects through the five channels, respectively using data on tariffs and imports/exports (hereafter ‘flows’). The tariff method exploits China’s 2001 accession to the WTO, while the flow method builds on Autor, Dorn & Hanson (2013) to isolate plausibly exogenous variation in Indian imports from, and exports to, China. Intuitively, fundamental changes in tariff regimes should have real effects in import and export flows, so I draw on both methods in the main results. I close the section with an overview of the outcome variables used in the analysis.

1.5.1 Tariff method

First, I measure each of the channels by changes in the relevant bilateral tariffs. The extent of direct import competition faced by Indian firms (channel (ii) in Figure 1.1.3) is directly related to the level of Indian tariffs on Chinese goods. Denote the annual tariffs on these flows from China into India as $CITariff_{it}$, where i is a five-digit CPC product code. I can then measure the input channel as a weighted average of the tariffs on each input used by firms:

$$InputTariff_{it} = \sum_k \alpha_{ik} \cdot CITariff_{kt} \tag{1.5.1}$$

where $\alpha_{ik} = \frac{Sales_{ki}}{\sum_k Sales_{ki}}$ is the value share of input k in total input use by producers of i, calculated using the 1998 input-output table compiled by MoSPI.[28] To avoid double-counting the direct import competition channel, I set α_{ii} to zero for all i. Similarly, I measure import competition effects through the output channel using a weighted average of the tariffs on those final goods that use a given input:

$$OutputTariff_{it} = \sum_k \gamma_{ik} \cdot CITariff_{kt} \tag{1.5.2}$$

where $\gamma_{ik} = \frac{Sales_{ik}}{\sum_k Sales_{ik} + FinalDemand_i}$ is the share of total usage of input i that is for production of k, again calculated using the 1998 input-output table and with γ_{ii} set to zero for all i.

I then measure export effects in a similar manner to direct import competition. Export competition (channel (iv) in Figure 1.1.3) relates to China's access to major export markets, and hence to the level of tariffs imposed by third countries on Chinese goods. I approximate this with $CRTariff_{it}$, the average of US, EU and Japanese tariffs on Chinese goods – destinations which together account for at least 25% of Chinese exports in every year in the sample. Lastly, I use the level of tariffs faced by Indian exports into China, $ICTariff_{it}$, to gauge the export opportunity channel.

The changes over time in the median levels of the three core tariff measures are shown in Figure 1.5.1 Panel (a).[29] Following China's accession to the WTO in 2001, there is a rapid reduction in bilateral tariffs between India and China,

[28] I use the 1998 input-output table in every year throughout the period to prevent potential endogeneity of the input-output structure with respect to tariff levels and/or trade flows. Results are also robust to using the less granular IOT from the OECD Structural Analysis Database.

[29] The input and output measures are not shown, as these are simply weighted combinations of 'China $\rightarrow$ India' variation.

then a subsequent stabilisation around the new lower level. This motivates a difference-in-differences approach, comparing products facing high and low initial tariff levels in the periods before and after China's accession to the WTO. Building on Lu & Yu (2015), I therefore run:

$$
\begin{aligned}
\ln y_{ift} = {} & \alpha_{(i)} \cdot Post2001_t \cdot \ln InputTariff_{i,2001} \\
& + \alpha_{(ii)} \cdot Post2001_t \cdot \ln CITariff_{i,2001} \\
& + \alpha_{(iii)} \cdot Post2001_t \cdot \ln OutputTariff_{i,2001} \\
& + \alpha_{(iv)} \cdot Post2001_t \cdot \ln CRTariff_{i,2001} \\
& + \alpha_{(v)} \cdot Post2001_t \cdot \ln ICTariff_{i,2001} \\
& + \boldsymbol{\alpha}'\mathbf{X}_{ft} + a_i + b_f + c_{st} + u_{ift}
\end{aligned}
\tag{1.5.3}
$$

where $Post2001_t$ is a dummy taking value one after 2001, and $\mathbf{X}_{ft}$ contains a vector of firm-time controls, specifically whether a plant is in a rural or urban area and whether it is privately owned, publicly owned or a mixture. Outcomes y_{ift} are at the firm-product-time level, and I include product, firm and state-time fixed effects.[30] Standard errors are clustered at the firm level to account for potential correlation in supply and demand shocks within firms over time.[31]

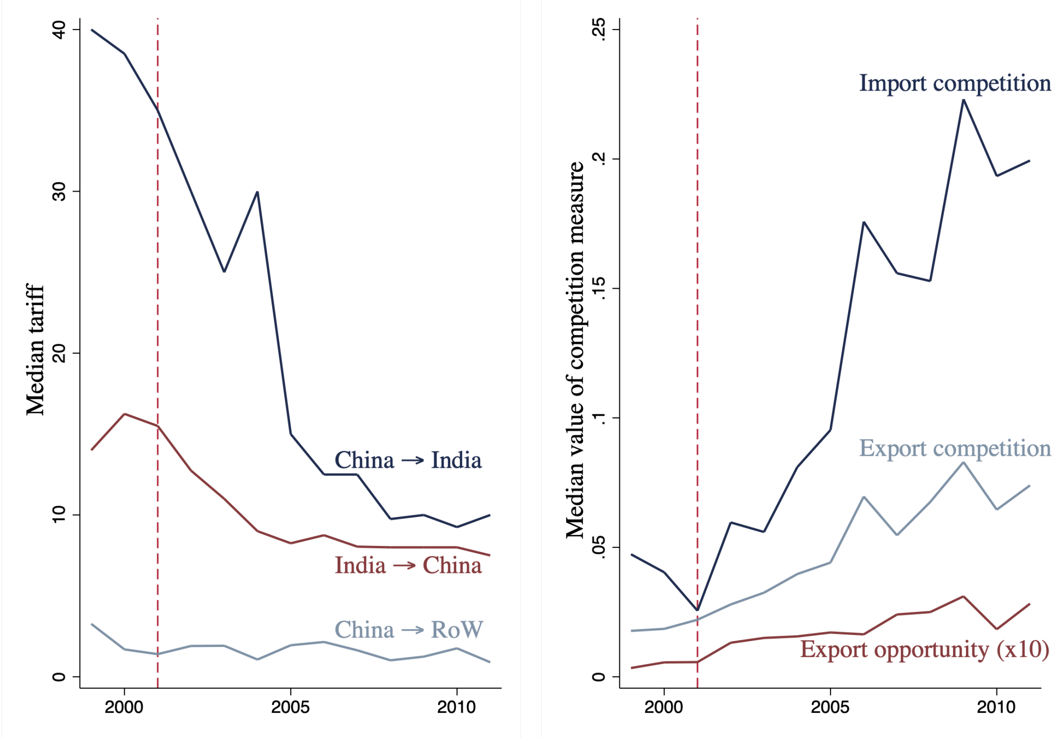
The estimated coefficient for each channel reflects the percentage impact on the outcome variable in the post-2001 period of having a tariff one percent higher prior to China's accession (and thus a larger fall in tariffs post-accession). I use only pre-accession tariffs, rather than annual tariffs, because the planned schedule of tariff reductions was released in 2002, so subsequent changes in tariffs were expected and hence could be pre-empted by producers (Lu & Yu 2015). In contrast, the exact timing of China's accession to the WTO was not clear until 2001, as many important issues were not resolved until mid-2001 –

[30] I describe the specific outcome variables used in Section 1.5.3 below.

[31] For instance, firms with strong management may be more likely to maintain high quality standards through an interval of slow growth. Results are also robust to clustering at the product-level.

Figure 1.5.1: Changes in tariffs and trade flow measures, by channel

(a) Tariffs (b) Flows



Notes: These graphs show the trends in the median values of the tariff and flow measures, as described in Sections 1.5.1 & 1.5.2 respectively. As noted in the text, the two other channels (input and output effects, i.e. (i) and (iii) in Figure 1.1.3) are simply weighted averages of the direct import competition channel (shown in dark blue in both graphs). The values of the export opportunity channel in Panel (b) are magnified by a factor of ten, so that the trend is visible despite the very low share of Indian goods in total Chinese imports.

for instance, Mexico held off on agreeing terms until September 2001, with the final accession agreement then following two months later (Lu & Yu 2015).[32]

The key identifying assumption is that outcomes in firms facing large falls in tariffs after 2001 would have followed the same path as in firms facing small falls, if there had been no trade liberalisation in 2001, conditional on the controls.

[32]Nonetheless, the results are robust to using a specification based on annual tariffs, as in Brandt et al. (2017).

Specifically, I require:[33]

$$
\begin{aligned}
E\big[u_{ift} | & Post2001_t \cdot \ln InputTariff_{i,2001}, \\
& Post2001_t \cdot \ln CITariff_{i,2001}, \\
& Post2001_t \cdot \ln OutputTariff_{i,2001}, \\
& Post2001_t \cdot \ln CRTariff_{i,2001}, \\
& Post2001_t \cdot \ln ICTariff_{i,2001}, \\
& \mathbf{X}_{ft}, a_i, b_f, c_{st}\big] \\
= E\big[u_{ift} | & \mathbf{X}_{ft}, a_i, b_f, c_{st}\big]
\end{aligned}
$$

The first major endogeneity concern is reverse causality. For instance, Indian tariffs could be lowered only for those industries where Chinese imports are least threatening, namely those with strong domestic sales or quality growth. The second major concern is misattribution, i.e. the existence of a third set of factors correlated with tariff cuts which also affect firm outcomes. Political influence is an archetypal case (e.g. Grossman & Helpman 1994); industries with lobbying power could ensure protective tariffs, along with preferential access to subsidies or other support for their firms.

Both these concerns are ameliorated by inspecting the tariff reductions. Figure 1.5.2 plots baseline tariffs, and the subsequent changes, for each of the channels. Consider initially the top four graphs, accounting for channels (i)-(iii) and (v). While there is wide dispersion in tariff levels in 1996, the subsequent changes align very closely with the grey reference line, with gradient -1. In other words, tariffs that are one percentage point higher in 1996 tend to fall by one percentage point more by 2011: tariffs converge tightly onto the low and

[33] Note with Lu & Yu (2015) that exogeneity of the control variables is not necessary for identification of the coefficients of interest; i.e. I do not require

$$E\big[u_{ift} | \mathbf{X}_{ft}, a_i, b_f, c_{st}\big] = 0$$

which would allow a causal interpretation of the coefficients on the control variables also (Stock & Watson 2014).

relatively uniform WTO rates.[34] The initial phase of this convergence is clear in the righthand graphs, which show less horizontal dispersion in 2001 tariff levels (as well as remaining close to the 1:1 perfect convergence line). By the end of the period there is little remaining variation, so there is limited scope for tariffs to have been selectively lowered for some industries relative to others.

With regard to misattribution, this tight convergence implies that there cannot be factors which caused both a large fall in tariffs and better firm performance, unless they were also present before 1996. Given that my fixed effects account for firm and industry characteristics, it is unlikely that such factors affect my results. Nonetheless, in robustness checks in Appendix 1.B.2, I take the additional precaution of controlling explicitly for various possible confounding factors, such as lobbying efforts or industrial strategy towards infant industries.

A similar argument alleviates reverse causality concerns. For strong firm performance in the 2000s to cause a larger fall in some tariffs, it would effectively have to determine tariffs as far back as 1996, given that subsequent changes are driven predominantly by convergence. This is implausible given the highly unpredictable nature of the rapid economic changes unleashed after China's WTO accession.[35]

Turning to the bottom two graphs of Figure 1.5.2, reflecting export competition, the picture is very different. There is substantially less variation in tariffs, and no clear fall in tariffs after 2001 – tariffs are already at a fairly uniform low rate. This reflects the fact that China's main trade partners negotiated

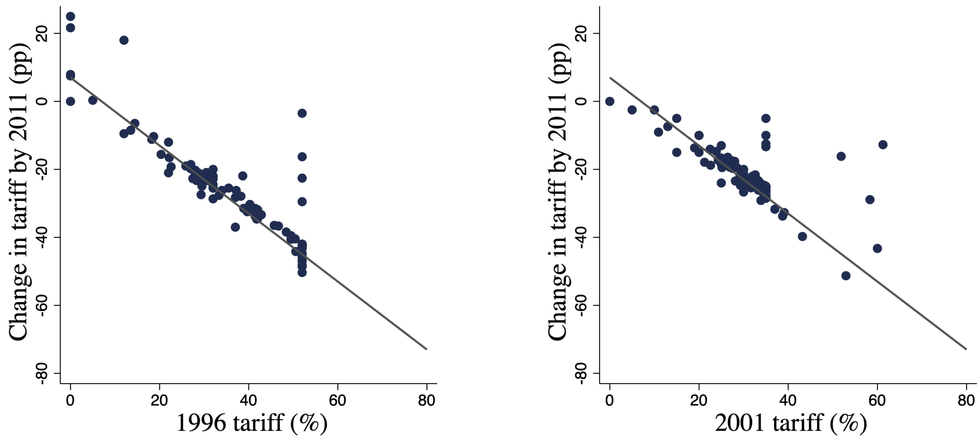
[34] I use 2011 as the end year because it is the last year in my sample for which TRAINS tariff data is available for all three channels. The patterns remain very similar when using different endpoints across 2012-2014, where available.

[35] For instance, the dramatic expansion in Chinese import competition in India was not widely predicted even by the early 2000s. One study in the *Economic and Political Weekly* concluded: "Bilateral trade ... is quite limited, with India's exports [to China] constituting about 2 per cent of its exports and India's imports from China constituting about 3 per cent of total imports in 2000-01. ... Thus, given the limited bilateral trade with China, it is unlikely there will be a significant impact of China's entry into WTO on India's imports" (Agrawal & Sahoo 2003). By 2010, Chinese products made up more than 25% of total Indian imports.

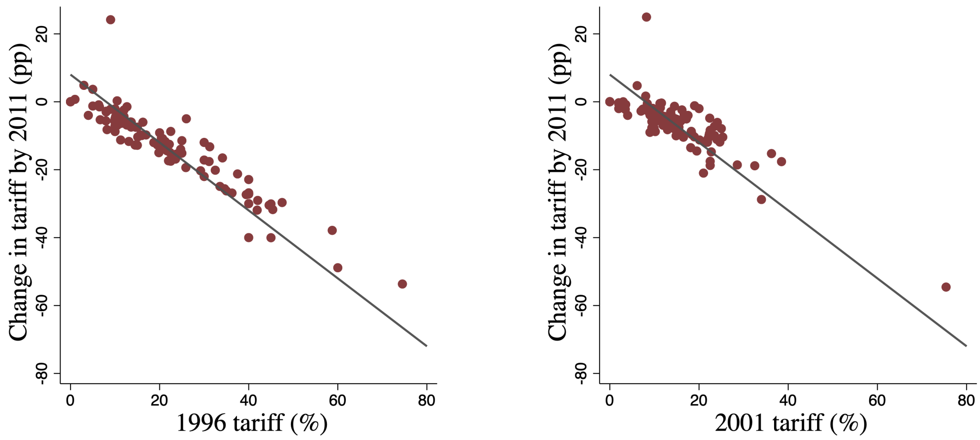
lower bilateral tariffs with China *before* 2001, whether on a 'Permanent Normal Trade Relations' basis (as in the EU from the 1980s), or in the form of annual renewals of NTR status (as in the USA until 2001, when China's new PNTR status became effective on its accession to the WTO). The key change in 2001 was thus the reduction in trade uncertainty, which allowed increased investment in production of exports, rather than a change in tariff levels *per se* (Pierce & Schott 2016).

To check that this export competition channel is not affecting my results on the impact of Chinese components, and to address any remaining endogeneity concerns, I therefore complement the tariff regressions with an alternative identification method. This uses import/export flows, building on Autor et al. (2013), and so picks up variation through all of the channels, as seen in Figure 1.5.1 Panel (b). I outline this method in the next section.

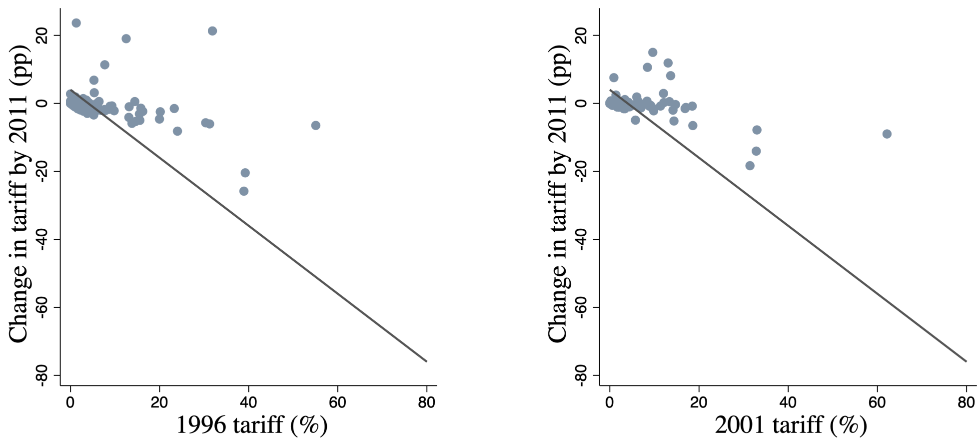
Figure 1.5.2: Inspecting the tariff changes



(i,ii,iii) Import competition



(v) Export opportunity



(iv) Export competition

Notes: These graphs plot the change in tariffs by 2011 against their initial levels in 1996 and 2001, for three-digit CPC industries. The grey reference line has a gradient of -1 for comparison.

1.5.2 Flow method

Intuitively, if the tariff changes outlined above have real effects, then these will be directly observable in import and export flows. I therefore construct analogous measures of the five channels using data on trade flows. Direct import competition can be measured, following Schott (2002), by China's share of total Indian imports, i.e.

$$CIFlow_{it} = \frac{M^{China}_{India,it}}{M^{World}_{India,it}} \tag{1.5.4}$$

where $M^{China}_{India,it}$ is Indian imports from China of product i in year t, and likewise $M^{World}_{India,it}$ is total Indian imports of i from the World.[36] The input channel is then a weighted average of this import competition, across inputs k used in production of good i, as in equation 1.5.1 in the previous section:

$$InputFlow_{it} = \sum_k \alpha_{ik} \cdot \frac{M^{China}_{India,it}}{M^{World}_{India,it}} \tag{1.5.5}$$

Intuitively, this reflects the extent to which Chinese components are entering the markets for a good's inputs. The third channel, output effects of input competition, follows in the same way:

$$OutputFlow_{it} = \sum_k \gamma_{ik} \cdot \frac{M^{China}_{India,it}}{M^{World}_{India,it}} \tag{1.5.6}$$

Similar to equation 1.5.2 in the previous section, this reflects the extent to which the products k using good i as an input are facing import competition from China (which could then spill upstream to reduce demand for good i itself).

I measure the final two channels analogously. My export competition

[36] I follow Schott (2002), Bernard & Jensen (2002) and Barua (2016) in using this value share measure of import competition rather than the import penetration rate (i.e. imports over domestic production plus imports) or import price measures due to the lack of availability of comprehensive product-level domestic production data or import price time series.

measure is essentially the same as the import competition variable, except applied to OECD export destinations rather than the Indian market:

$$CRFlow_{it} = \frac{M^{China}_{OECD,it}}{M^{World}_{OECD,it}} \tag{1.5.7}$$

In other words, I use China's share of total OECD imports to proxy for Chinese competitive pressure on India's export markets.[37] Lastly, I measure the export opportunity channel by the inverse of the import competition channel, i.e. by India's share in total Chinese imports:

$$ICFlow_{it} = \frac{M^{India}_{China,it}}{M^{World}_{China,it}} \tag{1.5.8}$$

Thus all five variables have the same structure – specifically, a share (or weighted average of shares) of the total imports of some country or group of countries.

The trends in the underlying variables are shown in Panel (b) of Figure 1.5.1. Import competition, export competition and export opportunity all rise substantially over the period, and particularly after 2001. In the graph, I multiply the values of the latter by ten so that the trend is visible – the export opportunity channel is by far the smallest of the three, reflecting the very small share of Indian products in China's imports.[38]

The next step is to identify exogenous variation in these measures, so I can examine their effects on firm outcomes. All except $CRFlow_{it}$ include either Indian imports or Indian exports, and so may reflect not just the exogenous supply-side shock from China's integration but also Indian supply-side or demand-side shocks. I therefore construct instrumental variables in the manner

[37] I use exports to the OECD, rather than to the whole world, to avoid any overlap between the set of export markets considered and the countries used in the instrument discussed below. Exports to the OECD are a large share of India's total exports; e.g. 22.6% of total exports in 1999 were to the USA alone, while the largest non-OECD market was Hong Kong at 6.1%.

[38] As well as having a substantial trade deficit with China, shown in Figure 1.3.1, total Chinese imports are far larger than total Indian imports (e.g. \$460 billion vs. \$93 billion in 2004).

of Autor et al. (2013), replacing the India-related terms with alternatives constructed from a basket C of comparable Southeast Asian countries (Bangladesh, Indonesia, Malaysia, Philippines, Thailand).[39] Specifically, I construct:

$$CIFlow_{it}^{IV} = \frac{\sum_{c \in C} M_{c,it}^{China}}{\sum_{c \in C} M_{c,it}^{World}} \tag{1.5.9}$$

$$InputFlow_{it}^{IV} = \sum_k \alpha_{ik} \cdot \left[\frac{\sum_{c \in C} M_{c,kt}^{China}}{\sum_{c \in C} M_{c,kt}^{World}} \right] \tag{1.5.10}$$

$$OutputFlow_{it}^{IV} = \sum_k \gamma_{ik} \cdot \left[\frac{\sum_{c \in C} M_{c,kt}^{China}}{\sum_{c \in C} M_{c,kt}^{World}} \right] \tag{1.5.11}$$

$$ICFlow_{it}^{IV} = \frac{\sum_{c \in C} M_{China,it}^{c}}{M_{China,it}^{World}} \tag{1.5.12}$$

In short, I instrument for Chinese import competition in India with import competition in the comparison countries, and I instrument for Indian export opportunities in China with the comparison countries' export opportunities in China.

I use these measures to run an alternative, complementary specification, which can exploit annual variation because China's WTO accession is no longer required for identification. Specifically, I run:

$$\begin{aligned} \ln y_{ift} = {} & \alpha_{(i)} \cdot \ln InputFlow_{it} \\ & + \alpha_{(ii)} \cdot \ln CIFlow_{it} \\ & + \alpha_{(iii)} \cdot \ln OutputFlow_{it} \\ & + \alpha_{(iv)} \cdot \ln CRFlow_{it} \\ & + \alpha_{(v)} \cdot \ln ICFlow_{it} \\ & + \boldsymbol{\alpha}'\mathbf{X}_{ft} + a_i + b_f + c_{st} + u_{ift} \end{aligned} \tag{1.5.13}$$

where $InputFlow_{it}^{IV}$, $CIFlow_{it}^{IV}$, $OutputFlow_{it}^{IV}$ and $ICFlow_{it}^{IV}$ are used to

[39] I choose these economies because they all (a) have a similar degree of diversification to India, and/or similar GDP per capita to India at the start of the period studied, and (b) have Comtrade data available throughout the period.

instrument for channels (i)-(iii) and (v) respectively.

1.5.3 Outcome variables

As modelled above, improved access to components affects several firm-product-level outcomes. I can observe any impacts on prices, quantities and sales directly in the ASI data. Building on Khandelwal et al. (2013), I can also use these to derive a measure of quality: intuitively, for a given utility function, if one product sells more units than another at the same price, this suggests that it is higher quality. Begin with the utility function previously assumed in equation 1.4.1 in the theory section.[40] As noted above, demand x_i for product i is:

$$x_i = RP^{\sigma-1} q_i^{\sigma-1} p_i^{-\sigma} \tag{1.5.14}$$

for expenditure R and price index P, where q_i is quality. Taking logs and moving prices to the left-hand side gives:

$$\ln x_i + \sigma \ln p_i = \ln R + (\sigma - 1) \ln P + (\sigma - 1) \ln q_i \tag{1.5.15}$$

Noting that quantity, quality and price vary with firm f over time t, and that expenditure R and price level P vary over time, this can be re-written as:

$$\begin{aligned} \ln x_{ift} + \sigma \ln p_{ift} &= \ln R_t + (\sigma - 1) \ln P_t + (\sigma - 1) \ln q_{ift} \\ &= \alpha_t + u_{ift} \end{aligned} \tag{1.5.16}$$

[40]Note that the narrow assumptions of a single representative consumer and a single vertical dimension of quality can also be justified in a model with many individual consumers making discrete choices, as shown by Anderson et al. (1992): quality is interpreted as a component of product attributes that all consumers value, assuming only that the residuals of consumers' heterogeneous valuations have mean zero.

Adding an extra product fixed effect to account for differing units of price or quantity across products gives:

$$\ln x_{ift} + \sigma \ln p_{ift} = \alpha_t + \alpha_i + u_{ift} \tag{1.5.17}$$

Thus for a given value of σ, quality $\ln \hat{q}_{ift} = \frac{\hat{u}_{ift}}{\sigma - 1}$ can be estimated as the residual in a regression of observable prices and quantities on a time and a product fixed effect.[41] Prices are effectively partialled out, leaving 'quantity conditional on price', i.e. quality. Quality-adjusted prices are then given by:

$$\ln \widehat{a}_{ift} = \ln p_{ift} - \ln \hat{q}_{ift} \tag{1.5.18}$$

Of the seven outcome variables in Table 1.4.3, this leaves just marginal costs and revenue to be explained. I estimate the former using the algorithm of De Loecker et al. (2016), which first backs out markups from observable firm-product variables, then combines these with observed prices to compute marginal costs. The procedure allows for very flexible functional forms, so does not clash with the assumptions required for the Khandelwal et al. (2013) quality-estimation method.

Finally, I measure product exit by observing whether a firm-product appears in the next year of the sample. Specifically, I follow Iacovone et al. (2013) in defining:

$$Ex_{ift} = \begin{cases} 1 & \text{in the last year that firm-product } if \text{ is observed in the sample} \\ 0 & \text{otherwise} \end{cases}$$

where the last year of the sample is dropped, as in that year it is not possible to measure Ex_{ift}. I focus on firms in the ASI census panel to allow exit to be measured, but also use the representative survey sample in robustness checks.[42]

[41] This paper uses $\sigma = 3.7$, the median estimated elasticity of substitution for India calculated by Broda, Greenfield & Weinstein (2006), as discussed in Section 1.B.1.

[42] I investigate the impact of selection out of the census panel on firm-product exit in

I do not log Ex_{ift} when including it in specifications 1.5.3 and 1.5.13 above, since it has mostly zero values. Thus each estimated α is the coefficient in a linear probability model – representing the marginal change in the probability of product exit resulting from the relevant tariffs being one percent higher in 2001.

1.6 Results: Baseline

My baseline specification uses the tariff method to investigate each of the relationships in row (i) of Table 1.4.3 – i.e. to test the theoretical predictions of the impact of improved access to Chinese components. Table 1.6.1 Panel A shows the impact, through the input channel, on marginal costs, quality, price, quality-adjusted prices, quantity, revenue and the probability of dropping a product. The specification follows equation 1.5.3, controlling for the other four channels, rural/urban location, public/private ownership, and product, firm and state-time fixed effects. Each coefficient represents the percentage impact in the post-2001 period of input tariffs being one percent higher in 2001 – and so falling by approximately that much more subsequently, as seen in Section 1.5.1.[43]

The results match the predictions of the model. Consistent with higher quality inputs, there is a significant rise in output quality. Consistent with the assumption in equation 1.4.9 that the rise in input quality outweighs the rise in their raw prices, quality-adjusted prices fall even as marginal costs and prices rise. Higher quality at lower quality-adjusted prices drives a rise in revenue, which increases product-wise profit and so reduces the probability of a product being dropped.[44]

Appendix 1.B.5, and find no material impact on the results.

[43]The exit variable has a slightly different interpretation, as it is binary and so not logged: each coefficient represents the *marginal* change in the probability of dropping the product, as described in Section 1.5.3.

[44]The minimal assumptions underlying the predictions in Table 1.4.3 do not imply a specific impact on quantity, and indeed I observe no significant effects in the quantity

Taken together, these results suggest that both firms and consumers benefit from improved access to Chinese components. Firms increase revenue and reduce product dropping – which is correlated with profit in a wide class of models, including the CES and linear demand setups used in this paper. Consumers experience a net gain *qua consumers*, i.e. in their role as goods-consuming agents: they receive higher quality products at lower quality-adjusted prices. The question of whether consumers gain in an 'all things considered' sense is beyond the scope of this paper and would require further assumptions on the structure of the labour market and the distribution of consumers' consumption bundles. Here I simply note (i) the robust finding that firms producing higher quality goods pay higher wages to their workers (e.g. Verhoogen 2008, Kugler & Verhoogen 2012), which suggests that consumers could also benefit from quality upgrading in their roles as workers, and (ii) the link between quality upgrading and development, which suggests that quality upgrading may also benefit them through long-run growth.[45]

These results relate closely to the work of Goldberg, Khandelwal, Pavcnik & Topalova (2010*a*), who consider the liberalisation of Indian tariffs in the early 1990s. They find that access to new intermediate inputs causes a substantial expansion in the range of goods produced by manufacturers, a 'variety in, variety out' result echoed by my 'quality in, quality out' mechanism. However, in the ASI data less than 20% of goods produced after 2001 are new products (at the seven-digit level), and the quality-upgrading effect holds strongly even when excluding new products from the sample, as in Table 1.6.1 Panel B. By the end of the 1990s Indian manufacturing had liberalised substantially, as documented extensively by Goldberg and coauthors. My findings therefore suggest that many of the initial extensive margin gains from liberalisation had played out by 2001, such that the primary benefit to India of China's

regressions.

[45]On (ii), see, for instance, Grossman & Helpman (1991), Kremer (1993), Hausmann & Rodrik (2003), Rodrik (2006), Hidalgo et al. (2007), Matsuyama (2008), Khandelwal (2010), Lane (2019), Verhoogen (2020).

Table 1.6.1: Input effects of China's WTO accession

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff$	0.298**	0.238***	0.194***	-0.0421***	-0.0821	0.0704**	-0.0180*
	(2.57)	(4.27)	(3.72)	(-2.84)	(-1.32)	(2.13)	(-1.95)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34408	165011	165579	165011	165017	175799	161072
Panel B: Intensive Margin Only							
$InputTariff$	0.310***	0.243***	0.199***	-0.0405***	-0.0928	0.0671**	-0.0163*
	(2.62)	(4.35)	(3.80)	(-2.72)	(-1.48)	(2.06)	(-1.73)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28460	137780	138229	137780	137785	147843	139739

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 1.5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (import competition, export opportunity, export competition and upstream spillovers). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Section 1.5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs.

WTO accession came through the intensive margin, specifically through quality upgrading of existing products.

Robustness: Table 1.6.2 tests the robustness of this 'supply-driven quality upgrading' story. The first two columns add two-digit sector-time fixed effects to account for broad industry trends, which would affect the above conclusions if, for instance, 2001 tariffs were systematically higher in sectors with faster average growth in quality. The next two columns use the alternative identification method from Autor, Dorn & Hanson (2013), as described in Section 1.5.2. Lastly, columns five and six test for upgrading using an alternative measure, firm-level total factor productivity (TFP), calculated using the method of Ackerberg et al. (2015).[46] In each case, I find significant positive effects, through the input channel, on quality, price or TFP. In addition, note that even if I did not make the CES assumption that allows me to derive a measure of quality and quality-adjusted prices, the other effects in Table 1.6.1 – on marginal costs (derived from a far weaker set of assumptions following De Loecker et al. (2016)) and on price, revenue and exit (all directly observed) – would all support a quality-upgrading interpretation, for instance in a model with linear demand as in Appendix 1.A.

Further robustness checks are provided in Appendices 1.B.2 to 1.B.6. In turn, these control explicitly for potential confounding factors, use annual variation in tariffs, assess the impact of other recent reforms in India, check for selection effects caused by firms dropping out of the ASI census panel, and control for potential district-level trends. Finally, in Appendix 1.B.7 I investigate whether the tendency of related industries to locate close to one another, rather than input-output relationships *per se*, could be driving the results. In all cases I confirm that the supply-driven quality-upgrading result is robust.

Comparing the channels: Turning to rows (ii)-(v) of Table 1.4.3, the model predicts that all five channels will affect the revenue and product exit margins. Table 1.6.3 shows the corresponding regression results. The revenue variable is in log form, so each coefficient represents the percentage impact of tariffs in the relevant channel being one percent higher in 2001. The exit variable is binary, so each coefficient is that of a linear probability model – i.e. each represents the marginal change in the probability of product exit resulting from the relevant tariffs being one percent higher in 2001.

The relationships are generally in the directions predicted by the model,

[46] Such measures of productivity are subject to well-known biases (see, for instance, Foster et al. 2008, De Loecker & Goldberg 2014, Ackerberg et al. 2015, Orr 2019, Verhoogen 2020), but this evidence from a different measure is at a minimum indicative of an underlying change in fundamentals.

Table 1.6.2: Input effects of China's WTO accession – robustness checks

	Product-level				Firm-level	
	Quality	Price	Quality	Price	TFP	TFP
InputTariff – DiD	0.278**	0.297**				
	(2.02)	(2.22)				
InputFlow – ADH			0.684***	0.577**		
			(2.61)	(2.29)		
InputTariff – DiD, firm-level					0.107***	
					(18.67)	
InputFlow – ADH, firm-level						0.147***
						(28.78)
FEs	i,f,jt,st	i,f,jt,st	i,f,st	i,f,st	f,st	f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat			19.51	19.56		127.5
N	164,996	165,564	267,150	268,079	68,231	95,779

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs. DiD = difference-in-differences specification using 2001 tariff levels, as in Section 1.5.1. ADH = Autor, Dorn & Hanson (2013) specification using plausibly exogenous import and export flows, as in Section 1.5.2. All regressions include firm, product (for product-level regressions) and state-year FEs and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Models 1 and 2 also add sector-year FEs. Quality is calculated using the procedure of Khandelwal et al. (2013), and firm-level TFP is calculated using the procedure of Ackerberg et al. (2015).

with the input channel the only one that is significant on both variables, and indeed with relatively large magnitudes. As in the previous table, a 10% higher average tariff on inputs in 2001, and hence a larger fall in tariffs post-accession, raises average product revenue in the post-accession period by 0.7% and lowers the probability of dropping the product by 0.18. While the model above only made qualitative predictions, rather than speaking to magnitudes, these results are consistent with the expectation from Figure 1.1.2 that China's expansion in the 2000s had particularly strong effects on India through the input channel.

Heterogeneity by firm size: Table 1.6.4 examines the heterogeneity of the quality-upgrading effect across the firm size distribution. I repeat the main regressions of Table 1.6.1 within four bins, each containing roughly a quarter

Table 1.6.3: Impact of China's WTO accession on Indian firms, by channel

	Revenue	Exit
(i) *InputTariff*	0.0704**	-0.0180*
	(2.13)	(-1.95)
(ii) *CITariff*	0.198**	0.0106
	(2.29)	(0.49)
(iii) *OutputTariff*	-0.000777	-0.00526*
	(-0.07)	(-1.78)
(iv) *CRTariff*	-0.0435***	0.00650
	(-2.92)	(1.54)
(v) *ICTariff*	-0.0187	-0.00728
	(-0.42)	(-0.67)
FEs	i,f,st	i,f,st
Controls	Yes	Yes
N	175799	161072

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 1.5.3. All regressions include firm, product and state-year FEs, and control for rural/urban location and public/private ownership. Each channel is measured as described in Section 1.5.1 – i.e. each coefficient gives the percentage (*Revenue*) or marginal (*Exit*) change in the average value of the outcome variable in the post-accession period resulting from a 1% higher pre-accession tariff on the relevant trade vector.

of firms.[47] The quality-upgrading effect appears in all but the smallest firms. One possible explanation is that there is a fixed cost to reconfiguring supply to exploit new input opportunities, such that only larger and more productive firms are able to access new higher-quality inputs. An alternative but similar explanation relies on positive assortative matching, whereby larger and more productive firms have better access to the higher-quality input producers. In each case, quality upgrading in large firms could segment the market such that small firms compete on cost to sell lower-quality goods, or could reduce small firms' access to complementary inputs (e.g. skilled labour) which in turn reduces their quality and price. I leave full exploration of these possible

[47]Non-census firms are now included, sacrificing the ability to examine the exit margin in favour of a representative sample of smaller firms.

mechanisms to future research.

Table 1.6.4: Heterogenous effects by number of employees

	0 – 20		20 – 100		100 – 350		350 +	
	Quality	Price	Quality	Price	Quality	Price	Quality	Price
Panel A: Full Sample								
$InputTariff$	-0.293*	-0.248*	0.404**	0.361**	0.257***	0.213***	0.214**	0.194**
	(-1.82)	(-1.65)	(2.25)	(2.23)	(2.88)	(2.81)	(2.16)	(2.16)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37117	37246	36966	37112	45528	45712	42248	42390
Panel B: Intensive Margin Only								
$InputTariff$	-0.0545	0.0265	0.303**	0.308**	0.292***	0.250***	0.231**	0.206**
	(-0.34)	(0.17)	(2.14)	(2.34)	(3.35)	(3.35)	(2.35)	(2.31)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13123	13157	18556	18610	37928	38060	36570	36698

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality is calculated using the procedure of Khandelwal et al. (2013). The input channel is measured as described in Section 1.5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs. The number of observations on quality is slightly lower within each bin because some firms which report price are missing other variables required to estimate quality.

1.7 Results: Spillovers

In this section I consider the broader spillovers of this core upgrading result. First, I unpack the dynamics to explore persistence over time. Second, I trace the propagation of the quality effect along supply chains, to explore the role of production networks in amplifying the initial effect.

1.7.1 Persistence over time

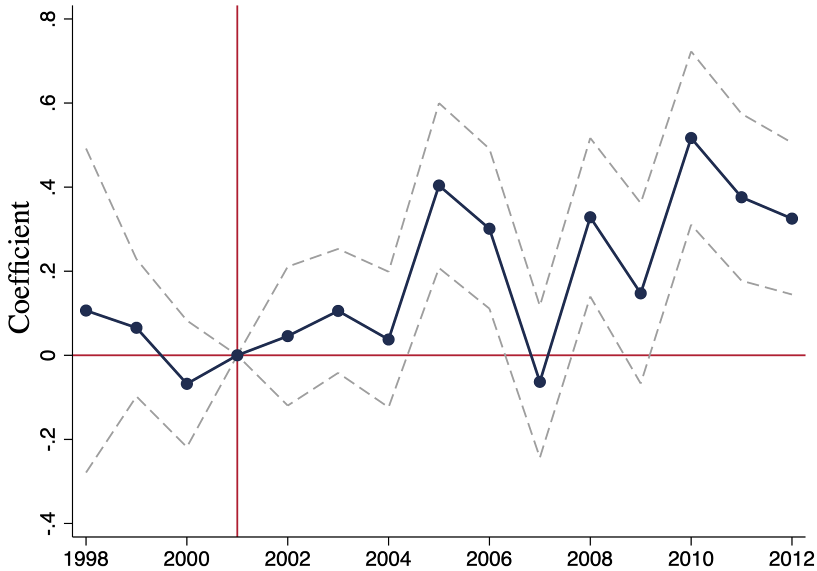
While Table 1.6.1 shows the average effect of tariff changes before vs. after 2001, it provides no insight into the dynamics of the rise in quality. I therefore interact 2001 tariff levels in each channel with dummies for each year, to ascertain the marginal impact in each year of having higher tariffs in 2001. The interaction coefficients for the input channel are shown in Figure 1.7.1. Note that the underlying trend in price and quality has been removed by the time fixed effects, so each of the graphs shows the *additional* percentage rise in price and quality for a product with a 1% higher tariff on inputs in 2001.

There is no significant effect in 1998-2000 relative to the 2001 baseline, for either price or quality, so there is no reason to reject the parallel pre-trends assumption. If anything, the marginal effect of having high 2001 tariffs was falling in those years, making its subsequent reversal more striking. Price and quality are then higher in high-2001-tariff products in all but one year in the decade following China's WTO accession, and significantly so in at least six years.[48] At the peak in 2010, products with a 10% higher input tariff in 2001 have 5.2% higher prices and 5.3% higher quality. The quality-upgrading effect is remarkably persistent, with prices and quality still significantly higher for affected products more than ten years after China's WTO accession. Moreover, the results so far only reflect the direct one-step impact of inputs on quality – they do not take into account the role of the wider production network. This is examined in the next section.

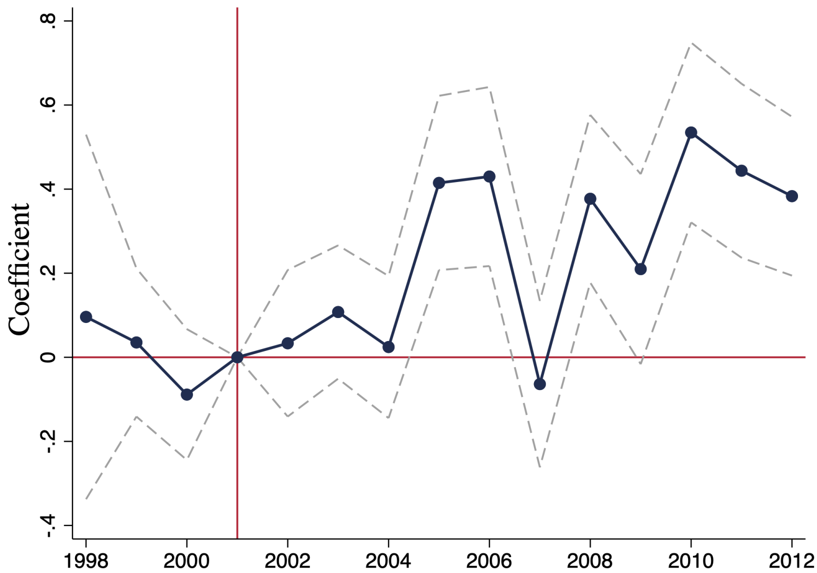
[48]Recall that the label '2007' in Figure 1.7.1 refers to the Indian financial year 2007-08 – the relative quality upgrade of the 'treated' firms paused during the Financial Crisis, before swiftly rebounding.

Figure 1.7.1: The dynamics of quality upgrading

(a) Price



(b) Quality

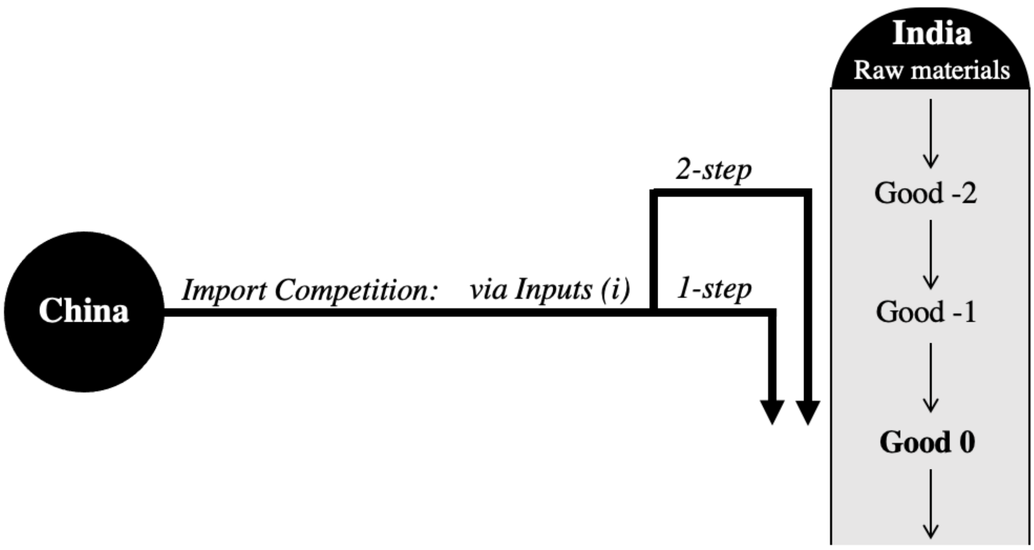


Notes: These graphs plot the coefficients on the interactions of 2001 input tariff levels with each year, relative to the 2001 baseline. The dashed lines show the 95% confidence interval. The underlying regression also interacts the year with each of the other channels, to control for the dynamics in each of direct import competition, output effects, export competition and export opportunities. The regression also includes firm, product and state-year fixed effects and clusters at the firm level, as in Table 1.6.1.

1.7.2 Propagation across the production network

The input channel and output channel measures described thus far are only informative on the direct spillovers from import competition, i.e. the 'one-step' impact on firms immediately ahead or behind in the supply chain. This matches the stylised supply chain in Figure 1.1.3, but may miss important aspects of reality. Consider instead Figure 1.7.2, which zooms in on the input channel and depicts a slightly longer supply chain. In addition to the previous channel, improved access to inputs can now also affect Good 0 through Good -2, via knock-on effects on Good -1. In other words, if Good 0's input suppliers in turn have better access to inputs, any quality upgrade to Good -1 could cascade onto Good 0.[49]

Figure 1.7.2: Input effects along the supply chain



Notes: This figure zooms in on the input channel in Figure 1.1.3, and presents a slightly longer supply chain to allow for 'two-step' effects. Thin lines depict the Indian manufacturing supply chain, and thick lines represent the effects of China's exports.

[49]Analogous effects could occur for the output channel. Denote the firm using a product as an input the 'customer', as in Section 1.4, for simplicity. Then if Good 0's customer's customer faces increased import competition from China, this could concertina back up the supply chain to reduce demand for Good 0.

To test for such effects, I construct intermediate measures of the 'two-step', 'three-step' (and so on) impacts on firms along the supply chain by repeatedly summing over the input value shares. For each measure of import competition M_{it} (i.e. $CITariff_{i,2001}$, $CIFlow_{it}$ or $CIFlow_{it}^{IV}$), I therefore have:

$$\begin{array}{lll} \text{One-step spillovers:} & InputM1_{it} = & \sum_k \alpha_{ik} \cdot M_{kt} \\ \text{Two-step spillovers:} & InputM2_{it} = & \sum_l \alpha_{il} \sum_k \alpha_{lk} \cdot M_{kt} \\ \text{Three-step spillovers:} & InputM3_{it} = & \sum_m \alpha_{im} \sum_l \alpha_{ml} \sum_k \alpha_{lk} \cdot M_{kt} \\ \vdots & \vdots & \vdots \end{array} \tag{1.7.1}$$

These in turn reflect the effect on product i of increased import competition in the markets for its inputs, its inputs' inputs, its inputs' inputs' inputs, and so on. I also construct equivalent measures for the output channel, by repeatedly summing over the usage shares γ_{ik}.

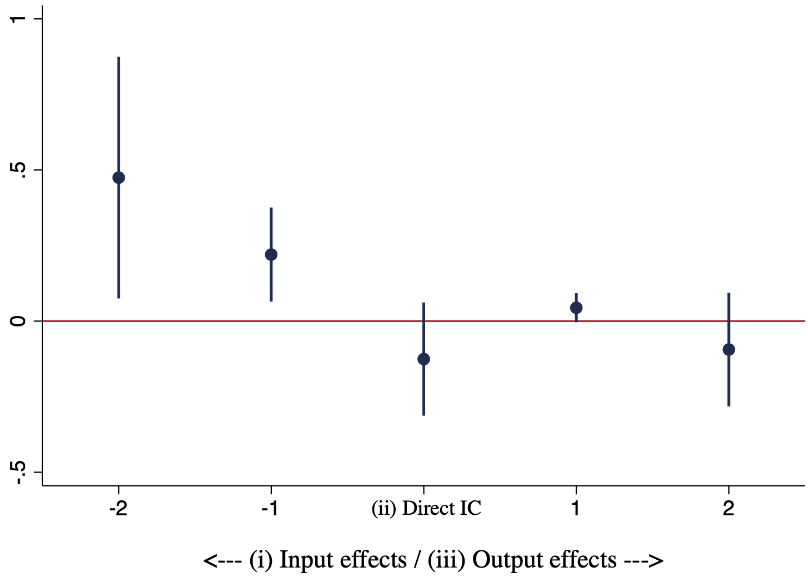
With these measures in hand, I repeat the baseline specification but include a further four 'degrees' of input spillovers, plus four further 'degrees' of output spillovers to ensure the controls are symmetric.[50] Figure 1.7.3 illustrates the results for price and quality. Increased import competition in the markets for Good -2 and Good -1 has significant positive effects on the price and quality of Good 0. In other words, improved access to the first good in the supply chain doesn't just drive quality upgrading in the product using it as a component – it also has a knock-on upgrading effect on the *next* good in the supply chain. (Effects beyond two steps are not significant, and not shown as the large standard errors would require a substantial rescaling of the y-axis, obscuring the other effects.)

Having established that upgrading effects propagate along the supply chain,

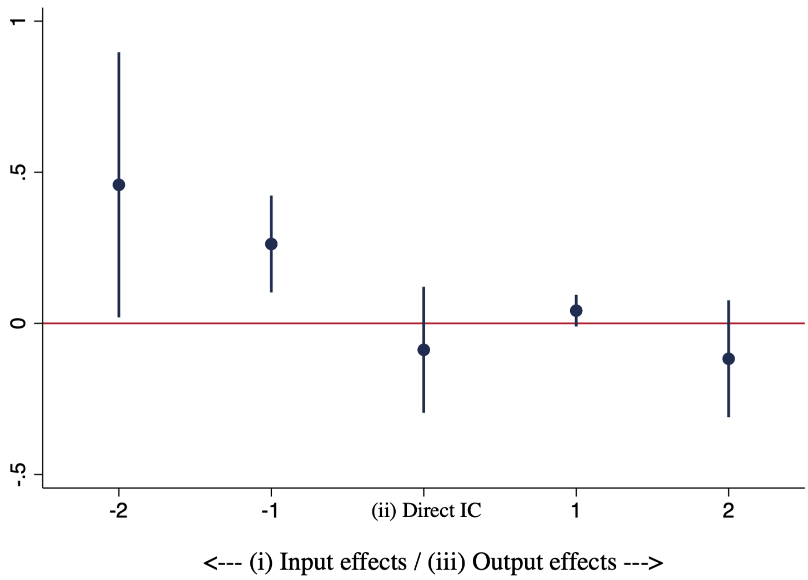
[50] Beyond this number of degrees, multicollinearity problems become severe and I lack sufficient observations or sufficient granularity in the input-output table to distinguish separate effects by degree.

Figure 1.7.3: Upgrading effects along the supply chain

(a) Price



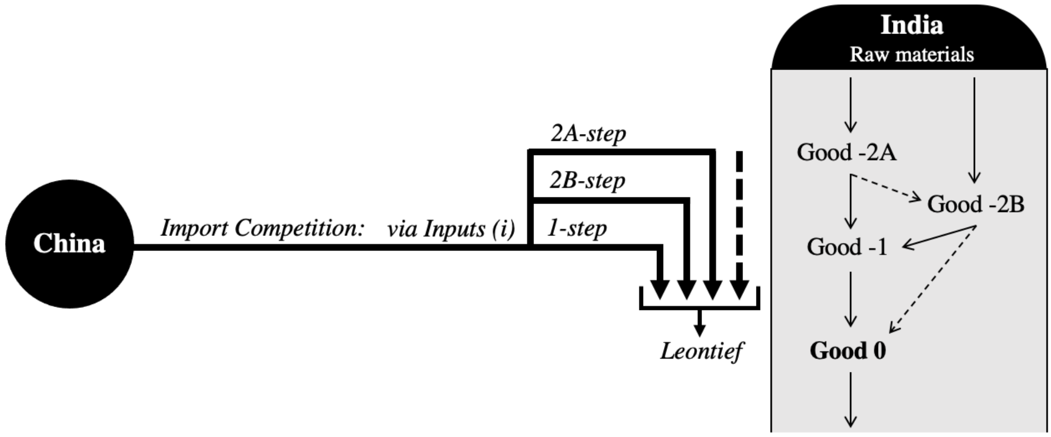
(b) Quality



Notes: These graphs show the effects on Good 0 of import competition at different points in the supply chain. For instance, the point '-1' shows the effect on the price or quality of Good 0 of an increase in import competition in the market for its immediate inputs. Each coefficient is from a regression as in equation 1.5.3, except including five degrees of input effects and five degrees of output effects. Error bars are shown at the 5% significance level, and coefficients on input/output effects are insignificant outside of the range shown.

the next step is to understand the full impact of these ripple effects. As is clear from the input-output network in Figure 1.3.2, the linear supply chain effects examined so far remain highly simplistic. Consider finally Figure 1.7.4, in which various input goods interact. Good 0 is now subject to one-step effects from Good -1, two-step effects from Goods -2A and -2B, and potentially even further effects if, for instance, the dashed supply relationships also exist.

Figure 1.7.4: Input effects along the supply chain



Notes: This figure zooms in further on the input channel in Figures 1.1.3 and 1.7.2, showing the upstream portion of a stylised production network centred on Good 0. Thin lines depict the Indian manufacturing supply chain, and thick lines represent the effects of China's exports. The dashed lines are examples of potential additional relationships that would also be captured by the Leontief measure.

To take such broader production linkages into account, I therefore follow Lane (2019) in using the Leontief inverse to take into account all input and output effects up to the 'nth-degree'. First define $\mathbf{A}$ as the matrix of the value share coefficients α_{ik} described in Section 1.5.1, and note that total output of each good (collected in vector $\mathbf{x}$) is equal to output for use as an intermediate input $\mathbf{Ax}$ plus output for final consumption $\mathbf{d}$: $\mathbf{x} \equiv \mathbf{Ax} + \mathbf{d}$. Rearranging gives

$\mathbf{x} \equiv (\mathbf{I}-\mathbf{A})^{-1}\mathbf{d}$, and hence the Leontief inverse $\mathbf{L}$ in equation 1.7.3:

$$\boldsymbol{A} \equiv \begin{bmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1k} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{i1} & \alpha_{i2} & \dots & \alpha_{ik} \end{bmatrix} \tag{1.7.2}$$

$$\mathbf{L} \equiv (\mathbf{I}-\mathbf{A})^{-1} \equiv \begin{bmatrix} l_{11} & l_{12} & \dots & l_{1k} \\ l_{21} & l_{22} & \dots & l_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ l_{i1} & l_{i2} & \dots & l_{ik} \end{bmatrix} \tag{1.7.3}$$

Each coefficient l_{ik} reflects the increase in production of i necessary to meet a one unit increase in final demand of k, taking into account all the interlinkages in the economy. This includes not just production of i as a direct input to k, but also as an input to other inputs to k, and so on. Substituting l_{ik} for γ_{ik} in equations 1.5.2, 1.5.6 and 1.5.11 therefore takes into account the total cumulated exposure to import competition of the sectors that i supplies (and of the sectors those sectors supply, and so on).[51] Similarly, substituting l_{ki} for α_{ik} in equations 1.5.1, 1.5.5 and 1.5.10 takes into account the total cumulated exposure to import competition of sector i's inputs (and the inputs to those inputs, and so on). This gives the new input channel variables:

$$\text{Total cumulated spillovers:}^{52} \qquad InputMT_{it} = \sum_k l_{ki} \cdot M_{kt} \tag{1.7.4}$$

where again M_{it} represents each of the import competition measures, and I also construct the equivalent variables for the output channel by substituting

[51] As in Section 1.5.1 above, set diagonals l_{ii} to zero to avoid double-counting the direct import competition channel.

[52] Crucially, the Leontief version reflects the cumulation of all degrees of spillovers, rather than merely the 'nth-degree' effect alone – which fades to zero for sufficiently large n, since nearly all γ_{ik} and α_{ik} are less than one.

l_{ik} for l_{ki}.

Table 1.7.1 repeats the baseline regressions using the Leontief measures. All significant coefficients are now larger, implying that interlinkages within the production network amplify the effect of China's WTO accession. Figure 1.7.5 compares the dynamics of price and quality when using both the one-step and full network measures. The amplification effect of the production network is clear. At the peak in 2010, products with a 10% higher input tariff in 2001 now have 8.7% higher prices and 9.4% higher quality – i.e. the effect is up to 75% larger, relative to the one-step measure.

Table 1.7.1: Impact of China's WTO accession – across full production network

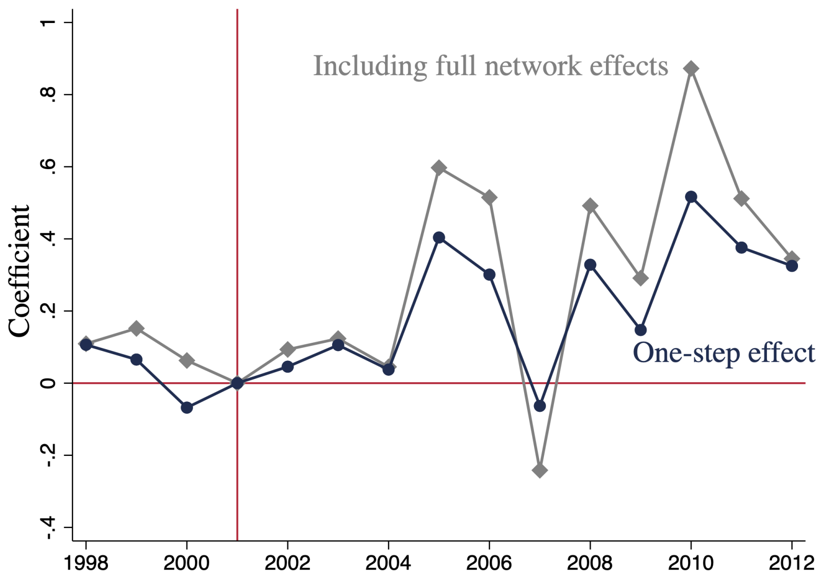
	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariffT$	0.374***	0.247***	0.199***	-0.0450**	-0.0807	0.111***	-0.0292**
	(2.78)	(3.92)	(3.36)	(-2.54)	(-1.09)	(2.59)	(-2.48)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34408	165011	165579	165011	165017	175799	161072
Panel B: Intensive Margin Only							
$InputTariffT$	0.368***	0.254***	0.206***	-0.0416**	-0.100	0.104**	-0.0263**
	(2.71)	(4.03)	(3.49)	(-2.33)	(-1.36)	(2.43)	(-2.22)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28460	137780	138229	137780	137785	147843	139739

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 1.5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in section 1.7.2: each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the Leontief-coefficient-weighted average of all the direct and indirect inputs to a firm across the whole production network.

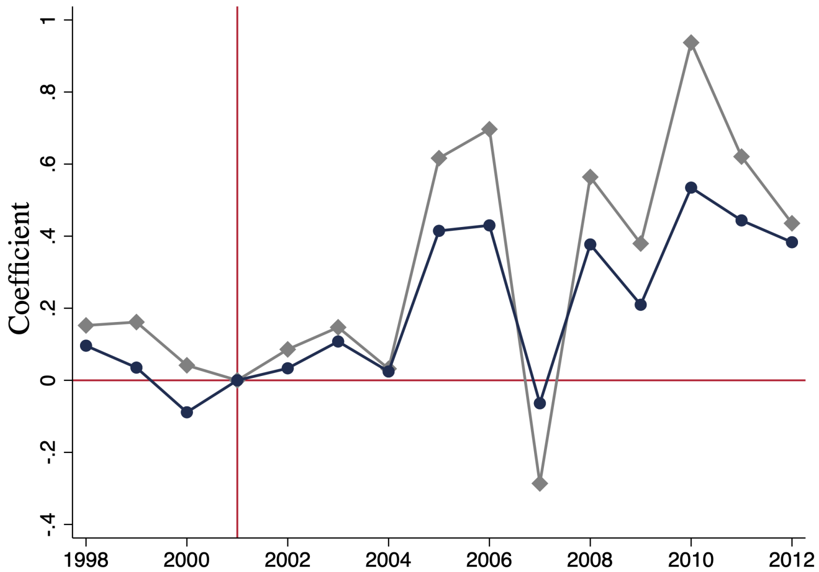
I therefore conclude that the production network plays an important role in propagating quality shocks downstream. How does the post-2001 Chinese input shock compare to an 'ideal' positive supply shock, from a policy perspective? As

Figure 1.7.5: Upgrading dynamics, including effect of production network

(a) Price



(b) Quality



Notes: These graphs again plot the coefficients on the interactions of 2001 input tariff levels with each year, relative to the 2001 baseline. The dark blue points remain the coefficients estimated using the one-step measures, as in Figure 1.7.1. The grey line instead uses the Leontief-coefficient-based measures described in Section 1.7.2, which take into account all interlinkages within the production network. Again, each underlying regression also interacts the year with each of the other channels, to control for the dynamics of direct import competition, output effects, export competition and export opportunities. Each regression also includes firm, product and state-year fixed effects and clusters at the firm level, as in Tables 1.6.1 and 1.7.1.

Acemoglu et al. (2012) observe, supply shocks in sectors with strong downstream connections (i.e. in sectors which supply many other sectors, whether directly or through or higher-degree linkages) have larger aggregate impacts. Returning to Figure 1.3.2, I note that the sectors with the largest increases in Chinese imports are generally neither multi-purpose raw materials (in the very centre of the network, with many downstream connections), nor final goods (towards the edge, with fewer) – instead they are mostly sophisticated manufactured inputs, in an intermediate ring. From a development perspective, the 'ideal' quality-upgrading supply shock would occur in the most central nodes of Figure 1.3.2, so that the amplification effect through downstream, forward linkages is the largest. However, in practice such raw materials and commodities may have the least scope for quality improvements. Thus, in broad terms, the 'China shock' was well-placed to have significant upgrading benefits for India, and for developing countries with a similar manufacturing structure.[53]

1.8 Conclusion

During the 2000s, China rapidly became a major provider of intermediate inputs to many developing countries. This paper exploits China's accession to the WTO to investigate the impact on Indian manufacturing firms. Consistent with a model of multi-product manufacturers gaining access to higher-quality components, a larger fall in the tariffs faced by Chinese inputs raises revenue, quality and prices whilst lowering quality-adjusted prices and the probability of product exit. These effects are driven by the upgrading of existing products, unlike in the widely studied Indian trade liberalisation of the early 1990s.

This supply-driven quality-upgrading effect persists for at least ten years, peaking in 2010. It also cascades along the supply chain: a shock to one input

[53] Conversely, the 'ideal' positive demand shock would occur in the most sophisticated final goods, i.e. those with lots of upstream linkages, as this would then benefit the long chains of producers back up the supply chain. For developing countries, this has generally not been the case with the China shock – instead Chinese demand has mostly been for primary commodities (as in e.g. Costa et al. 2016).

drives quality upgrading not only in the product which uses it, but also in the next product down the supply chain. Broader linkages in the production network further spread the upgrading effect, amplifying the one-step impact by up to 75%. In contrast to existing literature focused on negative demand effects of the 'China shock' in developed countries, these results highlight the potential for positive supply effects in many developing countries.

As with Lane (2019) and Liu (2019) for industrial policy, this study affirms the importance of understanding the production network context when setting international trade policy. The supply-driven quality-upgrading channel represents an additional source of 'gains from trade' forgone by India in rejecting the Regional Comprehensive Economic Partnership with large Asian economies. From a development perspective, the 'ideal' trade deal (i) improves import access to inputs as far upstream as possible, so that there is the maximum potential for benefits to spill downstream, and (ii) improves export access to the ultimate (i.e. 'most downstream') consumers, so that there is the longest possible chain of upstream firms to benefit from supplying them. Future policy work could explore the most promising trade deals from this perspective.

Finally, two main areas for future research stand out: (i) understanding the aggregate welfare implications of the supply-driven quality-upgrading mechanism, and whether a similar effect occurred in other countries with a similar initial level of manufacturing development to India, and (ii) understanding the role of the production network in amplifying negative input supply shocks, such as those caused by the Covid-19 pandemic.

1.A Theoretical Appendix

This Appendix derives similar predictions to those in Section 1.4 under the alternative assumption of linear demand. First, replace equation 1.4.1 with:

$$U = x_0 + \beta \int_{i\in\Omega} q_i x_i di - \frac{1}{2}\gamma \int_{i\in\Omega} (q_i x_i)^2 di - \frac{1}{2}\eta \left[\int_{i\in\Omega} q_i x_i di \right]^2 \qquad (1.A.1)$$

giving demand $x_i = \frac{R}{\gamma q_i}(\hat{P} - \frac{p_i}{q_i})$, where $P = \frac{1}{M}\int_{i\in\Omega}\frac{p_i}{q_i}di$ and $\hat{P} = \frac{\eta\int_{i\in\Omega}\frac{p_i}{q_i}di+\beta\gamma}{\eta M+\gamma}$ is the quality-adjusted 'choke price' above which demand is zero, with M the total number of (horizontally-differentiated) varieties available.[54] Profit maximisation by firms then gives:

$$\text{Price} \quad p_i(\phi_f, \lambda_{fi}) = \frac{1}{2}\left[\hat{P}(\phi_f\lambda_{fi}q_m)^{\theta+1} + m\phi_f\lambda_{fi}\right] \tag{1.A.2}$$

$$\text{Quantity} \quad x_i(\phi_f, \lambda_{fi}) = \frac{R}{2\gamma}\left[\hat{P}(\phi_f\lambda_{fi}q_m)^{-(\theta+1)} - m(\phi_f\lambda_{fi})^{-2\theta-1}q_m^{-2(\theta+1)}\right]$$

$$\text{Revenue} \quad r_i(\phi_f, \lambda_{fi}) = \frac{R}{4\gamma}\left[\hat{P}^2 - m^2(\phi_f\lambda_{fi})^{-2\theta}q_m^{-2(\theta+1)}\right] \tag{1.A.4}$$

$$\text{Mark-up} \quad \mu_i(\phi_f, \lambda_{fi}) = \frac{1}{2}\left[\hat{P}(\phi_f\lambda_{fi})^{\theta}q_m^{\theta+1}m^{-1} + 1\right] \tag{1.A.5}$$

$$\text{Profit} \quad \pi_i(\phi_f, \lambda_{fi}) = \frac{R}{4\gamma}\left[\hat{P} - m(\phi_f\lambda_{fi})^{-\theta}q_m^{-(\theta+1)}\right]^2 \tag{1.A.6}$$

Model improved access to new components as rises in q_m and m where $\frac{(\Delta q_m)^{\theta+1}}{\Delta m} > 1$ – i.e. let the rise in input quality outweigh the rise in input price, as in equation 1.4.9. Then model increased import and export competition as rises in M, output effects as a fall in R, and increased export opportunities as a rise in R. The resulting effects on observables are shown in Table 1.A.1. All predictions are qualitatively the same as in Table 1.4.3, except that prices now fall under direct import and export competition (as prices are no longer a constant mark-up over costs, as in the CES case).[55] The results in Section 1.6 are thus robust to using linear rather than CES demand.

[54] Note that, with linear demand, headquarter and product-line fixed costs are no longer required for demand to fall to zero in a sufficiently expensive product.

[55] I do not consider the impacts on quality-adjusted prices under linear demand, as these are only 'observed' when assuming CES as per Khandelwal et al. (2013). I leave quality q_i in Table 1.A.1 for reference, but I also do not observe this when assuming linear demand. Quality effects are instead inferred from the impacts on marginal cost, price and revenue, in the spirit of Verhoogen (2008) and Kugler & Verhoogen (2012).

Table 1.A.1: The China shock and observables – linear demand

			Channel	***Shock***	$\boldsymbol{c_i}$	$\boldsymbol{q_i}$	$\boldsymbol{p_i}$	$\boldsymbol{x_i}$	$\boldsymbol{r_i}$	$\boldsymbol{Ex_i}$
Import	Competition:	(i)	via Inputs	$\uparrow q_m > \uparrow m$	$\uparrow$	$\uparrow$	$\uparrow$	$\sim$	$\uparrow$	$\downarrow$
		(ii)	Direct	$\uparrow M \rightarrow \downarrow \hat{P}$	–	–	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$
		(iii)	via Outputs	$\downarrow R$	–	–	–	$\downarrow$	$\downarrow$	$\uparrow$
Exports:		(iv)	Competition	$\uparrow M \rightarrow \downarrow \hat{P}$	–	–	$\downarrow$	$\downarrow$	$\downarrow$	$\uparrow$
		(v)	Opportunity	$\uparrow R$	–	–	–	$\uparrow$	$\uparrow$	$\downarrow$

Notes: This table summarises, for each channel, the predicted effects on variables which can be observed in or derived from the ASI data. From left to right, the outcome variables are: c_i – marginal cost; q_i – quality; p_i – price; x_i – quantity; r_i – revenue; Ex_i – probability of dropping the product next period.

1.B Empirical Appendix

1.B.1 Estimating the elasticity of substitution

This paper currently uses $\sigma = 3.7$, the median elasticity of substitution across Indian goods calculated by Broda et al. (2006). Future work would ideally use industry-specific estimates, as in Bajgar & Javorcik (2016). Without such estimates available, using $\sigma = 3.7$ is a reasonable approximation: it is close to the typical median value for σ, 3.4, across all countries in Broda et al.'s study, and the authors also find that median elasticities do not differ significantly across product types – i.e. between commodities vs. reference-priced goods vs. differentiated goods (Broda et al. 2006).

1.B.2 Further controls

In an additional precaution against misattribution, I test for robustness to various possible confounding factors. Higher initial tariffs may reflect the lobbying power of large or well-connected industries, which may itself generate faster rises in quality or price over time.[56] Similarly, infant industry arguments or political concerns may encourage the government to protect labour-intensive industries or those paying high wages. Following Lu & Yu (2015), I account for these specific political and economic factors by controlling for five industry-level variables: log total employment, log total sales, the share of public firms, the capital-labour ratio and log average wage per worker. Table 1.B.1 shows the results: the main results for quality and price (repeated in columns 1 & 5 for convenience) are barely affected, whether including additional controls with annual variation (columns 2 & 6), or with their 2001 level interacted with the post-2001 dummy (3 & 7), or both (4 & 8).

[56]For example, lobbying has influenced Indian trade policy on spirits (which became the subject of an official complaint to the WTO by the EU (Sen 2007, World Trade Organisation 2008)), wine (see, for instance, telegraph.co.uk/finance/.../Tax-deal-to-uncork-India-for-wine-investors) and motorcycles (see economictimes.indiatimes.com/news/.../50-tariff-on-us-motorcycles-by-india-unacceptable-says-donald-trump). Thus while there is some evidence of strategic manipulation, it tends to be substantial in only narrow sectors with well-organised lobbies. Moreover, it is not clear that such tariffs allow for improved performance over time – they may instead encourage stagnation by reducing competition. Nonetheless, I control for correlates of such lobbying as a precaution.

Table 1.B.1: Input effects of China's WTO accession – additional controls

	Log Quality				Log Price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InputTariff	0.238***	0.217***	0.268***	0.256***	0.194***	0.179***	0.228***	0.221***
	(4.27)	(4.15)	(4.54)	(4.36)	(3.72)	(3.66)	(4.16)	(4.02)
Log Employment$_t$		-0.136***		-0.147***		-0.0568***		-0.0719***
		(-10.00)		(-8.81)		(-4.54)		(-4.73)
Log Sales$_t$		0.194***		0.198***		0.0682***		0.0773***
		(16.82)		(14.01)		(6.45)		(5.99)
Share of Public Firms$_t$		0.109		0.187*		0.0540		0.143
		(1.26)		(1.73)		(0.66)		(1.43)
K-L Ratio$_t$		0.000292		0.000210		0.000582**		0.000438
		(0.91)		(0.64)		(1.96)		(1.43)
Log Average Wage$_t$		-0.0169		-0.0481		0.0293		-0.00258
		(-0.55)		(-1.31)		(1.05)		(-0.08)
Post2001$_t$ × Log Employment$_{2001}$			0.0633*	0.00671			0.0177	-0.00833
			(1.93)	(0.20)			(0.57)	(-0.26)
Post2001$_t$ × Log Sales$_{2001}$			-0.0777***	-0.0223			-0.0351	-0.0117
			(-3.17)	(-0.90)			(-1.53)	(-0.50)
Post2001$_t$ × Share of Public Firms$_{2001}$			0.613**	0.733***			0.658***	0.727***
			(2.36)	(2.76)			(2.65)	(2.85)
Post2001$_t$ × K-L Ratio$_{2001}$			0.00602**	0.00493*			0.00427	0.00387
			(2.17)	(1.77)			(1.64)	(1.47)
Post2001$_t$ × Log Average Wage$_{2001}$			-0.0645	-0.0917			-0.0961*	-0.111**
			(-1.15)	(-1.59)			(-1.82)	(-2.06)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	165011	162961	131041	130049	165579	163523	131472	130477

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All regressions include firm, product and state-year FEs and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality is calculated using the procedure of Khandelwal et al. (2013). The input channel is measured as described in Section 1.5.1 – i.e. each coefficient in the first row gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs.

1.B.3 Annual tariffs

I also check the robustness of results to using an annual tariff specification, rather than the difference-in-differences method outlined in Section 1.5.1. While this is more vulnerable to endogeneity concerns, as noted in the main text, it does allow more of the variation in the tariff variable to be used. I follow Brandt et al. (2017) in regressing each dependent variable on tariffs in each year:

$$\begin{aligned}\ln y_{ift} = {} & \alpha_{(i)} \cdot \ln InputTariff_{it} \\ & + \alpha_{(ii)} \cdot \ln CITariff_{it} \\ & + \alpha_{(iii)} \cdot \ln OutputTariff_{it} \\ & + \alpha_{(iv)} \cdot \ln CRTariff_{it} \\ & + \alpha_{(v)} \cdot \ln ICTariff_{it} \\ & + \boldsymbol{\alpha}'\mathbf{X}_{ft} + a_i + b_f + c_{st} + u_{ift}\end{aligned} \tag{1.B.1}$$

where I first multiply each outcome variable y_{ift} by minus one, such that each coefficient α reflects the average percentage change in y_{ift} associated with a one percent *fall* in the respective tariff. The results are shown in Table 1.B.2. All relationships are in the same direction as with the difference-in-differences specification, and all previously significant relationships remain so, except for the exit margin. Once again, lower tariffs on inputs allow output quality to rise, and by more than prices, so that quality-adjusted output prices fall and revenue rises.

Table 1.B.2: Input effects of China's WTO accession – annual tariffs

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff_t$	0.267***	0.292***	0.218***	-0.0730***	-0.0218	0.152***	-0.00209
	(4.09)	(9.02)	(7.74)	(-7.03)	(-0.63)	(6.46)	(-0.32)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30131	149471	150084	149471	149479	160583	160649
Panel B: Intensive Margin Only							
$InputTariff_t$	0.273***	0.302***	0.221***	-0.0791***	-0.00942	0.169***	-0.00234
	(4.00)	(8.78)	(7.40)	(-7.44)	(-0.27)	(7.14)	(-0.34)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	27618	136506	137031	136506	136513	147049	147114

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 1.5.3. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Appendix 1.B.3 – i.e. each coefficient reflects the average percentage change in the outcome variable associated with a one percent fall in the average tariff on the firm's inputs.

1.B.4 Impact of other reforms in India

Several major reforms occurred in India during the 1990s and 2000s, but many had reached their conclusion by the beginning of the period considered here.[57] Almost 85% of industries had been delicensed by 1991, more than 90% by 2000, and almost all of these delicensed industries were eligible for automatic FDI approval by 2001 (Harrison et al. 2013, Arnold et al. 2016). The Indian government substantially reduced tariffs on many industrial goods in 2005 (World Bank 2006, Virmani 2005), but this reform was a continuation of the earlier trend in tariff reduction – as shown in Figure 1.5.1 Panel (a). Panel (b) shows a delayed impact of this reform on imports from China, which do not spike until 2006.

[57] An exception is service sector liberalisation, discussed in Arnold et al. (2016), which may have magnified the impact of China's WTO accession. An exploration of the interaction effects between goods tariff declines and service sector liberalisation is left for future work.

To alleviate possible concerns about endogeneity of these tariff changes, I therefore run additional robustness checks on the limited sample from 1998-2005, as shown in Table 1.B.3. The quality-upgrading effect still holds, in both product- and firm-level regressions and using both the difference-in-differences and Autor et al. (2013) methods, with the results merely slightly less significant due to the smaller sample.[58]

Table 1.B.3: Input effects of China's WTO accession – 1998-2005 only

	Product-level				Firm-level	
	Quality	Price	Quality	Price	TFP	TFP
InputTariff – DiD	0.176***	0.164***				
	(3.52)	(3.64)				
InputFlow – ADH			3.370*	3.030*		
			(1.94)	(1.94)		
InputTariff – DiD, firm-level					0.0618***	
					(8.30)	
InputFlow – ADH, firm-level						0.150***
						(14.78)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	f,st	f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat			1.24	1.191		121.7
N	53,025	53,053	70,201	70,240	24,597	27,434

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs. DiD = difference-in-differences specification using 2001 tariff levels, as in Section 1.5.1. ADH = Autor, Dorn & Hanson (2013) specification using plausibly exogenous import and export flows, as in Section 1.5.2. All regressions include firm, product (for product-level regressions) and state-year FEs and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality is calculated using the procedure of Khandelwal et al. (2013), and firm-level TFP is calculated using the procedure of Ackerberg et al. (2015).

[58] The over-large coefficients reported for the ADH method, in the third and fourth columns, reflect that the instruments are now much weaker than in Table 1.6.2. This is because China's export expansion did not take off in many countries until 2003, or even later (see Figure 1.1.1 for example), so there is limited variation in the instruments.

1.B.5 Census selection and the exit variable

Since the ASI is only a census for firms with more than 100 workers, a given firm-product exit from the data could be either a genuine exit or the result of the firm falling below the size threshold for the census panel. To test whether the latter is driving the results, I repeat the exit regressions using only the subset of firm-product exits for which the same firm continues in the panel – i.e. using only those product exits which are known to be due to the firm dropping the product, not the firm itself exiting. The results are shown in Table 1.B.4, for both the original exit variable and the new refined version. The results remain very similar, suggesting that census selection is not driving the exit effects. Indeed, the number of firm-product exits is only slightly lower in the refined version, implying a relatively limited role for firm (rather than firm-product) exit among these large firms.

Table 1.B.4: Robustness of the exit variable to sample selection

	Exit	
	Original	Refined
(i) *InputTariff*	-0.0180*	-0.0180*
	(-1.95)	(-1.93)
(ii) *CITariff*	0.0106	-0.0374*
	(0.49)	(-1.68)
(iii) *OutputTariff*	-0.00526*	-0.00910***
	(-1.78)	(-3.10)
(iv) *CRTariff*	0.00650	0.00131
	(1.54)	(0.31)
(v) *ICTariff*	-0.00728	-0.00656
	(-0.67)	(-0.60)
FEs	i,f,st	i,f,st
Controls	Yes	Yes
Number of firm-product exits	93464	70062
Observations	161072	161072

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. *Exit* measured as described in Section 1.5.3. The second column refines the exit variable to include only those firm-product exits for which the firm is not also exiting – i.e. only those exits which could not be caused by the firm falling below the census cutoff. All regressions include firm, product and state-year FEs, and control for rural/urban location and public/private ownership. Each channel is measured as described in Section 1.5.1 – i.e. each coefficient gives the marginal change in the probability of exit in the post-accession period resulting from a 1% higher pre-accession tariff on the relevant trade vector.

1.B.6 District-time fixed effects

Table 1.B.5 repeats the baseline regressions using district-time, rather than state-time, fixed effects. As noted in Section 1.3, I only have district identifiers for a subset of years, so these regressions use data between 1998 and 2009. Results remain very similar; several of the effects are actually strengthened, while the marginal cost and exit probability coefficients lose significance in the smaller sample.

Table 1.B.5: Input effects of China's WTO accession – state-district-time FEs

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff$	0.0897	0.292***	0.215***	-0.0729***	-0.0226	0.0885***	-0.00743
	(0.60)	(5.10)	(4.20)	(-4.40)	(-0.38)	(2.67)	(-0.75)
FEs	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19049	97629	97893	97629	97635	107680	107731
Panel B: Intensive Margin Only							
$InputTariff$	0.108	0.293***	0.218***	-0.0703***	-0.0328	0.0836**	-0.00480
	(0.71)	(5.12)	(4.26)	(-4.23)	(-0.55)	(2.53)	(-0.48)
FEs	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt	i,f,dt
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18519	94636	94898	94636	94641	104198	104248

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 1.5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and district-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Section 1.5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs.

1.B.7 Controlling for geographic collocation

This paper is focused on spillover effects through production linkages, yet geographic clustering could also play a similar role. Two industries which are closely connected in supply chains, e.g. iron foundries and industrial machinery manufacturing, may tend to locate close to one another to minimise transport costs or exploit other benefits of proximity. Locality-specific demand or supply effects could then correlate with input-output connections, biasing estimates of the true effect of the latter. Acemoglu, Akcigit & Kerr (2015, hereafter AAK) model local demand effects, such that, for instance, a negative shock to demand for cast iron has an adverse effect on all other industries in the region, within which industrial machinery may be over-represented. Such geographic collocation, if widespread, could lead to an overestimate of the importance of production linkages.

To control for such factors, I adopt AAK's empirical approach. This measures the contribution of this geographic overlay using the noncentred cross-region correlation coefficient of industries i and k, normalised by their national levels of production:[59]

$$geog_{ik} = \sum_{d} \frac{r_{d,i} r_{d,k}}{r_i r_d} \tag{1.B.2}$$

where $r_{d,i}$ is total sales of industry i in district d, and r_i and r_d are aggregates at the industry and district levels respectively.[60] As with equations 1.5.1 and 1.5.2, I then use these coefficients to take a weighted average of the import competition faced by geographically collocated industries – thus taking into account import competition effects through the geographic network, as distinct from the production network.[61]

Table 1.B.6 presents the results from including this collocation term in the main regressions. The results are very similar to those in Table 1.6.1 – collocation has only very minor effects on the coefficients, except for the product exit margin. This suggests that while local effects may impact profitability (for which the exit variable is a proxy, as in Section 1.4), they do not play a significant role in mediating the quality-upgrading mechanism. In other words, it is indeed input-output production linkages, rather than geographic collocation, that drive the upgrading effect.

[59]For a full derivation, see AAK sections II.B and III.C.

[60]As with the calculations of α_{ik} and γ_{ik} in Section 1.5, I use constant and predetermined coefficients throughout to prevent potential endogeneity of the geographic overlay with respect to tariff levels and/or trade flows. In this case, I use sales data from the year 2000 since this is the first year in which I have broad coverage across industry-district cells.

[61]Once again, I set $geog_{ii}$ equal to zero for all i to avoid double-counting the direct import competition channel.

Table 1.B.6: Input effects of China's WTO accession – including collocation

	MCs	Quality	Price	QAP	Quantity	Revenue	Exit
Panel A: Full Sample							
$InputTariff$	0.231*	0.234***	0.181***	-0.0498***	-0.0493	0.0751**	-0.00779
	(1.65)	(3.80)	(3.15)	(-2.99)	(-0.71)	(2.07)	(-0.77)
Collocation	0.414	0.0354	0.103	0.0631	-0.269	-0.0480	-0.117***
	(0.86)	(0.17)	(0.54)	(0.95)	(-1.08)	(-0.30)	(-2.92)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34401	164965	165533	164965	164971	175752	161038
Panel B: Intensive Margin Only							
$InputTariff$	0.248*	0.241***	0.188***	-0.0500***	-0.0565	0.0754**	-0.00646
	(1.75)	(3.94)	(3.27)	(-2.98)	(-0.81)	(2.10)	(-0.63)
Collocation	0.382	0.0117	0.0909	0.0786	-0.303	-0.0955	-0.113***
	(0.79)	(0.06)	(0.48)	(1.18)	(-1.21)	(-0.60)	(-2.81)
FEs	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st	i,f,st
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28460	137780	138229	137780	137785	147843	139739

Notes: t-statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All variables in logs, except *Exit* which is as described in Section 1.5.3. Panel A includes all products, while Panel B only includes those products which first appear in the dataset prior to China's WTO accession at the end of 2001. All regressions include firm, product and state-year FEs, and control for rural/urban location, public/private ownership, and the other four channels (direct import competition, output effects, export competition and export opportunities). Quality and quality-adjusted prices are calculated using the procedure of Khandelwal et al. (2013), and marginal costs are calculated using the procedure of De Loecker et al. (2016). The input channel is measured as described in Section 1.5.1 – i.e. each coefficient gives the percentage change in the average value of the outcome variable in the post-accession period resulting from a 1% higher average pre-accession tariff on the firm's inputs. Collocation is measured as described in Section 1.B.7, following Acemoglu, Akcigit & Kerr (2015): the interpretation of coefficients is analogous to that of the input channel, except with the average tariff calculation weighted by geographic correlation rather than input usage.

Table 1.B.7: Summary statistics by sector

NPCMS Section	**NPCMS Sector**	**Obs.**	**Fixed Assets (mean, INR million)**	**Employees (mean)**
Agriculture, Forestry, Fisheries	Products of agriculture, horticulture and market gardening	57	42	78
Beverages, Tobacco, Textiles	Beverages	2,668	327	488
	Grain mill products, starches and starch	3,194	131	189
	Knitted or crocheted fabrics; wearing apparel	4,393	98	378
	Leather and leather products; footwear	3,668	58	384
	Textile articles other than apparel	2,275	199	305
	Tobacco products	3,496	22	904
	Yarn and thread; woven and tufted textile fabrics	29,724	368	468
Metals, Machinery and Equipment	Basic metals	4,688	1290	550
	Electrical machinery and apparatus	9,705	195	330
	Fabricated metal products, except machinery and equipment	8,743	229	212
	General-purpose machinery	12,887	172	311
	Medical appliances, precision and optical instruments, watches and clocks	4,319	89	203
	Office, accounting and computing machine	8	20	122
	Radio, television and communication equipment and apparatus	887	423	350
	Special-purpose machinery	4,223	255	260
	Transport equipment	11,645	333	376
Other Transportable Goods	Basic chemicals	12,545	2220	424
	Furniture; other transportable goods n.e.c.	6,210	152	202
	Glass and glass products and other non-metallic products n.e.c.	3,621	313	275
	Other chemical products; man-made fibres	23,454	401	320
	Products of wood, cork, straw and plaiting materials	2,908	40	95
	Pulp, paper and paper products; printed matter and related articles	2,242	228	356
	Rubber and plastics products	21,008	212	194

Figure 1.B.1: Electric vehicle startup

Quality upgrade = lighter li-ion cells $\rightarrow$ lighter batteries, longer charge

Figure 1.B.2: Pharmaceuticals multi-national

Quality upgrade = fewer impurities in input chemicals $\rightarrow$ safer products

Chapter 2

AI, firms and wages: Evidence from India*

with **Ashley Pople** and **Katherine Stapleton**

We examine the impact of artificial intelligence on hiring and wages in the service sector using a novel dataset of 15 million vacancy posts from India's largest jobs website. We first document a rapid rise in demand for AI skills since 2016, particularly in the IT, finance and professional services industries. Vacancies demanding AI skills list substantially higher wages, but require more education and are highly concentrated in the largest firms and a small number of high-tech clusters. Exploiting plausibly exogenous variation in exposure to advances in AI technologies, we then examine the impacts of establishment demand for AI skills, as a proxy for AI adoption. We find that growth in AI demand has a direct negative impact on the growth of non-AI and total job posts by incumbent firms, and reduces the growth of wage offers across the distribution.

Keywords: *artificial intelligence, labour markets, wages, development*
JEL Classification Codes: *J23, O33*

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2.1 Introduction

Advances in artificial intelligence (AI), driven by progress in the sub-field of machine learning (ML), have spurred an intense debate about the impact of AI on jobs.[1] Yet, despite widespread discussion, detailed empirical evidence remains limited. This is particularly the case for middle- and low-income countries, where little is known to date about the extent of deployment of AI, what it is being used for, or how it is affecting labour markets. For countries pursuing a services-led development model, this question has broad ramifications: many of the services industries that have driven growth and job creation, such as Business Process Outsourcing (BPO), are now highly susceptible to ML-based automation. For instance, in India – the archetype of the services-led development path – the IT-BPO sector currently employs around 4 million people and contributes 8% of India's GDP (SESEI 2019).

The theoretical impact of AI on jobs is ambiguous. Advances in ML have reduced the cost of the task of 'prediction', which is prevalent in many occupations (Agrawal et al. 2018).[2] While this initially suggests displacement of workers, improved prediction could also expand employment through the 'productivity effects' of reducing overall costs or increasing quality. Some early works have therefore modelled ML in a comparable way to other forms of automation, such as industrial robots, which share these features (Webb 2020, Acemoglu, Autor, Hazell & Restrepo 2020).[3] In addition, AI could

[1] To fix definitions, we consider AI 'the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages' (Oxford English Dictionary 2020). ML, the sub-field responsible for many of the recent commercial applications of AI, comprises 'the statistical techniques that enable computers and algorithms to learn, predict and perform tasks from large amounts of data without being explicitly programmed' (Acemoglu & Restrepo 2019). We henceforth use 'AI' as an umbrella term encompassing ML.

[2] For example, a back office employee of a multinational bank takes the input of scrawled handwriting on a mortgage application form, then generates as predicted output the correctly spelled name of the applicant.

[3] These papers build on the canonical framework of Acemoglu & Restrepo (2018) in which task structure determines adoption. Beyond the boundary of the adopting firm, AI could also have broader indirect effects, as workers reallocate across occupations – as explored in

complement human labour, create entirely new tasks or incentivise changes in organisational structure; indeed, there is growing evidence that AI is a general-purpose technology (GPT), an 'invention of a method of invention' (Brynjolfsson et al. 2017, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021).[4] Emerging economies like India could benefit from new global AI value chains, capitalising on their abundance of low-cost engineering talent, existing expertise in IT outsourcing, and further declines in communications costs (Baldwin & Forslid 2020). Indeed, revenues in India's BPO sector nearly tripled over the past ten years (NASSCOM 2018).

In this paper, we investigate the labour market impact of AI in the white-collar services sector using novel data from 15 million vacancy posts on India's largest jobs website. Following Acemoglu, Autor, Hazell & Restrepo (2020) and Stapleton & O'Kane (2020), we gauge firm-level AI adoption using demand for AI-related skills, as observed in the text of posted job descriptions. Our data also include firm identifiers, locations, salary offers and skill, experience and education requirements. As a result, the data provide a granular insight into the Indian labour market, thereby allowing us to explore the impact of AI on other detailed proxies for labour demand.

We document a rapid take-off in 'AI demand' (shorthand for the demand for AI-related skills in vacancy posts) after 2016, particularly in the IT, finance and professional services industries. AI demand increased from 0.37% of all job vacancies in 2015 to 1.03% in 2019. Specifically, the take-off coincides with a rapid increase in demand for 'deep learning' skills, along with 'natural language processing' to a lesser extent. AI roles tend to require substantially more education, particularly graduate degrees, while also paying significantly more. Even after controlling for detailed region, industry, firm, occupation and role fixed effects, posts demanding AI skills still pay a 13-17% salary premium.

detail by Humlum (2019) in the case of robots. Here we focus on direct within-firm effects.

[4]Specifically, GPTs (1) are widely used across sectors, (2) have inherent potential for technical improvement, and (3) spawn further innovation in application sectors (Bresnahan & Trajtenberg 1995).

AI roles are heavily concentrated in a few key technology clusters – particularly Bangalore, Mumbai, Hyderabad, Pune, Chennai and Delhi – and in the largest 'superstar' firms. Consistent with this spatial clustering, we find evidence of local diffusion: after the first firm in a given industry and region adopts AI, other firms in the same industry and region are on average more likely to start demanding AI skills, even after taking into account industry and region trends.

We next consider the relationship between AI demand and total labour demand. As noted above, AI could have many effects across the economy. We aim to identify one narrow subset of these impacts empirically: the net direct effect of adopting AI on outcomes within pre-existing firm-city pairs (hereafter 'establishments'). Using a long difference specification between 2010-12 and 2017-19, we investigate the effects of growth in establishment demand for AI skills on the growth of non-AI job postings and wage offers at establishment level. To isolate causation, we exploit establishment-level variation in exposure to supply-side advances in AI capabilities developed outside of India, as reflected in the existing exposure measure of Webb (2020). Specifically, this measure captures the degree of overlap between occupations' tasks and the tasks which patented AI technologies are designed to perform. We aggregate this measure to the establishment level using establishment occupation vacancy shares at baseline, then use this variation as an instrument for AI demand. To isolate the impact of AI *usage*, rather than AI *production*, we exclude AI-producing sectors from our causal analysis – specifically IT and education, which are responsible for the vast majority of AI patents (Klinger et al. 2020).

We first examine the first stage and find that firms that are *ex ante* more exposed to AI see a relative increase in their demand for AI skills in online vacancy posts. Turning to the second stage, we find that growth in AI demand has a significant negative effect on growth in non-AI and total postings by establishments. A 1% increase in the AI vacancy growth rate results in a 3.61 percentage point decrease in establishment non-AI vacancy growth between 2010-12 and 2017-19, controlling for region, firm size and industry fixed effects.

Growth in total establishment vacancies (AI plus non-AI) falls by a similar 3.57 percentage points, reflecting that the increase within the small set of AI posts is far outweighed by the displacement effect in the larger set of non-AI vacancies.

How does this displacement affect wages? We find that a 1% higher growth rate in AI vacancies between 2010-12 and 2017-19 reduces the growth rate of non-AI median wage offers by 2.6 percentage points, instrumenting with AI exposure and controlling for region, firm size and industry fixed effects. This persists even when controlling for changes in the education and experience profile of jobs. Put simply, establishments offer lower wages to do similar work. These negative effects appear across the wage distribution, with effects largest for mid-wage offers. As with vacancy growth, the negative effects of AI demand on wage growth are barely affected when considering all posts, inclusive of AI vacancies – in this case, the net figure is a 2.5 percentage point fall in overall median wage offers.

These results are robust to various alternative econometric specifications, including using mean wages and weighting by establishment size (excluding outliers). The results also receive some support from alternative measures of AI exposure.[5] Finally, traditional sources of labour market data, such as the National Sample Survey and Periodic Labour Force Survey, also reveal consistent patterns at the industry-district level: there is a strong negative relationship between AI exposure and wage growth.

This paper makes several contributions to the literature. Firstly, we offer detailed new evidence on the demand for AI skills in India's service sector firms using a novel dataset. Building on studies using vacancy postings to assess AI adoption in the US and UK (Alekseeva et al. 2020, Acemoglu, Autor, Hazell &

[5]We use the Webb version as our main measure, because it most closely captures supply-side advances in the deployable capabilities of AI. We also consider the measures of Felten et al. (2018) and Mani et al. (2020), the latter of which applies the methodology of Brynjolfsson & Mitchell (2017) to India. Our first stage and wage results are very similar with the Felten et al. measure. In contrast, the Mani et al. measure captures a different phenomenon, and does not predict firm demand for AI skills. See Section 2.B for a detailed discussion.

Restrepo 2020, Stapleton & O'Kane 2020), we find that growth in the demand for AI skills in India has been similarly rapid, with a take-off around 2016 and broad adoption across industries. Such similarity across countries and income levels adds further support to existing evidence that AI is a GPT (Goldfarb et al. 2020). Our findings for India are also consistent with Alekseeva et al. (2020) that roles requiring AI skills now provide a substantial wage premium, with our estimate of 13-17% just above their estimate of 11%. In addition, our firm identifiers enable us to extend the literature by documenting the degree of concentration of AI demand in large firms, showing that this has been high and rising over time for India.

Second, we offer one of the first attempts to evaluate the causal effects of proxies for establishment-level AI deployment on labour demand and wages. Similar to evidence from the US (Acemoglu, Autor, Hazell & Restrepo 2020), but unlike evidence from the UK (Stapleton & O'Kane 2020), we find a substantial negative relationship between AI demand and non-AI labour demand at the establishment level. Our IV strategy also allows us to evaluate the causal effect of AI demand for those establishments that were induced to demand AI skills by their exposure to AI technological advances, limiting the effects to those resulting directly from firm AI adoption. This contrasts with other work studying solely the effects of AI exposure, such as Webb (2020) and Acemoglu, Autor, Hazell & Restrepo (2020).[6] Additionally, unlike in the existing studies using Burning Glass Technologies (BGT) data, our vacancy data also includes comprehensive information on wage offers, allowing us to study the effects of wage offers for new hires. Together, these innovations allow us to identify new insights on the significant negative effects of AI demand on wage offers.

Third, we contribute to a wider literature trying to understand how AI will affect emerging and developing countries, particularly through the channel

[6] Our first stage mirrors the tests of Proposition 1 in Acemoglu, Autor, Hazell & Restrepo (2020), while their tests of Proposition 2 are analogous to the reduced form of our estimates of non-AI vacancy growth.

of trade.[7] Baldwin (2019) and Baldwin & Forslid (2020) have conjectured that machine learning, along with online platforms and software robots, could benefit developing countries by increasing offshoring of white-collar services. Korinek & Stiglitz (2021) take an alternative view that developing countries will be negatively affected, because AI devalues their comparative advantages in abundant labour and natural resources. On the one hand, our finding that the rapid deployment of AI in India's services sector has had labour market effects at least as negative as those observed in high-income countries appears more in line with Korinek & Stiglitz (2021). On the other hand, our negative findings only concern within-firm effects for incumbent firms; we may observe offsetting effects through other channels, such as firm creation. Indeed, our focus on 'AI-using' industries means we exclude positive employment effects of 'AI production', particularly in the IT industry.

Finally, our paper adds to a growing literature which uses online vacancy postings to investigate labour market effects more broadly (e.g. Deming & Kahn 2018, Stapleton & O'Kane 2020, Adams et al. 2020, Javorcik et al. 2020). We contribute through a large new dataset of job posts in India, stretching back a decade to 2010. Here, we also build upon Chiplunkar et al. (2020) who use five months of 2020 data from India's second-largest job portal to study the impact of the COVID-19 pandemic.

The rest of this paper proceeds as follows. Section 2.2 introduces the data, and Section 2.3 presents detailed descriptives on AI demand in the Indian white-collar service sector. Section 2.4 then outlines the main empirical approach, and Section 2.5 presents our results on the relationships between AI demand and broader job postings outcomes. Section 2.6 concludes. Appendix 2.A contains additional figures and tables, Appendix 2.B addresses the robustness of the results, and Appendix 2.C provides a detailed description of the vacancy

[7] India's service sector is heavily export-intensive, so we might expect labour demand to be affected both by deployment of AI in Indian firms, and by deployment of AI in India's export markets. This paper addresses the former, while current work-in-progress explores the latter.

dataset.

2.2 Data

2.2.1 Vacancy data

We use a novel dataset that covers the near universe of online vacancies posted on India's largest national job board platform between 2010 and 2019.[8] Our primary dataset includes rich text data from 15 million job postings, which is a random sample of 80% of all posts. As illustrated in Appendix Figure 2.A.1, there is wide coverage of vacancy posts in India, mostly located in urban centres. Over 150,000 unique firms posted at least one vacancy over the ten-year period, with an average of 80 posts per firm. The online job board serves primarily as an advertising platform for the vacancies, with subsequent recruitment and hiring processes taking place directly with firms. When submitting a job vacancy on the platform, firms are required to upload information into a standardised template. Hence, all posts include information on the job title, industry, role category, location, skills required, salary and experience ranges and educational requirements. The job postings also include an open text section for the job description. We manually map industries and occupations into the National Industrial Classification (NIC) and National Classification of Occupations (NCO), covering 99% of all vacancies. We also harmonise city names. Firm names were removed for anonymity and replaced with a consistent panel identifier. Further discussion of the data can be found in Appendix 2.C.

We focus on the white-collar services sector, for which our vacancy data provider also has the best coverage, as shown in Table 2.C.1.[9] The white-collar service sector is an important subset of the Indian labour market through which

[8] To give a sense of market share, the second largest competitor has roughly 300,000 job postings over a six month period (*Shine.com* 2021, Chiplunkar et al. 2020), while the equivalent figure for our site is over 1.5 million.

[9] We also focus on full-time jobs and drop the small number of part-time and non-permanent positions from our sample.

to examine the impact of AI. The service sector in India has rapidly expanded in recent decades – the fastest growing in the world at 9.2% in 2015-16 – and contributes about 65% to Indian GDP. At the same time, other empirical studies have found that high-skilled tasks requiring higher levels of education are most exposed to AI (Webb 2020). In Section 2.4.2, we similarly show that the high-wage occupations are most exposed in our sample, with exposure peaking at the 80th percentile. We further discuss the representativeness of the vacancy data in Appendix 2.C.2, by benchmarking the vacancy data relative to nationally-representative labour surveys and Prowess.

2.2.2 Measuring AI demand

Despite the prominence of the topic of AI in popular discussion, firm-level data on AI adoption remains scarce (Seamans & Raj 2018). In the absence of data on the adoption of specific technologies, a growing body of work has started using technology-related human capital to proxy for technology adoption. For example, Rock (2019) and Benzell et al. (2019) use LinkedIn profiles to construct firm-level measures of engineering and IT talent, whereas Harrigan et al. (2016) use the firm-level employment share of 'technology workers' in French matched worker-firm data as a measure of technology adoption.

Human capital is one of the key inputs for deploying an AI system. It is well recognised that one of the primary obstacles to widespread adoption of AI is the available labour supply, with top-tier scientists earning extremely high salaries and being bought out of academic positions. It would be expected that firms wishing to implement an AI driven automation project would, at least to some degree, need to hire individuals with AI skills or experience. Alternative options would be to rely on external consultants, contract out the process to a third party software provider or retrain existing staff to develop AI skills.

There are a number of reasons to believe that the dominant channel is external hiring. Work by McKinsey Global Institute (2019) surveying around

2000 companies globally found that the primary method for sourcing AI talent and capabilities was to hire externally and that the majority of companies built their AI capabilities in house, as opposed to buying or licensing capabilities from large technology companies. Additionally, even if firms were to subcontract AI development, it would be expected that they would still require at least some related human capital in-house to oversee and manage the process.

While we cannot rule out these other channels, we assume that AI skills demand and actual AI deployment within a firm will be at least moderately correlated and follow the emerging literature in using the demand for AI skills as a proxy for the extent of AI adoption. Online job vacancy data lends itself well to the measurement of demand for very specific technology-related human capital owing to its detailed textual data.

We therefore measure firm demand for AI skills through job vacancies as a proxy for AI adoption. In the rest of the paper, we shorten firm demand for AI skills to 'AI demand'. To measure firm demand for AI skills, we classify job postings based on the text in the job description or skills requirements. Our main classification is the 'narrow' measure employed by Acemoglu, Autor, Hazell & Restrepo (2020), which categorises a post as an AI vacancy if it includes any word from a list of specific AI terms.[10] By using this narrow measure of AI skills, we reduce measurement error, although our estimates of demand for AI skills are likely to be a lower bound of the true level of adoption.

[10]Specifically, a post is categorised as AI-related if any of the following terms appear in either the 'job description' or 'skills required' fields: Machine Learning, Computer Vision, Machine Vision, Deep Learning, Virtual Agents, Image Recognition, Natural Language Processing, Speech Recognition, Pattern Recognition, Object Recognition, Neural Networks, AI ChatBot, Supervised Learning, Text Mining, Support Vector Machines, Unsupervised Learning, Image Processing, Mahout, Recommender Systems, Support Vector Machines (SVM), Random Forests, Latent Semantic Analysis, Sentiment Analysis / Opinion Mining, Latent Dirichlet Allocation, Predictive Models, Kernel Methods, Keras, Gradient boosting, OpenCV, Xgboost, Libsvm, Word2Vec, Chatbot, Machine Translation and Sentiment Classification.

2.3 Descriptives

In this section, we present five key descriptive findings about the demand for AI skills in the Indian white-collar services sector, using the vacancy data. Additional figures and tables are provided in Appendix 2.A.

1. AI demand increased rapidly after 2016, particularly in the the IT, finance, education and professional services sectors.

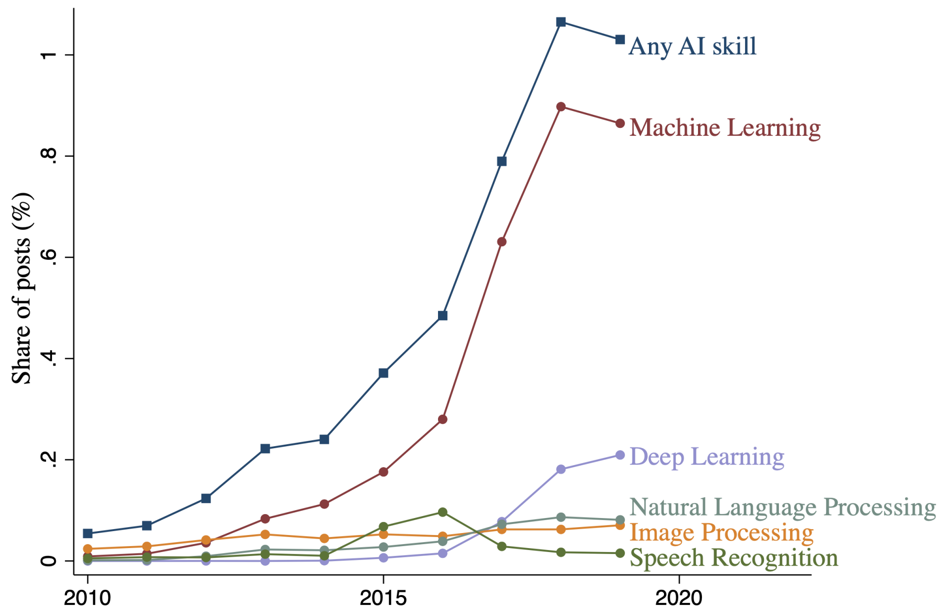
AI demand increased rapidly after 2016, rising from 0.37% of all job vacancies in 2015 to 1.03% in 2019. Figure 2.3.1 Panel (a) shows the share of posts that are tagged AI posts and the disaggregation of AI terms to examine which particular skills are most in demand. Panel (b) shows the share of AI posts over time and within the top five industries by AI share. Overall we see steady growth from our base year of 2010, which accelerates after 2016, especially in financial services and IT & software. This growth is driven largely by demand for general 'machine learning', with the sub-field 'deep learning' rising rapidly from relative obscurity to being the second most sought-after AI skill from 2017 onwards. Tellingly, the rapid take-off in the demand for AI skills after 2016 almost exactly matches patterns found in the US and UK (Acemoglu, Autor, Hazell & Restrepo 2020, Stapleton & O'Kane 2020).[11]

The heterogeneity in the demand for AI skills across sectors is striking, suggesting a broader diffusion of AI beyond AI-producing sectors. AI demand grew steadily in the IT sector since 2011, whereas AI demand in the financial sector started from a low base and grew by ten-fold between 2016 and 2018. In contrast, the business process outsourcing and call centre sector saw a small boom in AI demand in earlier years, before petering off. In 2015 and 2016, this sector had the second-highest share of AI demand, corresponding to a rise in

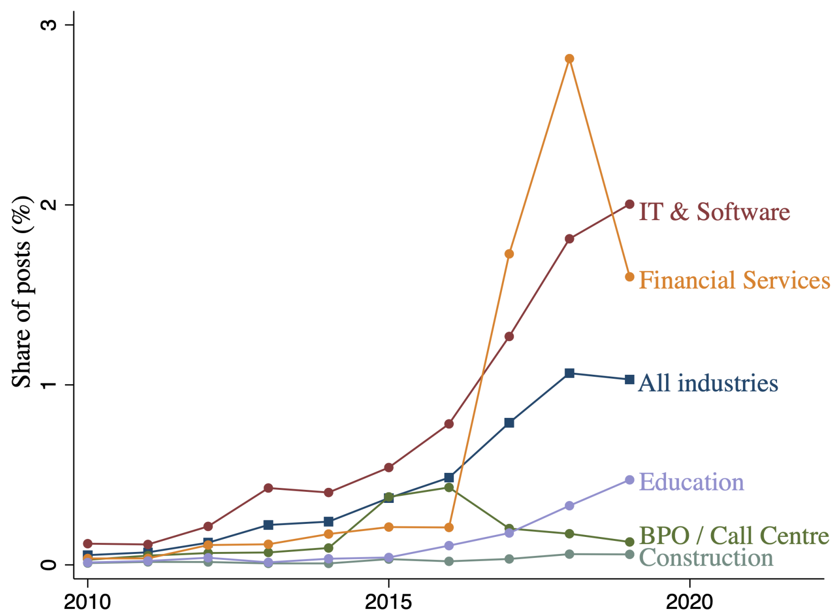
[11] For discussion of possible causes of the rapid acceleration, such as the open-source release of Google's TensorFlow software library, see Stapleton & O'Kane (2020).

Figure 2.3.1: Trends in AI demand

(a) Most demanded AI skills



(b) AI share of posts, by industry



Notes: Panel (a) shows the share of all vacancies that specify particular AI skills, for the top five most demanded skills. Panel (b) shows the share of vacancies that are AI vacancies, both for all industries together and within each of the top five industries by AI share.

the demand for 'speech recognition'. The subsequent decline in the sector's AI share is therefore curious.[12]

2. AI roles require more education, but offer substantially higher wages than other white-collar services jobs.

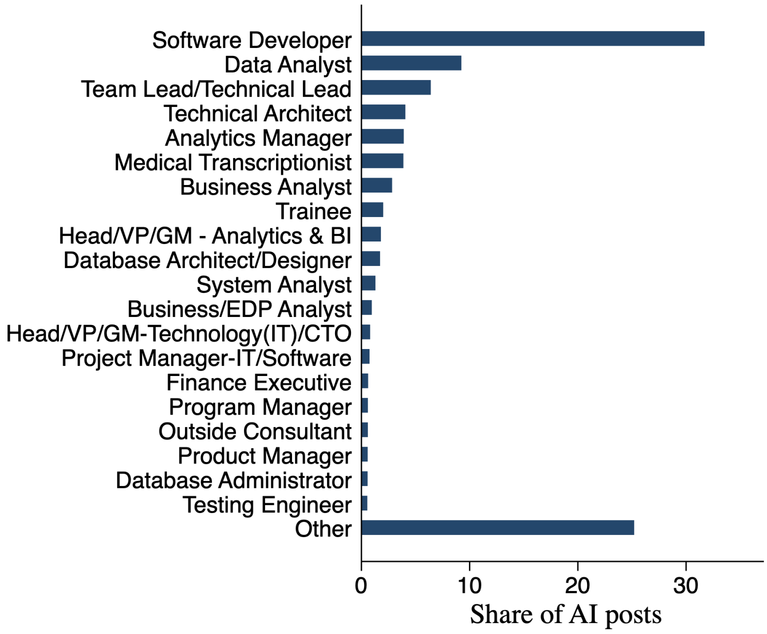
What are these AI roles, and how do they compare to the rest of the vacancies advertised? By far the most common AI role title is 'Software Developer', followed by other technical roles such as 'Data Analyst', 'Technical Lead' and 'Technical Architect' (Figure 2.3.2). AI skills are also required in technical management roles, with titles as 'Analytics Manager', 'VP - Analytics & BI', and 'Project Manager-IT/Software' also appearing in the top 20 AI-related roles. Yet there is also a long tail of more generalist roles, including 'Business Analyst', 'Trainee', 'Program Manager' and 'Product Manager'. The size of the 'Other' category grouping all other vacancy posts (25%) indicates how widespread the hiring of AI skills is across multiple job titles, albeit each with a small share of overall posts.

Moreover, we see that AI-hiring firms are seeking candidates who are slightly more experienced and substantially more educated than average – and for that they are willing to pay a substantial salary premium (Figure 2.3.3). AI vacancies are almost twice as likely as non-AI vacancies to require a master's degree, and more than seven times more likely to require a doctorate. They post a median salary of ₹250,000 (approximately US$3,333, without adjusting for PPP), twice the median non-AI salary of ₹125,000 (US$1,666).

The 'AI wage premium' persists, even after controlling for experience, education and other fixed effects. When including industry-region, industry-time and region-time fixed effects, we find that AI posts on average offer 30% higher wages than non-AI posts (see Model (1) of Table 2.3.1). However, this may

[12]Looking at the components of the share measure, we see that the absolute number of AI posts in the sector also fell substantially in 2017 (see Figure 2.A.3 in the Appendix).

Figure 2.3.2: Top 20 AI-related roles, 2010-2019

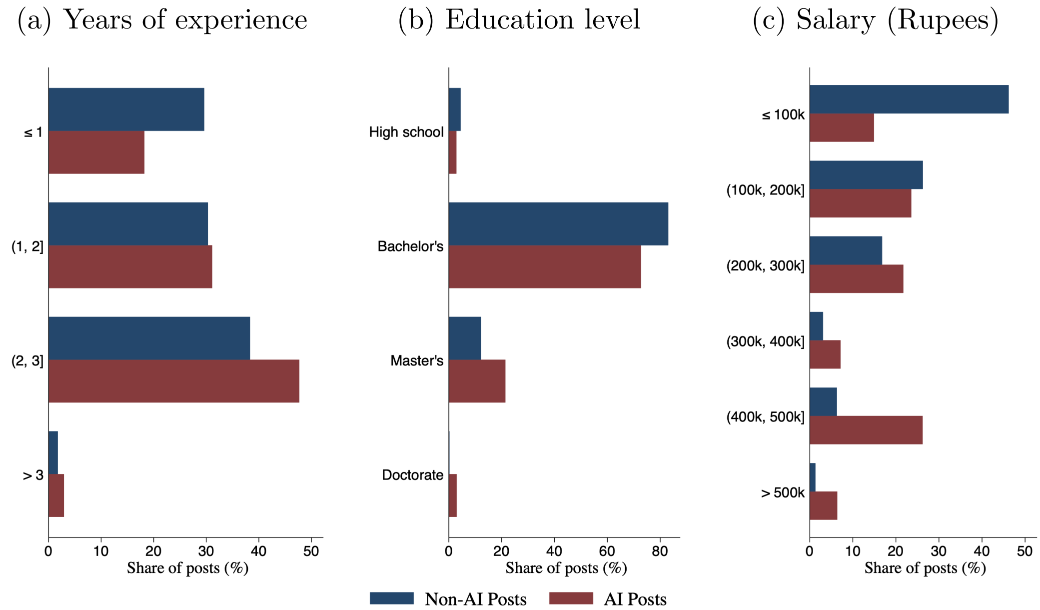


Notes: We rank the roles hiring AI skills by their share of AI posts. The top twenty are shown; all other roles hiring AI skills are grouped into the 'Other' category.

be driven by the highest-paying firms also disproportionately hiring AI roles. Therefore, we add firm fixed effects to control for differences between firms in Model (2). Even in this case, AI posts pay 19% more relative to the average non-AI post. Finally, posts that require AI skills may simply be different types of jobs. Models (3) and (4) therefore include fixed effects for the occupation and role, respectively using the NCO 2004 classification codes and the more granular role label built into the online jobs site. A substantial AI premium of 13-17% remains.[13]

[13]The interpretation of the control variables is as follows. An extra year of experience is associated with a more than 35% higher salary (at least within the predominantly early-career jobs posted on the site – see Figure 2.3.3), while having a Master's degree is associated with up to 10% higher salary. In this sample, having only a high school education is associated with wage offers 3-6% below the baseline of having an undergraduate degree, though this figure is likely a dramatic underestimate of the effect, given the major under-representation of lower-skilled occupations on the platform. The relationship between wage offers and having a doctoral degree is expressed predominantly through the firm- and role-effects: conditional on firm and occupation/role, there is no significant relationship to salary, but without such conditioning salaries are 7-13% higher. This is consistent with the wage offer premium for workers with doctorates being driven by taking higher-skilled jobs at more advanced firms.

Figure 2.3.3: Hiring profile of AI vs. non-AI vacancies



Notes: These graphs compare the distribution of posts, for AI and non-AI vacancies, across experience, education and salary. This information is reported directly in the online jobs platform. For experience and salary, the vacancy posts record a minimum and maximum value, so we take the midpoint of the specified range. AI posts are classified based on keywords, as described in Section 2.2.2.

3. AI roles are highly concentrated in a few key technology clusters, particularly Bangalore.

AI demand is highly concentrated in large cities, particularly the major technology clusters around Bangalore, Mumbai, Hyderabad and Delhi (Figure 2.3.4). This reinforces the notion that AI adoption is occurring predominantly in the urban white-collar service sector. Bangalore alone has more than 30% of all AI vacancies across India. Panel (a) compares the shares of all posts across cities with their shares of AI posts, and shows that AI demand is even more spatially concentrated than hiring generally. The tail of all other cities are represented by the 'Other' category, which is significantly shorter for AI posts relative to the listed cities. Panel (b) shows the distribution of AI posts across districts.

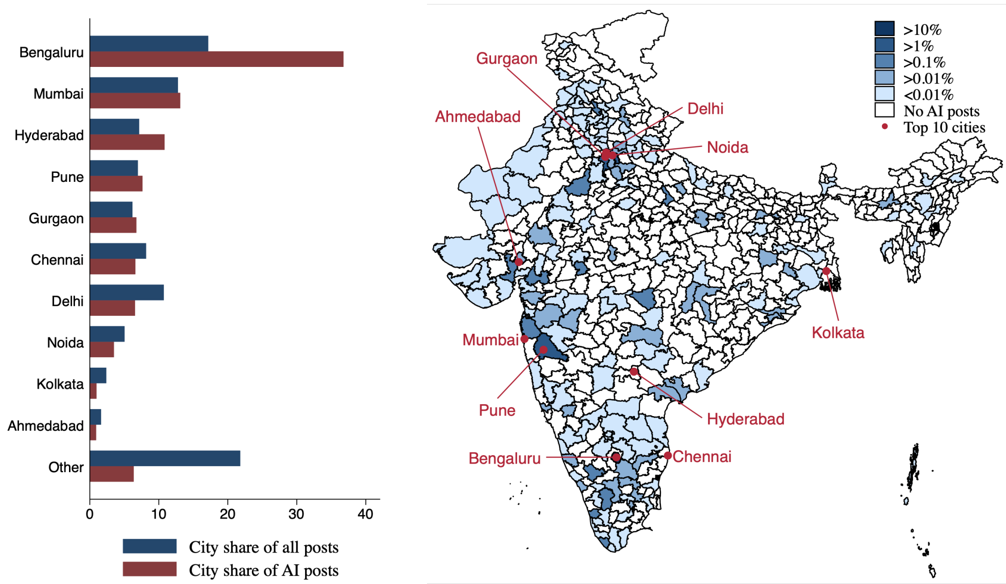
Table 2.3.1: Wages in AI vs. non-AI roles

	log Annual Salary			
	(1)	(2)	(3)	(4)
AI post	0.308***	0.194***	0.131***	0.170***
	(6.99)	(5.78)	(6.32)	(4.31)
Experience Required (Years)	0.469***	0.411***	0.386***	0.351***
	(68.46)	(52.10)	(48.95)	(43.49)
High School	0.00519	-0.0642***	-0.0364**	-0.0396**
	(0.07)	(-3.37)	(-1.97)	(-2.31)
Master's	0.103***	0.0772***	0.0414***	0.0199**
	(7.35)	(8.03)	(5.51)	(2.54)
Doctorate	0.131**	0.0719*	0.00589	0.000334
	(2.22)	(1.73)	(0.19)	(0.01)
Fixed Effects:				
– Industry-Region	✓	✓	✓	✓
– Industry-Year	✓	✓	✓	✓
– Region-Year	✓	✓	✓	✓
– Firm		✓	✓	✓
– Occupation Code			✓	
– Role Label				✓
R^2	0.345	0.536	0.557	0.577
Observations	14080455	14044610	12933816	14044608

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. All regressions include industry-region, industry-time and region-time fixed effects, and models (2)-(4) also include firm fixed effects. *AI post* is a dummy such that the coefficient is the percentage increase in annual salary associated with posts requiring AI skills, after accounting for the control variables and fixed effects. Similarly, *Experience* is measured in years, so the coefficient reflects the percentage salary increase associated with an additional year of experience. The education variables are dummies, with the baseline category being a Bachelor's degree; for instance, *High School* reflects the percentage salary decrease associated with posts that only require a high school education. The *Occupation Code* fixed effect also accounts for variation across India's 4-digit National Classification of Occupations codes, while the more granular *Role Label* fixed effect accounts for variation across the self-selected role classifications built into the jobs portal.

Figure 2.3.4: Distribution of AI demand across cities

(a) Shares of posts across cities (b) Share of all AI posts, by city, 2010-2019



Notes: The bar graph shows the shares of all posts and AI posts across cities, for the entire period 2010 to 2019. AI shares at the top end are larger than general post shares, indicating that online AI demand is more spatially concentrated than general hiring. The map shows the distribution of the share of all AI posts by particular districts. Labels are shown for the top ten cities with the most AI posts. The vast majority of districts have few AI posts, since hiring is clustered in the largest cities.

The vast majority of districts have few AI posts, since hiring is clustered in the largest cities. Shares of AI demand in cities have been remarkably constant over the last decade, as shown in Appendix Figure 2.A.4, except for a prominent increase in AI activity in Mumbai as AI demand took off in the financial sector.

*4. **AI roles are highly concentrated in the largest 'superstar' firms.***

Which firms hire AI skills? We proxy for firm size by the number of postings made on the platform. Figure 2.3.5 plots the cumulative share of AI posts against the corresponding cumulative share of all posts. This traces out a Lorenz-type curve, where the deviation from the 45° line shows the extent to which AI vacancies are disproportionately posted by the largest firms. Inspecting the top right corner reveals that the largest 14 'superstar' firms are responsible for

10% of all vacancies, with each posting at least 50,000 vacancies, and these account for 31% of all AI posts. While there are some smaller firms that post a disproportionate number of AI posts, the largest AI-hiring firms are also the largest hirers in general.

AI posts have also becoming increasingly concentrated in the largest firms over time. Figure 2.3.6 plots the trend in the Herfindahl Index of each of AI and non-AI vacancies. In every year, AI posts are substantially more concentrated among the largest firms, with the gap widening rapidly from 2015. This implies that the take-off in AI demand in Figure 2.3.1 coincided with increased concentration in the hiring of AI skills, consistent with the notion that the larger firms are disproportionately more able to invest in emerging deep learning technologies.

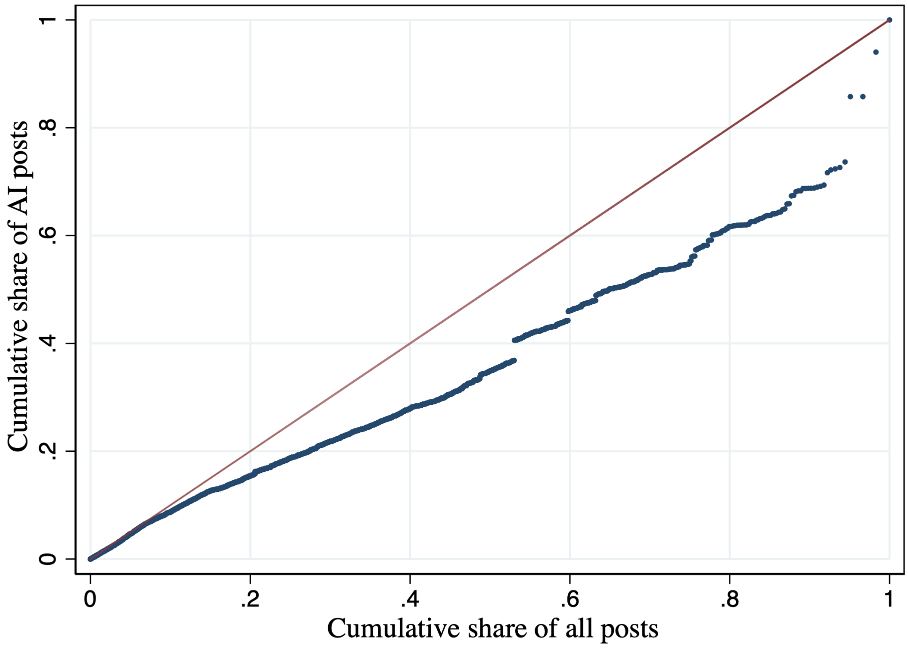
5. AI adoption can spur local AI diffusion, over and above industry and region trends, particularly in the IT sector.

How did AI demand diffuse through the economy? The vast majority of industry-city pairs had zero postings seeking AI skills at the start of our period, so we can examine descriptively through an event study how other local firms started hiring AI skills after the first AI hire in a given city and industry. We first construct a time-varying dummy for each industry-city pair ir:

$$\text{FirstAI}_{irt} = \begin{cases} 1 \text{ in the first month where a firm } F \text{ in } ir \text{ posts an AI vacancy} \\ 0 \text{ otherwise} \end{cases}$$

We then construct the outcome AI $\text{share}_{irt,-F}$ by pooling all posts in the industry-city *except* those from the first adopter F. Combining these together,

Figure 2.3.5: Distribution of AI posts across all firms, 2010-2019



Notes: We plot the cumulative share of AI posts against the corresponding cumulative share of all posts. The red 45° line indicates a perfectly even distribution of AI posts among all posts, i.e. a Gini coefficient of zero. The deviation of our scatter plot from the 45° line shows the extent to which AI vacancies are disproportionately posted by the largest firms.

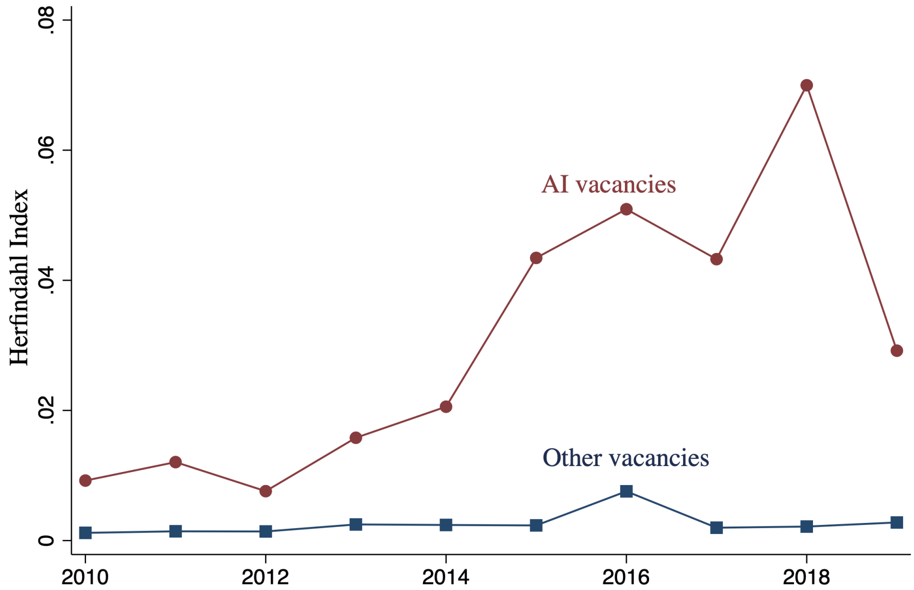
we run the event study specification:

$$\text{AI share}_{irt,-F} = \sum_{j=-2}^{2} \beta_{1j} \cdot \text{FirstAI}_{ir,t-j} + \alpha_{ir} + \alpha_{it} + \alpha_{rt} + \epsilon_{irt} \qquad (2.3.1)$$

This gives the descriptive coefficients β_{1j}, which reflect the average percentage point increase in the AI share of vacancies posted in each year j after the first adoption of AI in the city-industry pair. Crucially, this association is that which remains even after controlling for the broader industry- and city-level trends. In other words, we measure the additional impact of another firm in the same industry-city having recently adopted AI.

We find that there is a significant positive relationship between initial AI adoption and the share of AI postings by other local firms in subsequent years,

Figure 2.3.6: Firm concentration of AI posts, 2010-2019



Notes: We plot the trend in the Herfindahl Index for AI and non-AI vacancies over time. These are calculated for each year as the sum of squared firm market shares of all AI or non-AI posts, respectively.

as plotted by Figure 2.3.7 Panel (a). In the first year after the first AI post within an industry and city, the AI share is more than 0.2 percentage points higher ($p = 0.042$) than in the absence of local diffusion effects. This is a substantial difference considering that the average AI share of posts across all industries was only 1% by 2019 (see Figure 2.3.1). We also investigate heterogeneity in the diffusion of AI adoption across industries.[14] Results are shown in Figure 2.3.7 Panel (b) for the top five industries by AI share. There is substantial dispersion in the magnitude of the local effect, with by far the strongest relationship in IT & Software. We conclude that while local influence can be relevant for AI diffusion, its importance varies substantially across

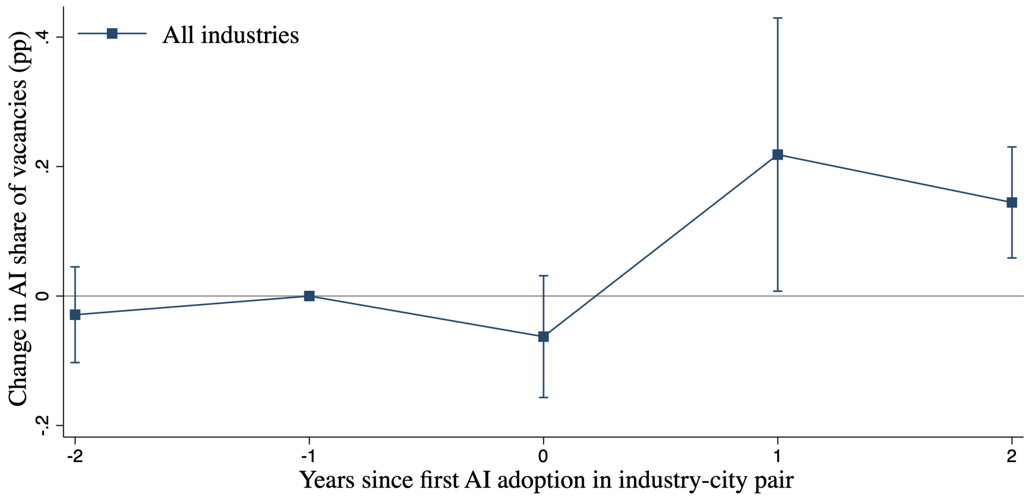
[14]Specifically, we estimate separate βs across industries X_i by running the following specification:

$$y_{irt,-F} = \sum_{j=-2}^{2} \beta_{2j} \cdot \text{FirstAI}_{ir,t-j} \cdot X_i + \alpha_{ir} + \alpha_{it} + \alpha_{rt} + \epsilon_{irt}$$

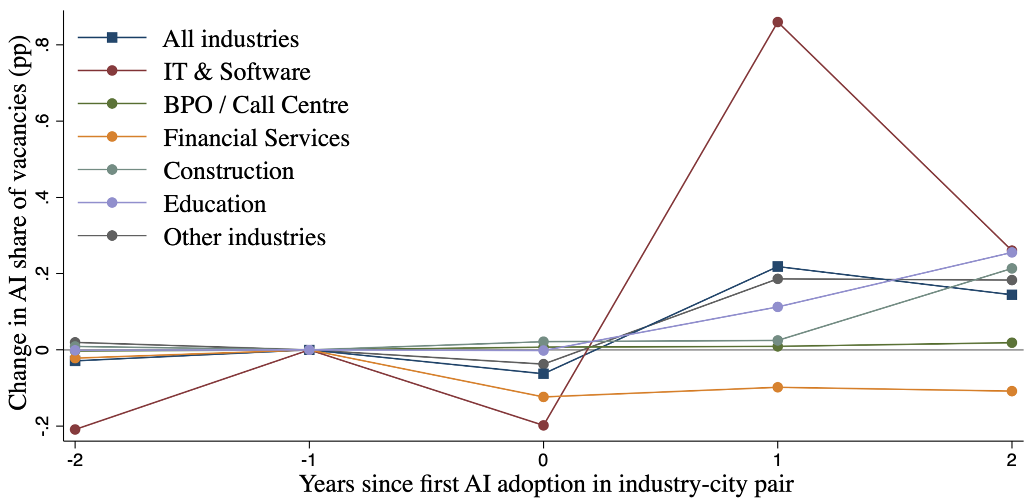
industries.

Figure 2.3.7: AI diffusion

(a) Change in AI share after first AI adoption in industry-city



(b) Heterogeneity across industries



Notes: Panel (a) shows the change in the share of vacancies that are AI vacancies, for years before and after the first adoption of AI in an industry-city pair. Panel (b) plots heterogeneity in the diffusion of AI adoption across industries. In all cases, AI posts by the initial AI adopter are excluded in order to focus on diffusion of AI posting to other firms in the industry-city pair.

2.4 Empirical Strategy

2.4.1 AI demand and establishment outcomes

The demand for AI skills ('AI demand') has been relatively widespread across occupations and industries and accounts for approximately 1% of all job postings in 2019, as discussed in Section 2.3. We now measure the effect of AI demand on the white-collar service sector more broadly and in particular, on firm hiring decisions.

Our three primary outcomes of interest are (1) the volume of AI posts, (2) the volume of non-AI posts, and (3) the wages offered by non-AI posts. We measure these outcomes as the long-difference growth between our baseline period, 2010-2012, and our endline period, 2017-2019, shortly after the take-off in AI demand in 2016.[15] Our primary unit of analysis is firm-city pairs (hereafter 'establishments'), reflecting that many large firms have autonomous establishments in several different cities. We thus estimate the effect of AI demand on employment outcomes for a panel of almost 25,000 establishments together posting approximately two million vacancies on the platform across our baseline and endline periods.

We estimate the following empirical model for our main specifications in Section 2.5:

$$\Delta y_{fr,t-t_0} = \beta \cdot \Delta Adoption_{fr,t-t_0} + \alpha_r + \alpha_i + \alpha_{f10} + \epsilon_{fr,t-t_0}, \qquad (2.4.1)$$

where $\Delta y_{fr,t-t_0}$ is the change in the inverse hyperbolic sine of outcome Y_{fr}, between 2010-2012 and 2017-19. $\Delta Adoption_{fr,t-t_0}$ is the change in the inverse hyperbolic sine of the number of AI posts by an establishment between 2010-12 and 2017-19. α_i and α_r are industry and city fixed effects. α_{f10} is a firm decile fixed effect, where firm deciles are calculated over the baseline period 2010-2012.

[15] We pool within these periods in order to improve precision and maximise the probability that a firm advertises on the job postings platform during both time periods.

We employ some or all of the fixed effects when reporting results in Section 2.5. Our preferred specification controls for region, industry and firm size fixed effects. Given that our unit of analysis are firm-city pairs, we cluster standard errors at the firm level. $\epsilon_{fr,t-t_0}$ is the mean zero error term.

The coefficient β approximates the elasticity of an outcome with respect to AI demand: increasing the growth rate of AI demand by 1% between 2010-12 and 2017-19 causes a β percentage point rise in the growth rate of the outcome variable across the same time period. Intuitively, the key variables $\Delta y_{fr,t-t_0}$ and $\Delta Adoption_{fr,t-t_0}$ are (approximately) the growth in establishment outcomes and AI demand between 2010-12 and 2017-19.[16]

2.4.2 Instrumenting AI demand by AI exposure

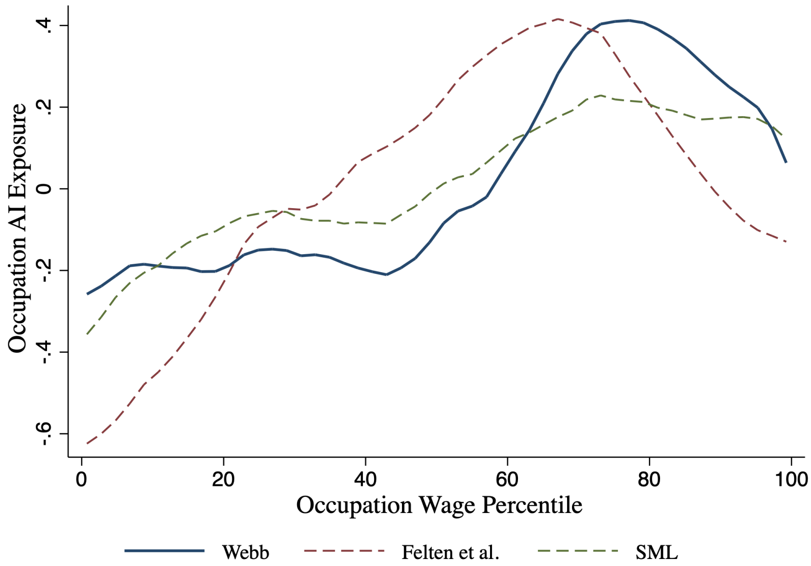
When considering the relationship between AI demand and establishment-level outcomes, we note that AI demand is likely to be endogenous, reflecting unobserved differences in establishment productivity.[17] Therefore, we instrument AI demand by 'AI exposure' to isolate supply-side pressures to AI adoption and employ a two-stage least squares model. Specifically, we use an AI exposure measure developed by Webb (2020) that captures the the degree of overlap between workers' tasks and tasks that can be performed by patented AI technologies. Specifically, Webb (2020) measures the overlap between the text of AI patents and the text of O*NET job task descriptions.[18] Occupations with a greater overlap in tasks that are capable to be automated by AI are assigned a higher exposure measure. We use publicly-available crosswalks to

[16]Mathematically, for growth rate g defined by $Y_t = (1+g)Y_{t_0}$, and using the approximation that $\ln(1+g) \approx g$ for small g, we have $g = \ln Y_t - \ln Y_{t_0} = \Delta y_{t-t_0}$.

[17]For example, more innovative managers are more likely to hire more AI workers, but they are also more productive and grow the business more quickly, increasing labour demand in general.

[18]These task descriptions are based on US occupations. Whilst Indian occupations in general may have very different task compositions, the white-collar service sector is relatively similar. To the extent that this is not the case, it would merely count against the strength of our first stage – a further advantage of our two-stage least squares approach over simply correlating exposure with outcomes.

Figure 2.4.1: AI exposure by occupation wage offers



Notes: This graph shows a smoothed local polynomial regression of the Webb AI exposure measure on occupational wage offers. We first rank occupations by their average salary across all vacancy posts 2010-2019. We then plot the AI exposure associated with each, smoothing across a bandwidth 10 of percentage points. In addition to our main measure, from Webb (2020), we also show analogous results for the alternative measures (Felten et al. 2018, Mani et al. 2020) which we use in robustness checks.

map the Webb (2020) exposure measure to the Indian National Classification of Occupations (NCO) 2004 at the four-digit level (see Appendix 2.C for more detail). By aggregating this measure up to the establishment level using baseline establishment occupation shares, we capture exogenous variation in the technological feasibility of using AI to perform elements of the business. We can also aggregate this exposure score to an industry or district level (see Figure 2.A.5). In Figure 2.4.1, we map the exposure score across the occupational wage offer distribution and find that AI exposure rises with wage offers up to a peak around the 80th percentile, before falling thereafter.[19]

To speak to the validity of the instrument, we note that India is not a

[19]Intuitively, many low-paid services jobs require elements of manual dexterity or social interaction which are hard to automate (e.g. waiters or school-teachers), then there is a middle range (e.g. insurance brokers, legal associates) which are highly exposed, while the top end (e.g. CEOs) are again hard to automate.

significant producer of new AI research and lags far behind major AI research hubs, particularly the USA and China, as well as Singapore on per capita terms (Figure 2.A.2).[20] In our analysis, we drop vacancy posts from AI-producing sectors in order to focus on AI-using sectors.[21]

Formally, we estimate the following first stage in our main specifications:

$$\Delta Adoption_{fr,t-t_0} = \gamma \cdot Exposure_{fr,t_0} + \alpha_r + \alpha_i + \alpha_{f10} + \epsilon_{fr,t-t_0}, \qquad (2.4.2)$$

where baseline AI exposure $Exposure_{fr,t_0}$ is a weighted average of the occupation-level exposure measure of Webb (2020). Specifically, we construct establishment-level exposure as the baseline-occupation-share-weighted average of occupation-wise exposure to AI adoption based on US patents:

$$Exposure_{fr,t_0} = \sum_o PostShare_{fro}^{t_0} \cdot ExposureMeasure_o \qquad (2.4.3)$$

$Exposure_{fr,t_0}$ is standardised to have a mean of zero and a standard-deviation of one. Therefore, the first stage coefficient γ in Equation 2.4.2 approximates the proportional change in AI posts between 2010-12 and 2017-19 that is associated with a one standard deviation rise in AI exposure.

2.5 Results

We run a two-stage least squares model to estimate the effect of AI vacancy growth on the growth of establishment-level hiring outcomes for our panel of vacancy-posting firms. We first document the first stage, and show that firms more exposed to AI significantly increase the growth of AI demand over time.

[20] Despite strengths in applied computer science and engineering founded on the Indian Institutes of Technology, India is not a significant producer of new AI patents (Perrault et al. 2019). Figure 2.A.2 ranks each country on a wide range of AI progress metrics. In terms of the number of AI patents, the USA is dominant. Similarly, the USA, China and Singapore are also significant producers of AI conference papers and journal articles.

[21] These sectors include education, IT, internet and e-commerce, telecom and internet service providers, which make up 34.8% of our sample.

We then turn to the second stage to examine impact of the exogenous growth in AI demand on the change in establishment-level non-AI vacancies and wage offers over time.

2.5.1 AI exposure predicts AI demand

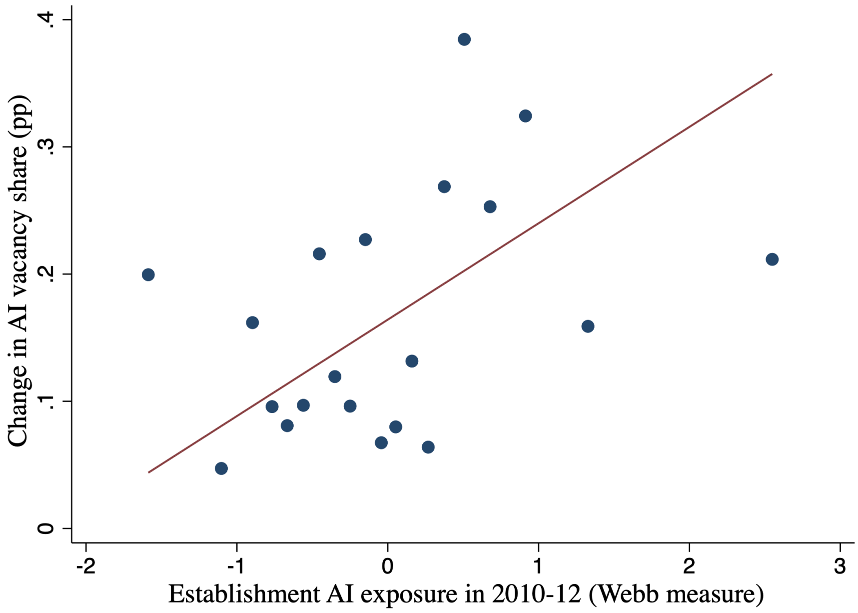
Firms with higher AI exposure scores are increasingly demanding more AI skills, using the Webb (2020) exposure measure. A one standard deviation rise in the baseline AI exposure score at the establishment level is associated with a 1.93% statistically significant increase (p<0.01) in the number of AI vacancies between 2010-12 and 2017-19. Table 2.5.1 summarises the first-stage results and shows that the relationship holds after controlling for region, firm size and industry fixed effects (Column 2). The result is also robust to controlling for region and firm size (Column 1) and region and firm fixed effects (Column 3), albeit with a weaker relationship (0.06%, p<0.05), which is unsurprising given that the variation is derived solely across establishments within firms. We conclude that AI exposure is a relevant instrument for the growth in demand for AI skills.

The relationship also holds when examining the impact of AI exposure on the AI share of vacancies at establishment level, both in long differences (Figure 2.5.1 panel (a)) and by quantile of AI exposure and year (Figure 2.5.1 panel (b)). The most exposed establishments have the highest AI share of vacancies (almost 8% in 2019), driving most of the take-off in AI demand after 2016. However, in our main regressions we focus on the growth in the *number* of AI vacancies to avoid spurious correlations.[22]

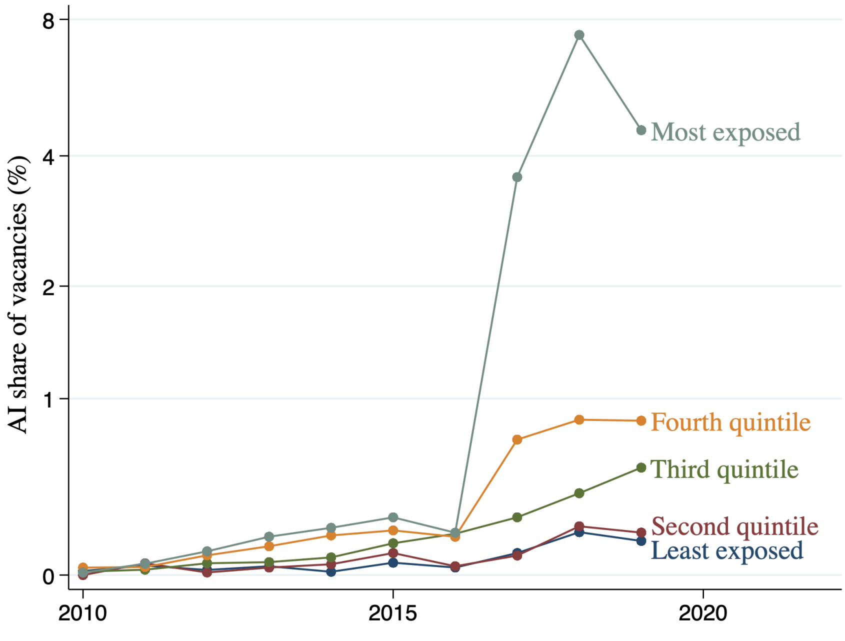
[22] Specifically, regressing total posts on the AI share (AI posts over total posts) would likely have a mechanical negative relationship, as demand shocks for non-AI workers would affect the denominator of AI share and the outcome variable. By using the growth in the number of AI posts as the independent variable, such demand shocks instead count against our story: a positive demand shock for AI workers raises the number of AI posts, and the number of total posts. Thus, our findings of a negative impact of AI demand growth on the change of total establishment employment over time are if anything an under-estimate.

Figure 2.5.1: Impact of AI exposure on establishments' AI share of posts

(a) Long differenced AI share vs. exposure



(b) Annual AI share by exposure quintile



Notes: These graphs show the relationship between AI exposure and establishments' shares of AI posts. The binned scatter plot in (a) summarises the relationship between baseline AI exposure and establishments' change in AI vacancy share between 2010-12 and 2017-19. The covariates from column (2) of Table 2.5.1 are partialled out. Panel (b) plots the time variation in this relationship, using an inverse hyperbolic sine scale for the y-axis.

Table 2.5.1: First stage: Impact of AI exposure on establishment AI adoption

	Growth in AI Vacancies		
	(1)	(2)	(3)
Establishment AI Exposure	0.0170***	0.0193***	0.00607**
	(5.13)	(5.21)	(2.05)
Fixed Effects:			
– Region	✓	✓	✓
– Firm Decile	✓	✓	
– Industry		✓	
– Firm			✓
R^2	.0341	.049	.3774
Observations	22,251	22,251	19,383

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The dependent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. The independent variable is establishment AI exposure, calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020). Each coefficient therefore represents the proportional impact on AI hiring of a one-standard deviation rise in AI exposure.

2.5.2 AI demand lowers non-AI demand

We now turn to the second stage to examine the effect of AI demand on non-AI vacancies and wage offers. We note that these outcomes pertain to new hires that firms intend to make, rather than those of existing workers. Table 2.5.2 shows the effect of growth in AI vacancies on the growth of non-AI vacancies and total vacancies, instrumenting with AI exposure using the Webb (2020) measure. The growth in AI demand reduces the growth in non-AI hiring intent: a 1% increase in the growth rate of AI vacancies results in a 3.6 percentage point decrease (p<0.01) in the change in non-AI vacancies at establishment level between 2010-12 and 2017-19, controlling for region, firm size and industry fixed effects. There is a similarly sized decrease of 3.57 percentage points in the growth rate of total vacancies, highlighting that the growth in AI vacancies disproportionately displaces growth in other vacancies in the white-collar service sector. Importantly, we examine this relationship in the years directly following the sharp take-off in AI demand. This negative relationship is consistent with the finding by Acemoglu, Autor, Hazell & Restrepo (2020) that AI exposure – rather than AI demand – results in lower non-AI hiring in the USA, using Burning Glass Technologies job postings data. Both results are robust to controlling for only region and firm size fixed effects (Column 1), and to controlling for region and firm fixed effects (Column 3). However, the latter result is only marginally statistically significant at the 10% level and the instrument is weak, given the limited variation across establishments within firms.

Table 2.5.2: Second stage: Impact of AI adoption on establishment non-AI vacancies

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-5.942***	-3.605***	-9.944*	-5.909***	-3.566***	-9.923*
	(-3.66)	(-3.16)	(-1.84)	(-3.64)	(-3.14)	(-1.84)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	26.31	27.17	4.185	26.31	27.17	4.185
Observations	22,251	22,251	19,383	22,251	22,251	19,383

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

2.5.3 AI demand lowers non-AI wage offers

Does increased AI demand reduce the growth in wage offers for non-AI vacancies? We exploit the fact that firms use a standard template to advertise vacancies on the jobs platform, providing us with wage data for all job postings. Table 2.5.3 documents the effect of the growth in AI vacancies on the growth of median wages for non-AI postings and all job postings.

Table 2.5.3: Second stage: Impact of AI adoption on establishment non-AI wages

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.101***	-2.599***	-5.973*	-3.017***	-2.527***	-5.696*
	(-3.47)	(-3.43)	(-1.83)	(-3.50)	(-3.46)	(-1.87)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.64	26.39	4.294	26.84	27.71	4.602
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure, over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

We find that a 1% higher growth rate in AI vacancies between 2010-12 and 2017-19 reduces the growth rate of non-AI wage offers by 2.6 percentage points (p<0.01) across the same time period, when instrumenting with AI exposure and controlling for region, firm size and industry (Column 2). As with vacancy growth, the negative effects of AI demand are hardly changed when considering all posts, inclusive of AI postings. We observe a similar decrease of 2.5 percentage points (p<0.01) in the growth rate for the median wage offer of all job postings (Column 5). Again, our results are robust to alternative use of fixed effects, with the same caveats for firm fixed effects.

The reduction in the growth of non-AI wage offers persists, even when controlling for changes in education and experience requirements over time.[23] Table 2.5.4 shows the residual effect of the growth of AI vacancies on the growth of the median wage offers of non-AI posts and all posts, instrumenting with AI exposure and controlling for the growth in experience and education. Even when controlling for changes in job profiles over time, a 1% higher growth rate in AI vacancies reduces the growth rate in the median wage offers of non-AI posts by 1.93 percentage points (Column 2) and of all posts by 1.89 percentage points (Column 5) between 2010-12 and 2017-19, both precisely estimated at the 1% level of significance.

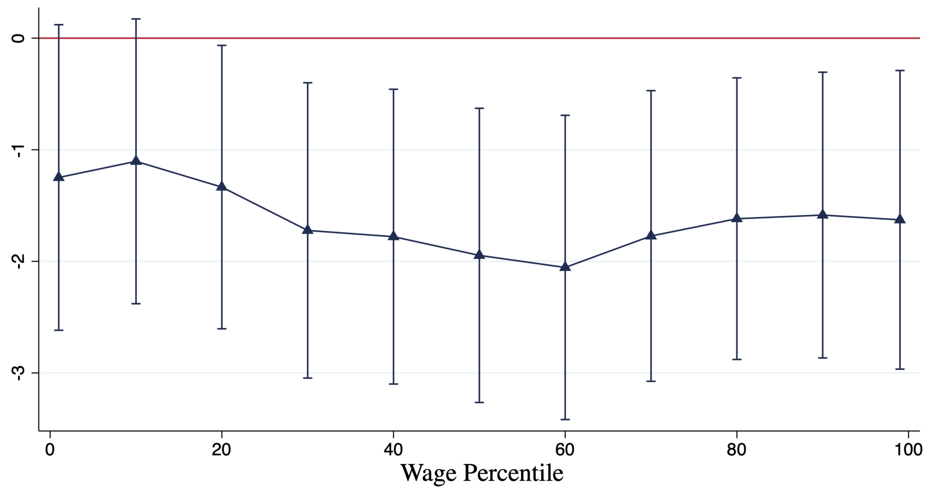
The reduction in the growth rate of non-AI wage offers in response to increased AI demand occurs across the entire wage offer distribution. Figure 2.5.2 illustrates the percentage point impact of a 1% higher growth rate in AI demand on the growth rate of a given percentile of the wage offer distribution, estimated in regressions analogous to those above. From the 20th percentile onwards, we observe a statistically significant reduction in wage offers for non-AI jobs over time, ranging from 1.3 to 2 percentage points ($p<0.05$). Even the reduction in the growth of wage offers at the 10th percentile is marginally statistically significant at the 10% level of significance, with a t-statistic of 1.92. Mid-wage offers are most affected by the changes in wage growth over time, although these results are not statistically significantly different from the changes to low and high-wage offers.[24]

[23]In particular, we note that higher growth in AI demand reduces the growth rate of non-AI education requirements slightly, and that of non-AI experience requirements significantly (Table 2.B.1).

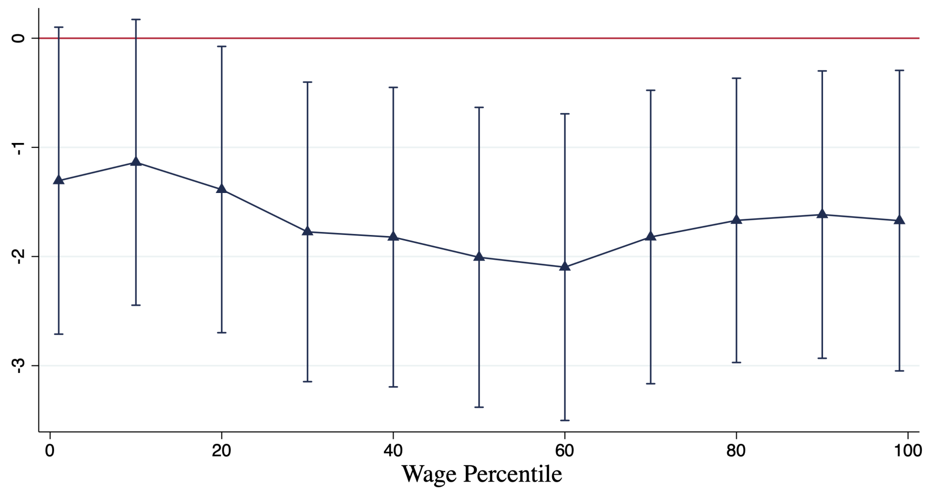
[24]This pattern parallels a long literature on 'hollowing out' (Goos & Manning 2007), as well as more recent findings focused on the impact of industrial robotics (e.g. Dixon et al. 2019).

Figure 2.5.2: Impact of AI demand on the wage offer distribution

(a) Wage growth in Non-AI posts only



(b) Wage growth in all posts



Notes: These coefficient plots show the impact of increased establishment AI demand on wage growth across the distribution of establishment wage offers. Each coefficient in panel (a) is from a regression of type (2) in Table 2.5.4, and likewise each coefficient in panel (b) is from a regression of type (5). In other words, each coefficient represents the percentage point impact of a 1% higher growth in establishment AI demand on wage growth for a given percentile of the wage offer distribution. We report the 1st and 99th percentile of the wage offer distribution and deciles in-between the two extremes, alongside 95% confidence intervals. As in Table 2.5.4, AI demand is instrumented with AI exposure, standard errors are clustered at the firm level, and we include region, firm decile and industry fixed effects. Since AI posts make up only a small share of all roles in most establishments, the pattern is very similar across the two distributions.

Table 2.5.4: Second stage: Impact of AI adoption on establishment non-AI wages, controlling for job profiles

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-2.132***	-1.933***	-5.340*	-2.088***	-1.891***	-5.103*
	(-3.16)	(-3.25)	(-1.84)	(-3.20)	(-3.29)	(-1.89)
Growth in Experience (Years)	0.836***	0.824***	0.708***	0.836***	0.823***	0.711***
	(27.95)	(29.03)	(15.46)	(28.10)	(29.15)	(16.21)
Growth in High School share	-0.0662	-0.0830	-0.177**	-0.0692	-0.0860	-0.179**
	(-0.73)	(-0.98)	(-2.03)	(-0.78)	(-1.04)	(-2.10)
Growth in Master's share	0.254***	0.257***	0.282***	0.252***	0.255***	0.280***
	(7.15)	(7.21)	(3.85)	(7.11)	(7.18)	(3.94)
Growth in Doctorate share	2.669**	2.385**	3.549	2.624**	2.345**	3.384
	(2.08)	(2.14)	(1.26)	(2.09)	(2.15)	(1.27)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	26.1	26.84	4.21	27.31	28.16	4.522
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure, over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

2.5.4 Broader spillovers

Thus far, we have examined the effect of AI demand on establishment-level job posting outcomes. How does AI demand affect broader employment outcomes within industries and districts? We aggregate our vacancy data to the industry-district level and find that AI exposure does predict AI demand (Table 2.B.13 columns (1) and (2)). A one standard deviation increase in AI exposure is associated with a 1.1% increase in AI vacancies, controlling for industry and district fixed effects. However, the first stage is not sufficiently strong to detect significant effects on the growth of non-AI vacancies or wage offers (columns (3) to (6)). We interpret these results to suggest that, while improvements in AI technologies have indeed spurred AI demand within the white-collar services sector, AI adoption is not yet sufficiently widespread to have general effects on aggregate labour market outcomes.

2.6 Conclusion

In this paper we use a novel dataset of online vacancy posts to shed light on the demand for AI skills in India's white-collar service sector and the impact on establishment-level labour demand. We first show that there was a rapid take-off in AI demand after 2016, particularly in the IT, finance and professional services industries – aligning with trends in the USA and UK (Acemoglu, Autor, Hazell & Restrepo 2020, Stapleton & O'Kane 2020). AI roles attract a substantial wage premium of 13-17%, strikingly similar to that documented in the USA by Alekseeva et al. (2019), and are highly concentrated in the largest firms and a few key technology clusters. These descriptive results are consistent with rapid global diffusion of AI capabilities, at least to those large and high-performing firms close to the technological frontier.

We next investigate the effects of growth in establishment AI demand between 2010-2019 on other establishment-level outcomes. To isolate causation, we exploit establishment-level variation in exposure to supply-side advances in AI capabilities, aggregated up from the occupational exposure measure of Webb (2020), as an instrument for AI demand. In the first stage, establishments that were *ex ante* more exposed to advances in AI significantly increase demand for AI skills in their online vacancy posts. In the second stage, this growth in AI demand has a significant negative effect on growth in non-AI and total postings by establishments. These results suggests that, at the establishment level, the displacement effects of AI outweigh any productivity or labour reinstating effects, consistent with findings in the USA by Acemoglu, Autor, Hazell &

Restrepo (2020). A 1% establishment-level increase in the AI vacancy growth rate results in a 3.6 percentage point decrease in the growth of non-AI vacancies between 2010-12 and 2017-19, and a similar effect for total vacancies, controlling for region, firm size and industry fixed effects.

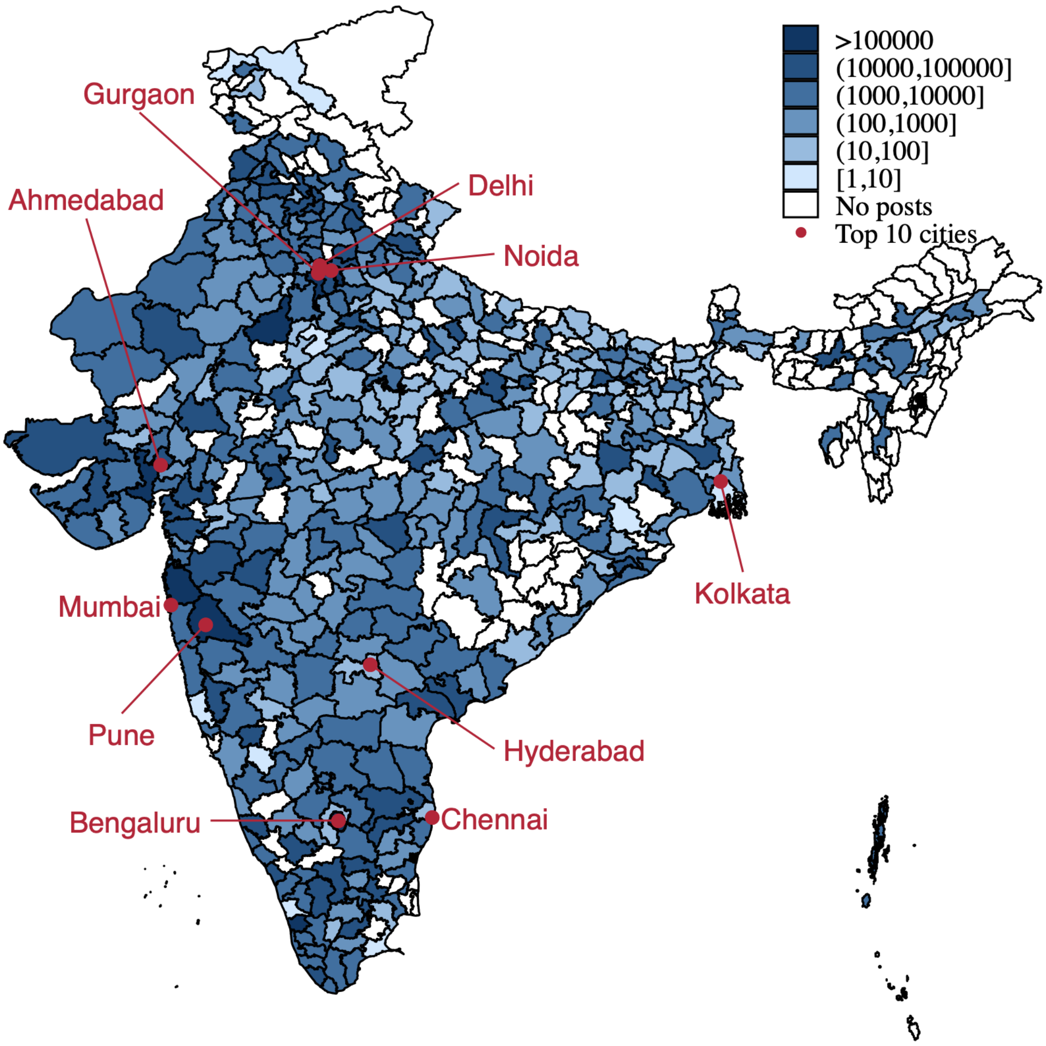
Finally, we show that growth in AI demand also reduces growth in the average wage offers of the vacancies posted, both for non-AI roles only and overall. We find that a 1% higher growth rate in AI vacancies between 2010-12 and 2017-19 reduces the growth rate of non-AI wage offers by 2.6 percentage points, instrumenting on AI exposure and controlling for region, firm size and industry. This negative effect appears across the entire wage offer distribution, with the impact particularly severe for mid-wage offers.

Taken together, our findings suggest that, at least in the short run, AI is a 'double-edged sword' for Indian white-collar services workers. AI jobs pay a substantial wage premium, but these opportunities are highly concentrated in certain industries, cities and 'superstar' firms. For the vast majority unable to obtain AI-related jobs, AI adoption within an establishment reduces both the number of other job opportunities and the available salaries. Such net displacement effects within the firm could have important negative consequences for India – and indeed for other countries looking to follow a services-led development path – if they are not balanced out by positive effects elsewhere in the economy. Thus our conclusions are reminiscent of those in Acemoglu & Restrepo (2019), that advances in AI are being channelled too much towards automation and not enough towards creating new sources of labour demand.

However, in this paper we have only explored the net direct effect of adopting AI on pre-existing establishments. We cannot say whether this AI adoption has had positive effects on other firms, or has created new jobs elsewhere in the economy. Tracing these potential 'creative' effects, and evaluating whether they offset our 'destructive' effects, are important tasks for future research.

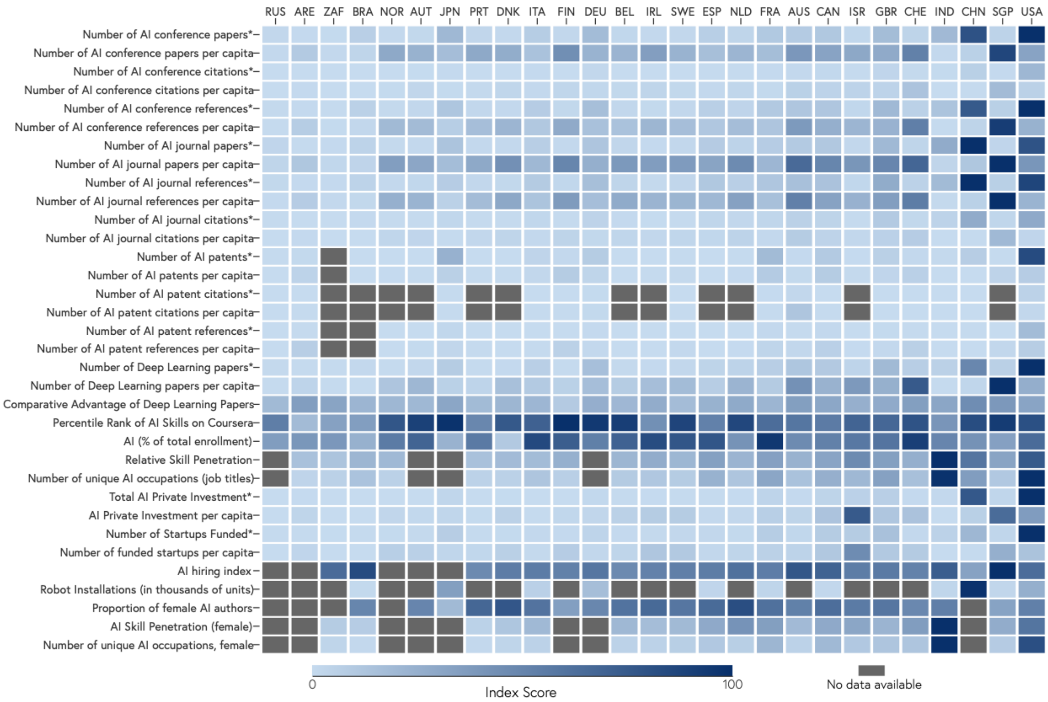
2.A Additional Figures and Tables

Figure 2.A.1: Total posts by district, 2010-2019



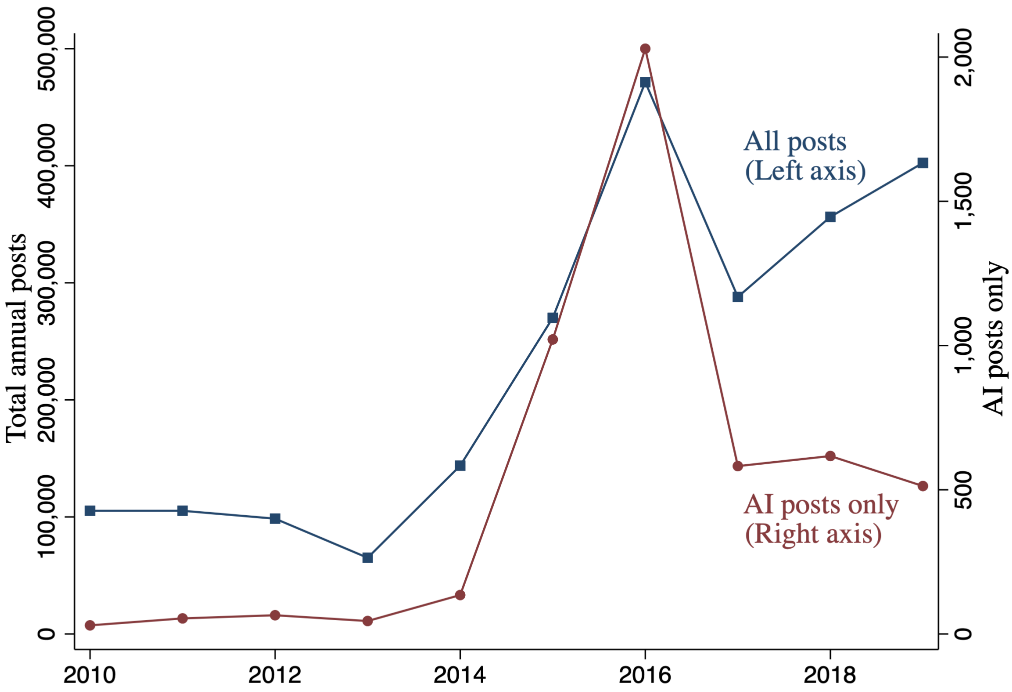
Notes: This map shows the distribution of our online vacancy posts across Indian districts. Labels are shown for the ten cities with the largest numbers of posts.

Figure 2.A.2: Global AI Vibrancy, from Perrault et al. (2019)



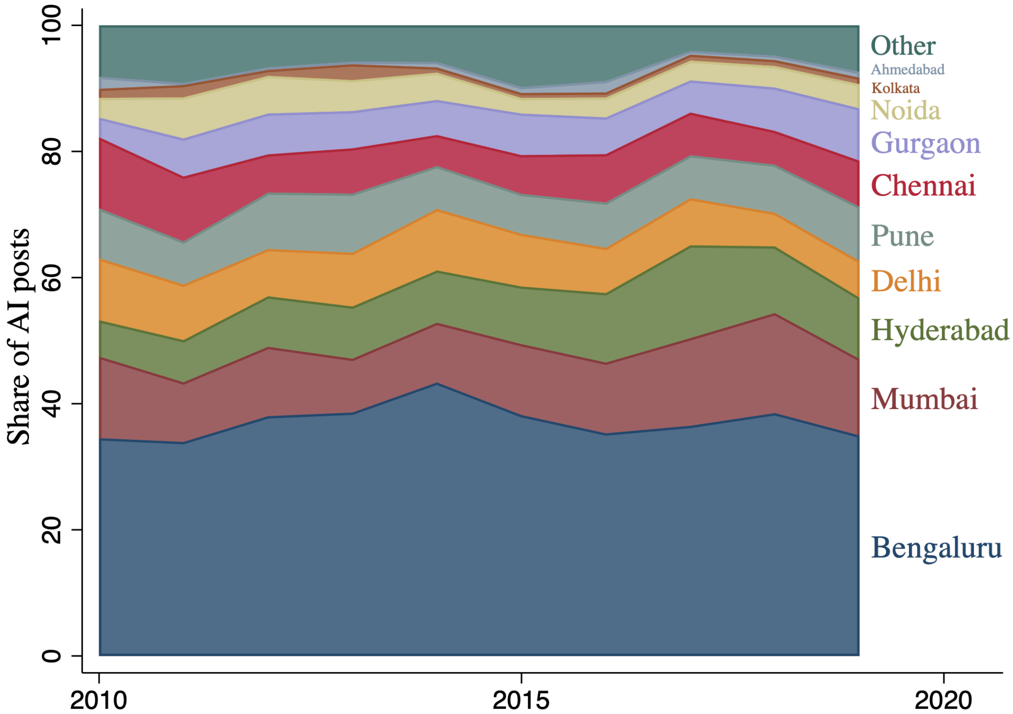
Notes: This chart shows relative country scores on a wide range of AI progress metrics. India (fourth from right) scores highly only on skill penetration (the average share of AI skills among all the top 50 skills in each occupation, across all occupations in the country) and number of unique AI occupations (those that have any AI skills in their top 50 skills). These are both calculated using LinkedIn data – which is far less representative in India than in developed countries due to low coverage. Skill penetration is thus likely an overestimate, while the number of AI occupations is largely driven by India's population size.

Figure 2.A.3: AI demand in the Business Process Outsourcing & Call Centre industry



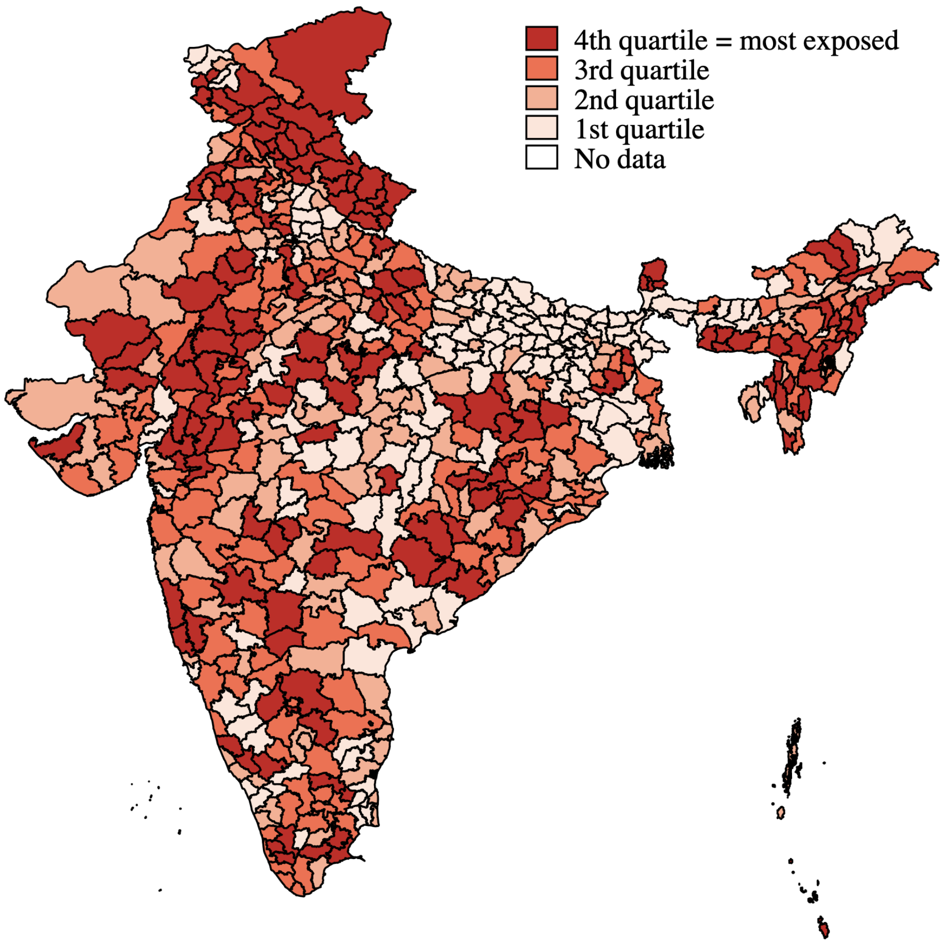
Notes: This graph shows the trend in general posts and AI posts in the BPO and call centre industry. The decline in the number of AI posts after 2016 is proportionately larger than the decline in the number of overall posts.

Figure 2.A.4: Cities' shares of AI posts over time



Notes: This graph shows the distribution of AI posts across cities over time. Each year reflects the share of all AI vacancies in that year which were in each city. Shares have been remarkably constant. Bangalore's share peaked at just over 40% in 2014, then Mumbai's share in particular has risen subsequently as AI demand increased in finance (see Figure 2.3.1).

Figure 2.A.5: AI exposure by district – Webb (2020) measure



Notes: This map shows the distribution of AI exposure across Indian districts, combining the Webb (2020) measure with district-wise occupation shares from the National Sample Survey.

2.B Robustness

In this section, we demonstrate that our establishment-level results are robust to alternative AI exposure measures and model specifications. We also find support for our results in other administrative datasets.

2.B.1 Alternative exposure measures

For our main specifications, we use the AI exposure measure proposed by Webb (2020), as it measures which tasks overlap with capabilities outlined in AI patents, thereby objectively capturing supply-side advancements in the AI technological frontier. Webb (2020) also validates the measure against previous IT and robotic trends. However, alternative AI exposure measures have also been proposed in the literature to date. Therefore, we examine whether our results remain robust to alternative definitions of our instrument.

We first consider the AI exposure measure proposed by Felten et al. (2018). Their AI Occupational Impact measure draws on data from the AI Progress Measurement project from the Electronic Frontier Foundation. The data identify nine application areas in which AI has made progress since 2010. Felten et al. (2018) crowdsource assessments on the applicability of these applications to 52 O*NET ability scales using Amazon MTurk. The AI Occupational Impact assigns an AI exposure score to each O*NET occupation as the weighed sum of the 52 O*NET ability assessments, where the weights are equal to the O*NET-reported prevalence and importance of each ability within each occupation. We map the Felten et al. (2018) measure to Indian NCO using a publicly available crosswalk (see Appendix 2.C).

Our results remain robust to the use of the Felten et al. (2018) AI exposure instrument. We first observe that the AI exposure predicts AI demand in the first stage (Table 2.B.2). Turning to the second stage, we observe that the negative effects on the growth of wage offers in response to increased AI demand remains robust to the use of Felten et al. (2018) as an instrument. A 1% higher growth in AI demand results in a 1.51% decrease (p<0.05) in the growth rate in wage offers between 2010-12 and 2017-19 (Table 2.B.4). This result strengthens to a 1.95% reduction (p<0.01) in the growth rate for the non-AI median wage offer, after controlling for changes in the education and experience requirements over time (Table 2.B.5). Moreover, we similarly observe a negative effect on the growth rate across the entire wage offer distribution, except for the very lowest percentiles (Figure 2.B.1). However, we do not observe any significant effects on the growth of non-AI vacancies (Table 2.B.3).

We also consider the Suitability for Machine Learning (SML) methodology from Brynjolfsson et al. (2018), which uses surveys to score O*NET direct work activities against a rubric of suitability for machine learning (e.g. inputs and outputs are machine-readable, feedback is immediate, task is principally concerned with matching or prediction, etc.). We use an India-specific version of the SML index created by Mani et al. (2020), who interviewed more than 3000 Indian employees using the SML rubric and mapped a SML score onto every occupation in the 2004 NCO at the three-digit level. However, the SML exposure measure fails to predict firm demand for AI skills using our job vacancy data. In fact, we find that establishments scoring high on the SML measure are actually *less* likely to adopt AI over the period, in contrast to the other two measures (Tables 2.B.2 and 2.5.1).

2.B.2 Alternative specifications

The wage results are robust to using mean rather than median wage offers (Table 2.B.6). Our results are also robust to weighting by baseline establishment size, proxied by number of job postings advertised between 2010 and 2012, with the top 5% winsorised (Tables 2.B.7, 2.B.8 and 2.B.9). The results are also qualitatively robust to weighting by establishment size even when winsorising only the top 0.5% (approximately 100 firms) (Tables 2.B.10, 2.B.11 and 2.B.12).

The median size of these 100 largest firms is 200 times that of the median firm overall, with the very largest firm almost 1500 times the size of the overall median firm. Thus, these very largest firms dominate the distribution when the full set of weights are used, and the first stage becomes very weak.

2.B.3 Alternative data sources

As an additional robustness check, we investigate potential wage effects of AI exposure in the Prowess (balance sheet) and NSS/PLFS (nationally-representative labour surveys) administrative datasets. As noted in Section 2.C.2, we cannot observe AI adoption in these datasets. However, we can use the baseline industry-region occupation distribution to assess AI exposure, and hence examine reduced form relationships. Table 2.B.14 thus presents results on the relationship between AI exposure and wage growth in Prowess firms and NSS/PLFS industry-districts. Columns 1-2 show the relationship between baseline AI exposure and the growth between 2011-12 and 2017-18 in large services firms' wage bills, from Prowess.[25] As noted in Section 2.C.2, Prowess only contains large and predominantly publicly-listed firms, hence the comparatively small number of observations. We estimate baseline exposure by combining the Webb (2020) measure with the industry-state distribution of white-collar services occupations in the 2011-12 National Sample Survey.[26] Perhaps due to the data limitations, we do not find statistically significant results – but we do find a negative relationship, qualitatively consistent with our other findings.

Columns 3-6 show the relationship between AI exposure and the growth between 2011-12 and 2017-18 in industry-district-level average wages, using the National Sample Survey and Periodic Labour Force Survey. In this case we can measure exposure at the industry-district level, and find a strong negative

[25]There is no statutory obligation to report the number of employees, and fewer than 10% do in practice, so we focus on impacts on the total wage bill – which can be seen as a composite of our hiring and wage margins.

[26]Prowess only provides information on firms, not establishments, which are too broad to calculate district-level exposure.

relationship between AI exposure and wage growth. Specifically, having one standard deviation higher AI exposure is associated with 7.7% lower growth in median wages over the period. While we do not consider this correlational evidence causal, it is consistent with a negative impact of AI adoption on the wages of workers in services firms.

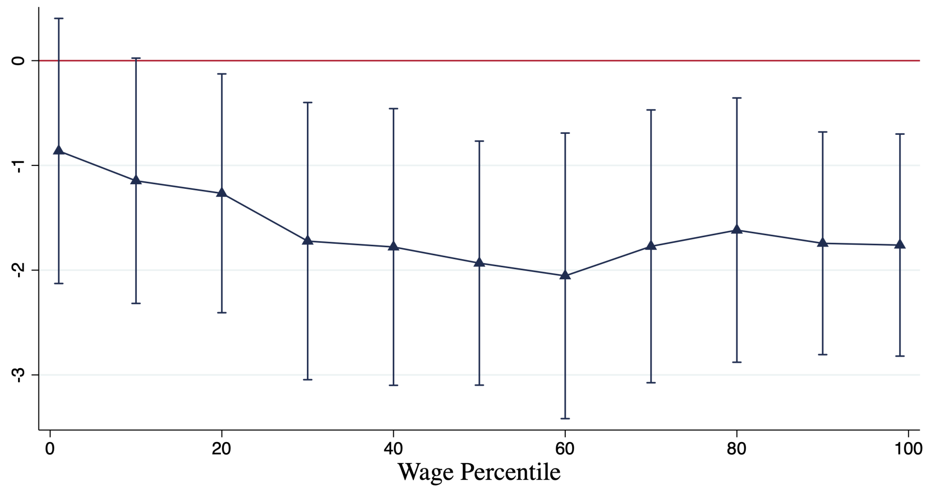
Table 2.B.1: Impact of AI adoption on establishment non-AI education and experience

	Growth in Non-AI Postgraduate Vacancy Share			Growth in Non-AI Years of Experience		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.225	-0.319	-0.573	-1.065***	-0.691**	-0.705
	(-1.00)	(-1.55)	(-0.76)	(-2.81)	(-2.29)	(-0.72)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.12	25.87	3.894	25.12	25.87	3.894
Observations	22,244	22,244	19,377	22,244	22,244	19,377

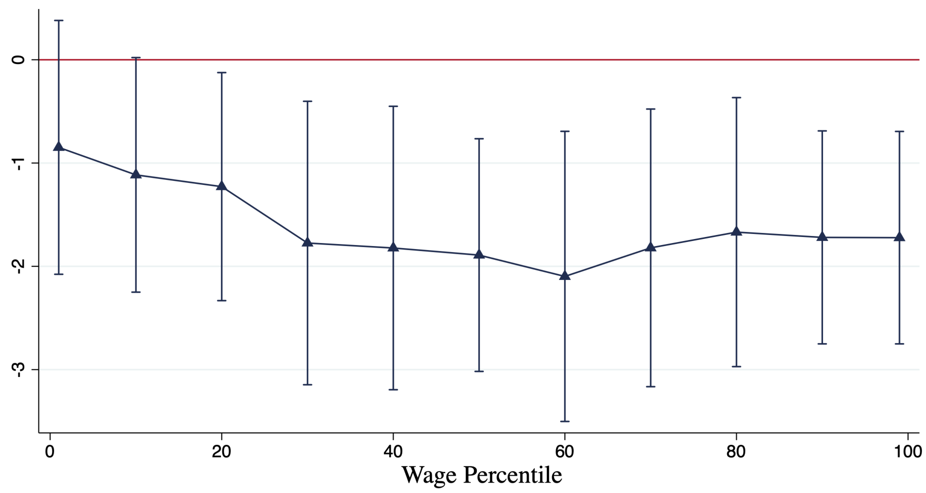
Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020). *Non-AI Postgraduate Vacancy Share* is defined as the establishment-level share of non-AI posts requiring either a Master's or a Doctorate.

Figure 2.B.1: Impact of establishment AI adoption on the wage offer distribution – Felten et al. measure

(a) Non-AI posts only



(b) All posts



Notes: These coefficient plots show the impact of establishment AI adoption on the distribution of establishment wage offers. Each coefficient in panel (a) is from a regression of type (2) in Table 2.5.4, and likewise each coefficient in panel (b) is from a regression of type (5). In other words, each coefficient represents the percentage point impact of a 1% increase in establishment AI demand upon a given percentile of the wage distribution.As in Table 2.5.4, AI demand is instrumented with AI exposure, standard errors are clustered at the firm level, and we include region, firm decile and industry fixed effects. Since AI posts make up only a small share of all roles in most establishments, the pattern is very similar across the two distributions.

Table 2.B.2: First stage: Impact of AI exposure on establishment AI adoption – alternative exposure measures

	Growth in AI Vacancies					
	(1)	(2)	(3)	(4)	(5)	(6)
AI Exposure	0.0202***	0.0142***	0.00629*	-0.0151***	-0.0102***	-0.00778**
	(5.91)	(4.61)	(1.65)	(-5.71)	(-3.68)	(-2.56)
Exposure Measure	Felten et al.	Felten et al.	Felten et al.	SML	SML	SML
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
R^2	.0349	.0481	.3774	.0338	.0476	.3775
Observations	22,251	22,251	19,383	22,251	22,251	19,383

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The dependent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. The independent variable is establishment AI exposure, calculated as the standardized average of occupation AI exposure (from either Felten et al. 2018, or Mani et al. 2020 building on Brynjolfsson & Mitchell 2017), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020). Each coefficient therefore represents the proportional impact on AI hiring of a one-standard deviation rise in AI exposure.

Table 2.B.3: Second stage: Impact of AI adoption on establishment non-AI vacancies – Felten et al. exposure measure

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	1.076	0.698	-1.966	1.095	0.714	-1.968
	(1.44)	(0.64)	(-0.79)	(1.47)	(0.66)	(-0.79)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	34.97	21.25	2.73	34.97	21.25	2.73
Observations	22,251	22,251	19,383	22,251	22,251	19,383

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Felten et al. 2018), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.4: Second stage: Impact of AI adoption on establishment non-AI wages – Felten et al. exposure measure

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.108**	-1.512**	-5.856	-1.133**	-1.567**	-5.797
	(-2.51)	(-2.24)	(-1.48)	(-2.51)	(-2.24)	(-1.49)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	36.02	22.15	2.567	35.05	21.22	2.607
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Felten et al. 2018), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.5: Second stage: Impact of AI adoption on establishment non-AI wages, controlling for job profiles – Felten et al. exposure measure

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.348***	-1.947***	-6.437	-1.374***	-2.007***	-6.377
	(-3.17)	(-2.90)	(-1.55)	(-3.14)	(-2.86)	(-1.56)
Growth in Experience	0.826***	0.824***	0.699***	0.826***	0.824***	0.701***
	(30.71)	(28.73)	(12.98)	(30.61)	(28.46)	(13.25)
Growth in High School share	-0.103	-0.0825	-0.175*	-0.103	-0.0812	-0.176*
	(-1.48)	(-0.96)	(-1.77)	(-1.47)	(-0.94)	(-1.79)
Growth in Master's share	0.251***	0.257***	0.297***	0.250***	0.256***	0.298***
	(7.48)	(7.21)	(3.01)	(7.42)	(7.12)	(3.02)
Growth in Doctorate share	1.847**	2.399**	4.245	1.876**	2.461**	4.191
	(2.17)	(2.10)	(1.24)	(2.17)	(2.09)	(1.24)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	35.06	21.5	2.597	34.09	20.57	2.639
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Felten et al. 2018), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.6: Impact of AI adoption on establishment non-AI mean wages

	Growth in Non-AI Mean Wage		Growth in Overall Mean Wage	
	(1)	(2)	(3)	(4)
Growth in AI Vacancies	-2.606***	-1.785***	-2.531***	-1.746***
	(-3.59)	(-3.28)	(-3.63)	(-3.32)
Controls for Experience & Education		✓		✓
Fixed Effects:				
– Region	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓
– Industry	✓	✓	✓	✓
First Stage F-Stat	26.39	26.93	27.71	28.25
Observations	22,064	22,064	22,071	22,071

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020). Models (2) and (4) also control for changes in establishment job profiles over the period, specifically the mean number of years of experience required and the shares of posts requiring different levels of education.

Table 2.B.7: Second stage: Impact of AI adoption on establishment non-AI vacancies, weighted (top 5% winsorized)

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.523**	-0.968*	-5.993	-1.500**	-0.941*	-5.984
	(-2.42)	(-1.95)	(-1.14)	(-2.39)	(-1.90)	(-1.14)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	18.8	16.23	1.522	18.8	16.23	1.522
Observations	22,251	22,251	19,383	22,251	22,251	19,383

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. Establishments are weighted by baseline number of posts, with the top 5% winsorized. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.8: Second stage: Impact of AI adoption on establishment non-AI wages, weighted (top 5% winsorized)

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.512**	-0.362**	-3.149	-0.507**	-0.357*	-3.084
	(-2.44)	(-1.97)	(-1.14)	(-2.44)	(-1.96)	(-1.16)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	18.53	15.95	1.513	18.79	16.24	1.58
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. Establishments are weighted by baseline number of posts, with the top 5% winsorized. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.9: Second stage: Impact of AI adoption on establishment non-AI wages, controlling for job profiles, weighted (top 5% winsorized)

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.331**	-0.248	-2.841	-0.329**	-0.244	-2.784
	(-2.00)	(-1.64)	(-1.19)	(-2.00)	(-1.64)	(-1.21)
Growth in Experience	0.781***	0.764***	0.730***	0.781***	0.763***	0.729***
	(22.91)	(24.92)	(9.23)	(22.93)	(24.93)	(9.41)
Growth in High School share	-0.217**	-0.221**	0.118	-0.218**	-0.222**	0.114
	(-2.24)	(-2.32)	(0.37)	(-2.25)	(-2.34)	(0.37)
Growth in Master's share	0.292***	0.312***	0.302**	0.288***	0.309***	0.306**
	(5.93)	(6.55)	(2.22)	(5.84)	(6.47)	(2.24)
Growth in Doctorate share	3.033**	2.412**	6.693	3.024**	2.395**	6.567
	(2.48)	(2.43)	(1.07)	(2.48)	(2.43)	(1.08)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	18.61	15.95	1.585	18.86	16.23	1.652
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. Establishments are weighted by baseline number of posts, with the top 5% winsorized. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.10: Second stage: Impact of AI adoption on establishment non-AI vacancies, weighted (top 0.5% winsorized)

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.091	-0.826	-9.747	-1.071	-0.801	-9.740
	(-1.33)	(-1.20)	(-0.41)	(-1.31)	(-1.17)	(-0.41)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	7.28	6.69	.1804	7.28	6.69	.1804
Observations	22,251	22,251	19,383	22,251	22,251	19,383

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. Establishments are weighted by baseline number of posts, with the top 0.5% winsorized. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.11: Second stage: Impact of AI adoption on establishment non-AI wages, weighted (top 0.5% winsorized)

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.149	-0.0604	-4.566	-0.151	-0.0602	-4.429
	(-1.00)	(-0.49)	(-0.42)	(-1.01)	(-0.49)	(-0.43)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	7.236	6.646	.1826	7.274	6.692	.1921
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. Establishments are weighted by baseline number of posts, with the top 0.5% winsorized. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.12: Second stage: Impact of AI adoption on establishment non-AI wages, controlling for job profiles, weighted (top 0.5% winsorized)

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.0830	-0.0252	-4.174	-0.0854	-0.0255	-4.052
	(-0.65)	(-0.23)	(-0.44)	(-0.67)	(-0.23)	(-0.45)
Growth in Experience	0.720***	0.701***	0.814**	0.720***	0.701***	0.809**
	(17.47)	(18.97)	(2.22)	(17.53)	(19.02)	(2.33)
Growth in High School share	-0.332**	-0.321**	0.227	-0.334**	-0.324**	0.213
	(-2.47)	(-2.36)	(0.21)	(-2.48)	(-2.37)	(0.21)
Growth in Master's share	0.357***	0.381***	0.363	0.354***	0.380***	0.361
	(3.47)	(3.65)	(0.86)	(3.44)	(3.65)	(0.88)
Growth in Doctorate share	2.308	1.449	15.99	2.335	1.445	15.51
	(1.61)	(1.18)	(0.44)	(1.63)	(1.18)	(0.45)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	7.156	6.471	.1972	7.195	6.516	.207
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the firm level. Establishments are weighted by baseline number of posts, with the top 0.5% winsorized. The independent variable is the growth in establishment AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. Likewise the dependent variables are the change in the inverse hyperbolic sine of the respective establishment-level outcomes. Each coefficient therefore represents the percentage point impact upon the outcome variable of a one percent increase in establishment AI hiring. The latter is instrumented by establishment AI exposure. This is calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the establishment posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020).

Table 2.B.13: AI adoption at the industry-district level

	AI Vacancies		Non-AI Vacancies		Non-AI Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
First stage:						
AI Exposure	0.0126***	0.0110**				
	(2.82)	(2.14)				
Second stage:						
Growth in AI Vacancies			-1.038	-2.375	2.264	-0.166
			(-0.68)	(-1.07)	(1.57)	(-0.11)
Fixed Effects:						
– District		✓		✓		✓
– Industry		✓		✓		✓
First Stage F-Stat			7.964	4.593	7.499	4.544
Observations	4207	4165	4207	4165	4204	4161

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Standard errors clustered at the district level. The dependent variables are the growth between 2010-12 and 2017-19 in industry-district AI vacancies, non-AI vacancies and non-AI wages, each approximated by the change in the inverse hyperbolic sine. The independent variable for the first stage is industry-district AI exposure, calculated as the standardized average of occupation AI exposure (from Webb 2020), over the occupations for which the industry-district cell posts vacancies in 2010-12, weighted by the number of vacancies posted per occupation, as in Acemoglu, Autor, Hazell & Restrepo (2020). The first two coefficients therefore represent the percentage point impact on AI hiring of a one-standard deviation rise in AI exposure. The independent variable for the second stage is the growth in industry-district AI vacancies between 2010-12 and 2017-19, approximated by the change in the inverse hyperbolic sine. The latter four coefficients therefore represent the percentage point impact upon the outcome variable of a one percent increase in industry-district AI hiring, instrumented by industry-district AI exposure.

Table 2.B.14: AI exposure and wages in alternative datasets

	Growth in Firm Wage Bill		Growth in Industry-District Median Wage		Growth in Industry-District Mean Wage	
	(1)	(2)	(3)	(4)	(5)	(6)
AI Exposure	-0.0866	-0.0505	-0.0758***	-0.0765***	-0.0798***	-0.0723***
	(-1.66)	(-0.65)	(-4.12)	(-2.93)	(-4.80)	(-3.10)
Fixed Effects:						
– State		✓		✓		✓
– District				✓		✓
– Firm Decile		✓				
– Industry		✓		✓		✓
R^2	.0092	.1658	.0053	.2372	.0077	.2644
Observations	489	460	3,451	3,297	3,451	3,297

Notes: t statistics in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1-2 use firm-level balance sheet data from services firms in Prowess, and cluster standard errors at the industry level. The independent variable is industry-state AI exposure, calculated using the 2011/12 National Sample Survey. Specifically, it is the standardized average of occupation AI exposure (from Webb 2020), over white-collar services occupations in the industry-state in 2011-12, weighted by the share of workers per occupation. The dependent variable is the growth in the total firm wage bill between 2011-12 and 2017-18, approximated by the change in the inverse hyperbolic sine. Each coefficient therefore represents the proportional impact on total firm wages of a one-standard deviation rise in baseline AI exposure. Columns 3-6 use industry-district-level representative survey data on white-collar services workers, from the National Sample Survey and Periodic Labour Force Survey. Standard errors are clustered at the district level. The independent variable is industry-district AI exposure, calculated using the 2011/12 National Sample Survey. Specifically, it is the standardized average of occupation AI exposure (from Webb 2020), over white-collar services occupations in the industry-district in 2011-12, weighted by the share of workers per occupation. The dependent variable is the growth in the industry-district median or mean wage between 2011-12 and 2017-18, approximated by the change in the inverse hyperbolic sine. Each coefficient therefore represents the proportional impact on average industry-district wages of a one-standard deviation rise in baseline AI exposure.

2.C Data Appendix

This paper uses four main datasets: vacancy data from India's largest jobs site; balance sheet data from Prowess, which contains longitudinal financial information on all publicly-listed and many large private Indian firms; and nationally representative labour surveys conducted in 2011-2012 (the National Sample Survey) and in 2017-2018 (the Periodic Labour Force Survey). Table 2.C.1 summarises the number of observations across these datasets.

In this Appendix, we provide more details on the composition of the data and the construction of the variables used. We first describe how we classify the occupations, industries and locations in the vacancy data. We then assess the representativeness of the vacancy data by benchmarking it against Prowess and the nationally-representative labour surveys.

Table 2.C.1: Number of observations by data source

Online vacancy postings 2010-2019	#Firms	#Posts
Agriculture	13,811	463,675
Manufacturing	57,980	2,543,995
Services[1]	167,969	15,481,330
— *Financial*	*17,805*	*1,815,798*
— *Information*	*72,057*	*5,834,878*
— *Professional*	*38,533*	*834,932*
— *Other*	*106,798*	*6,995,722*
Prowess (balance sheets)	#Firms	#Observations
Agriculture	123	590
Manufacturing	2,276	11,257
Services	3,675	16,722
— *Financial*	*1,020*	*4,830*
— *Information*	*516*	*2,557*
— *Professional*	*199*	*811*
— *Other*	*1,940*	*8,524*
Surveys (demographics)	#Districts	#Households
NSS 2012	626	101,725
PLFS 2018	646	102,063

Notes: Some services firms post in multiple sub-sectors, hence the total number of services firms is less than the sum of all firms posting in the sub-sectors.

2.C.1 Construction of vacancy dataset

We received 80% (randomly sampled) of all vacancies posted on the largest online jobs platform in India between 2010 and 2019. All posts include text data on the job title, industry, role category, location, skills required, salary and experience ranges and educational requirements. We manually map 99% of role titles to the 2004 Indian National Classification of Occupations (NCO) at the four-digit level. We also manually map all industries to the 2008 Indian National Industrial Classification (NIC) at the three-digit level. We cleaned 95% of city names and added geo-locations, separating out oversees job postings. Using the geolocations, we then match cities to districts.

We use publicly-available crosswalks to translate AI exposure measures to the Indian context. We use a crosswalk to map the 2000 Standard Occupational Classification used by Webb (2020) to the 2004 Indian National Classification of Occupations (NCO), via the 1988 International Standard Classification of Occupations (ISCO), at the four-digit level. For the Felten et al. (2018) measure, we translate the original 2008 ISCO to the 1988 ISCO, before mapping onto the 2004 NCO.

2.C.2 Benchmarking against administrative data

We address the representativeness of our vacancy data in relation to the broader Indian labour market by benchmarking against widely-used administrative datasets. The industry distribution of services firms in the vacancy data and the Prowess dataset are shown in Figure 2.C.1 Panel (a). The distribution of vacancies is shown in Panel (b), alongside the distribution of white-collar services workers in the pooled National Sample Survey and Periodic Labour Force Survey.[27] The vacancy data has relatively fewer finance, insurance and real estate firms than Prowess, but a greater share in that sector relative to the

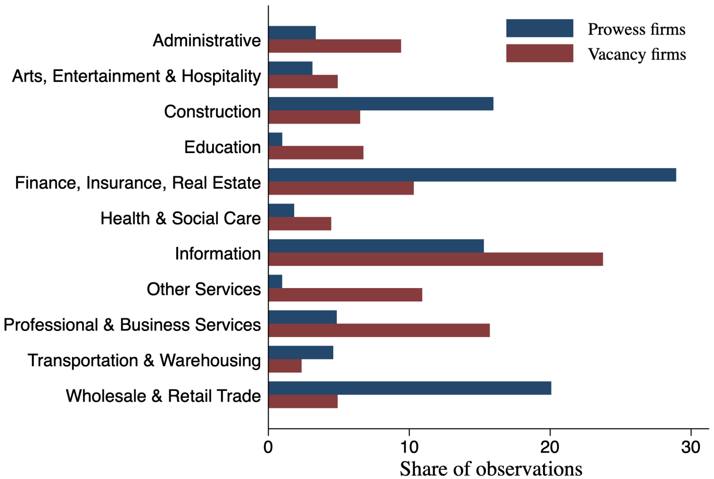
[27] We define white-collar services workers in the NSS context as salaried workers in divisions 1-5 of the 2004 Indian National Classification of Occupations, i.e. excluding agricultural, fishery, craft, manufacturing, elementary and unclassified workers.

representative sample surveys. The national surveys also report many more workers in education and transportation, likely because they include public sector workers, whereas the vacancies and Prowess balance sheet data include only private firms. This likely explains in part the large over-representation of the IT sector in the vacancy data, along with IT firms naturally being more comfortable using online tools to advertise vacancies. Panel (c) shows the distribution of services occupations in the vacancy data in contrast to the national surveys. The online posts focus on relatively high-skill white-collar jobs, with fewer roles in lower-skilled jobs, such as shop assistants or security guards, which are more typically filled through referrals and offline hiring.

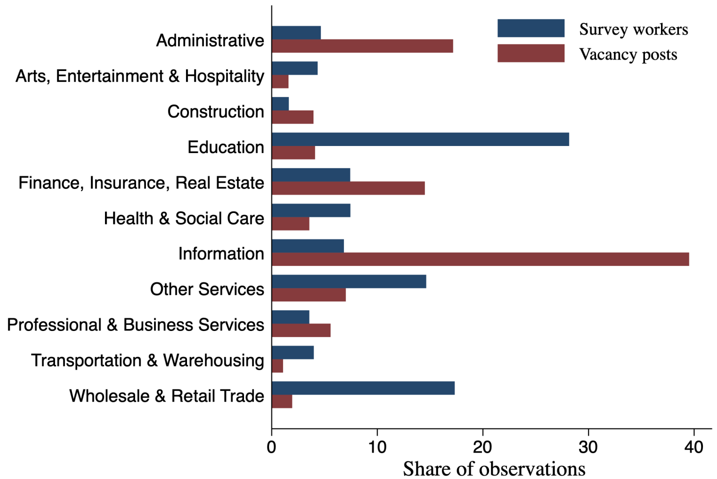
Our dataset has several advantages over the administrative datasets. The representative sample surveys only took place in 2011-12 and 2017-18, so provide no information on short-term fluctuations or more recent developments in the Indian services sector. Prowess, while useful for studying the largest firms, only contains a limited selection, and did not yet have good coverage for recent years at the time of writing. As illustrated in Figure (d), our vacancy dataset has roughly 30 times the number of firms, and includes many firms in 2018 and 2019. With only balance sheet data, Prowess also offers no clear window on AI exposure or adoption. Similarly, the sample surveys can only inform us about AI exposure, through the data on occupation shares, but not AI adoption. In contrast, we can directly observe AI skills in the online job descriptions. Specifically, the closest category to a machine learning engineer in the national survey data is National Occupational Classification code '2132 – Computer Programmers' or '3122 – Computer Assistants'. These broad job classifications alone would be insufficient to identify the use of machine learning, so motivate our move beyond the traditional data sources.

Figure 2.C.1: Comparison of datasets on the Indian services sector

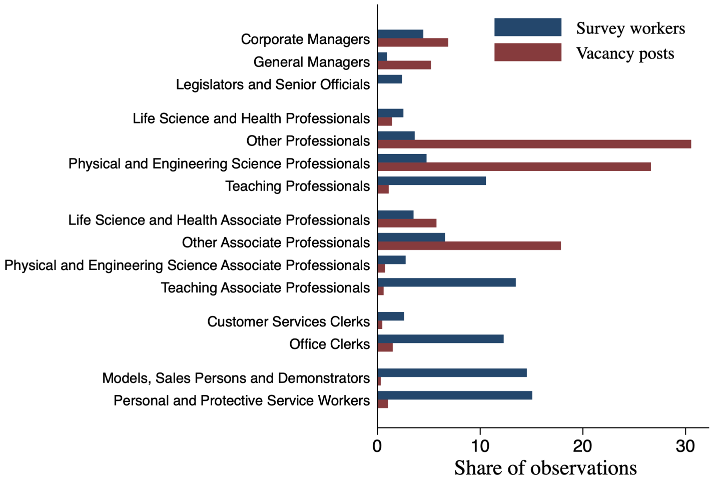
(a) Firm distribution



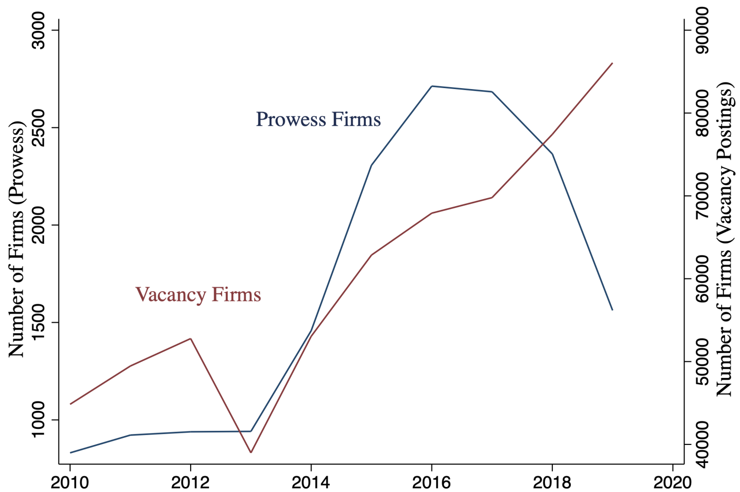
(b) Worker/vacancy distributions



(c) Occupation distribution



(d) Number of firms by year



Chapter 3

Robots and trade: Implications for developing countries*

with **Erhan Artuc**, **Paulo Bastos**, and **Bob Rijkers**

We examine the effects of industrial robotics on developing countries, extending the Ricardian model of Artuc et al. (2018) and drawing on new firm-level robotisation data from eleven developing countries. We present four main results. First, robot adoption in advanced economies can ultimately benefit workers in developing countries through lower prices and increased demand for intermediate inputs – though there may be adverse effects in the short run, particularly for the least mobile workers. Second, continued Chinese subsidisation of robots is likely to reduce China's trade with OECD countries, while increasing that with developing countries – as China's profile of comparative advantage increasingly aligns with the former. Third, larger and more globally-connected firms in developing countries are more likely to adopt robots, aligning with findings in developed countries, as they can afford the fixed costs of upgrading, and value the resulting precision more highly. Fourth, these firms expand post-adoption, increasing the competitive pressure on the smaller, less international firms in which those workers most vulnerable to replacement by robots are also more likely to work.

Keywords: *robots, tasks, jobs, global value chains, gains from trade*
JEL Classification Codes: *F1, J23, J24, O3, O4*

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3.1 Introduction

Modern industrial robots can perform a variety of repetitive tasks with consistent precision and are increasingly used in a wide range of industries and applications. The global operational stock of industrial robots reached a record high of 2.7 million units last year (IFR 2020) and robot adoption is projected to grow steadily. The accelerating automation of industrial production has stoked concerns that large swaths of the workforce, especially the unskilled, may suffer wage and job losses (e.g. Bloom et al. 2018). These fears are in part predicated on the experience of OECD countries, where robot adoption has contributed to productivity growth at the expense of the employment share and wages of low-skilled workers Graetz & Michaels (2018), Acemoglu & Restrepo (2020). Recent estimates suggest that around 14% of jobs across the OECD area are at risk of disappearing because of automation, while another 32% are likely to see significant changes (OECD 2018*b*).

While robotisation has been especially pronounced in advanced economies, workers in developing countries could also be at risk. Low-skilled workers, for whom robots substitute particularly well, are disproportionately located in developing countries. Robotisation might move production closer to consumers in high-income markets and undermine prospects for industrialisation and export-led development (Rodrik 2018, Hallward-Driemeier & Nayyar 2019). Developing countries are particularly exposed to automation-induced trade declines, since reduced trade and communication barriers have allowed the offshoring of repetitive and labour-intensive tasks to low wage countries (Grossman & Rossi-Hansberg 2008, Antràs 2016, Bank 2020). Low-income countries may lack the skills and infrastructure that are needed to meaningfully participate in emerging global value chains, as automation diminishes the importance of low labour costs as a determinant of international competitiveness (Rodrik 2018, Baldwin & Forslid 2020).

In this chapter, we first use a Ricardian framework to examine the impact on developing countries of robotisation in developed countries. Drawing on Artuc et al. (2018), in Section 3.2 we present theory and evidence indicating that robot adoption in the high-wage advanced economies promoted trade between developed and developing countries. We highlight that such adoption can ultimately benefit workers in developing countries, particularly through lower prices and increased demand for intermediate inputs. In Section 3.3, we extend this framework by adding China explicitly to the calibrated model, noting that its robot stock has expanded rapidly in recent years to become by far the world's largest (in absolute terms). We analyze the impact of China's subsidies for robotisation, as described in Cheng et al. (2019), and find ambiguous effects on wages of Chinese workers depending on the size of the subsidy. Interestingly, the more China subsidises industrial robots, the more similar its pattern of comparative advantage to that of OECD countries, so the smaller its total trade with them. The opposite conclusion applies to trade between China and developing countries.

In Section 3.4, we widen our scope to consider broader empirical evidence and mechanisms outside the Ricardian framework. After noting early support for the long-run predictions of the model in recent work on global value chains, we investigate two additional complexities: short-run worker immobility and long-run differences in sectors' learning potential. On the former, we catalogue evidence of negative short-run employment effects in the local labour markets of some middle-income countries, particularly for the least mobile workers previously performing tasks that can now be executed by robots. These adverse impacts on local labour markets highlight the role for policy to alleviate distributional issues arising from frictions during the automation transition. On the latter, we look beyond comparative statics to note that developed-country automation could exacerbate 'premature de-industrialisation' (Rodrik 2016) by discouraging investment in sectors with the highest growth potential. This mechanism, for which we find suggestive evidence, in turn helps explain the emergence of robot subsidies in some developing economies, particularly China.

Furthermore, robot adoption may be driven by factors other than just the relative prices of robots and workers. Within each country, larger firms are more likely to be able to afford the fixed costs of upgrading production technology, while firms engaged in complex production networks may attach higher value to the increased precision and reliability enabled by robotics. In Section 3.5 we therefore move beyond relative prices to provide new evidence on firm-level drivers of adoption in developing countries, while in Section 3.6 we consider the impact of this adoption on firm-level outcomes. Our empirical analysis draws on firm-level data from 10 developing countries. We find support for both the scale and precision hypotheses, aligning with firm-level evidence from developed countries. After adopting robots, these initially larger and more globally-connected firms tend to expand further. These firm-level mechanisms help to explain why we observe more and earlier robot adoption in developing countries than our stylised Ricardian model would predict. But they also add a firm-side element to the earlier distributional concerns: it is not just more disadvantaged workers who are most threatened by robotisation, but also smaller, less productive, less internationally active firms. Given that low-skilled workers are also disproportionately more likely to work in these firms, the dual threat is a key issue for policymakers to consider.

We conclude by surveying these opportunities and challenges for developing countries raised by automation. In the long run, industrial robots in developed countries could promote trade between advanced and developing countries, and enhance global welfare. And while China's growing robotisation (driven in part by subsidies) might reduce productivity differences with advanced economies, and thereby the gains from inter-industry trade with them, it need not hinder future prospects for industrialisation and export-led growth in lower-income countries. However, technological change, both in advanced and developing countries, necessitates labour market adjustment and could create severe distributional tensions during the transition. As robots catch up with humans in many abilities, so policy must keep pace with adoption.

3.2 Implications of robotisation in rich countries for developing economies

Drawing on Artuc et al. (2018), we first use a Ricardian framework to model and empirically examine the impact on developing countries of robotisation in developed countries. We start by inspecting drivers of robot adoption at the country and industry level (see Figure 3.2.1). Potential cost savings seem to be an important determinant since richer, higher-wage countries tend to adopt more robots (Panel A). There is wide variation across industries in the proportion of jobs that are replaceable (calculated using the share of occupations involving tasks for which robots exist, following Graetz & Michaels (2018), and this indeed predicts realised robot density (Panel B).

Motivated by these patterns, the multi-country, multi-sector Ricardian model features: (i) a higher cost of labour in the North, and (ii) an industry-specific robotisation frontier (i.e. the range of tasks for which humans are substitutable by robots varies across sectors).[1] The model features two-stage production, where intermediate goods are produced in the first stage and final goods are produced in the second stage. In the production process, robots can take over some tasks previously performed by humans.[2]

In the model, a subset of tasks required in the production of intermediate and final goods can be executed either by workers or robots, while other tasks can only be performed by humans. The range of tasks that can be performed by robots varies across sectors. The industry-specific robotisation frontier, relative factor prices and productivity determine the extent of robot use within sectors. Production of each final good variety further requires a composite intermediate good from the same industry. In equilibrium, varieties of intermediate inputs

[1]A technical outline of the model is provided in the Appendix.

[2]The model combines elements from a large number papers in the literature, including Grossman & Rossi-Hansberg (2008), Eaton & Kortum (2002), Acemoglu & Restrepo (2020), Caliendo & Parro (2015), Lee & Yi (2018) and Artuç & McLaren (2015).

and final goods are sourced from the country that supplies at the lowest price. Thus, there are two layers of competition: (1) between robots and workers in factor markets; and (2) between countries in sector-specific product markets for inputs and outputs.[3] Relative production costs (driven by factor prices and technology) determine country-specific robotisation and trade patterns.

With many countries in the model, a fall in the global price of industrial robots initially induces robotisation in Northern countries, defined as those with a higher initial cost of labour.[4] This shift impacts relative production costs between countries, and therefore trade patterns. Producers substitute robots for domestic labour in automatable tasks, leading to lower costs of production in Northern countries, and hence to an increase in exports to Southern countries.[5] The more striking growth in same-sector imports from Southern countries reflects the sum of two competing forces. On one hand, lower costs in Northern countries make domestic producers and input suppliers there more competitive relative to foreign ones, which lowers the demand for goods produced abroad. On the other hand, the expansion of production in Northern countries also leads to an overall surge in the demand for intermediate inputs. If these are sourced from abroad, imports from lower-wage Southern countries in these industries can rise.

The two-stage production structure helps us to differentiate comparative advantage patterns for intermediate inputs and final goods. Robotisation in

[3]Offshoring in the model takes place through imports of intermediate inputs, which embody tasks performed abroad. This allows us to calibrate all trade flows, production functions and labour shares using the World Input-Output Database. Given our focus on industrial robots and trade in manufactures, the distinction between offshored tasks and intermediate inputs is largely semantic (Grossman & Rossi-Hansberg 2008). Future research could extend the model by allowing direct offshoring of tasks, to consider cases where this distinction is more substantive (e.g. in services trade).

[4]Throughout this paper, the set of tasks that can feasibly be performed by robots is fixed. Increased robotisation results only from a fall in the price of existing robots, not an expansion in their functionality. Technological advances which enable robots to perform new tasks, or indeed create new human-only tasks, are a distinct issue, which we leave to other work (e.g. Acemoglu & Restrepo 2018).

[5]In the model, which assumes full employment, the displaced workers compete for the remaining non-automated tasks, bidding down wages and generating a second-order increase in hiring.

Northern countries increases productivity of North in both stages of production but does not necessarily overturn South's comparative advantage for the intermediate inputs. As a result, South specialises further in intermediate input production, and increases its exports to North to meet their increasing demand for parts and components.

Between 1995 and 2015, the latter production expansion effect seems to have dominated. Indeed, empirical results in Artuc et al. (2018) reveal that the robot-induced surge in Northern imports from the South is concentrated in intermediate inputs such as parts and components. To gauge the relationship between robotisation and North-South trade, the empirical analysis combined robot stock data from the International Federation of Robotics, labour hours data from EU KLEMS, and trade data for 1995-2015 from CEPII BACI. The following baseline specification was estimated:

$$Trade_{nmit} = \beta \cdot Robots_{nit} + \Psi_{nmt} + \Lambda_{it} + \epsilon \tag{3.2.1}$$

where $Trade_n mit$ denotes the log of one plus exports from developed country n to developing country m in sector i and year t or alternatively the log of one plus imports sourced from developed country n in sector i and year t; $Robots_{nit}$ denotes a measure of robot usage in country n in sector i in year t; Ψ_{nmt} denotes a fixed effect by exporter-importer-year; Λ_{it} denotes an industry-year fixed effect; and ϵ the error term. Equation 3.2.1 includes exporter-importer-year fixed effects both to allow for pair-specific shocks (such as fluctuations in relative income and exchange rates) and to control for country pair specific determinants of trade (e.g. distance, having a common language etc.). It further includes industry-year fixed effects to account for factors that are specific to each industry in each year. Standard errors are clustered by developed country. To address the possibility of reverse causality in the relationship between robotisation and trade, as well as potential biases caused by omitted variables or measurement error, an instrumental variables approach was followed. Specifically, the analysis uses the triple interaction between the (pre-determined) share of workers engaged in replaceable tasks in each sector, the country's initial income per capita, and the global stock of robots as an instrument for robotisation.[6]

The instrumental variables estimates reveal that a 10% increase in robot density in a robotising industry in the North boosts its exports to the South by 11.8%. Surprisingly, it also induces a 6.1% increase in its imports from the South within the same broad sector. The latter effect is primarily driven by imports of parts and components.[7] These empirical results can be explained by two key features of the Ricardian trade model with a multi-stage production technology: (1) productivity effects of robotisation in the North, such that replacing workers with (cheaper) robots increases output and exports; and (2) trade in intermediate goods, such that an expansion in Northern final production can increase imports of inputs from the South within the same broad sector.[8]

Given these patterns, how are further reductions in robot prices likely to impact global trade, wages and welfare? To answer this question, the Ricardian model was calibrated with three countries and three sectors. In particular, the quantitative model features a representative high-income Northern country, a representative country in the South, and a group of other (lower-income) devel-

[6]Following Graetz & Michaels (2018), we measure replaceability by comparing robot applications recorded by the IFR with three-digit occupation names and descriptions in the US Census, then aggregating to the industry level using the occupation-composition of industries. See Artuc et al. (2018) for further details of the empirical strategy and variable construction.

[7]When running separate regressions for intermediates vs. other goods, the respective increases in imports from the South are 6.8% and 5.6% (using BEC classification of goods types) or 8.6% and 4.9% (using the classification from Schott 2004).

[8]Specifically, the net increase in imports of parts and components implies that the robotisation-induced scale effect, which increases demand for imported intermediates, outweighs any robotisation-based reshoring (i.e. substitution effects from increased robot use by Northern intermediates producers).

oped countries.[9][10] Among the three sectors considered, two sectors are tradable and the other sector is non-tradable. Production is subject to robotisation in just one of the tradable sectors, consisting of the automotive, rubber and plastic, electronics, chemicals, metal and machinery industries. The non-robotised tradable sector consists of all other manufacturing industries, including food and textiles, agriculture, mining and utilities. The non-tradable sector consists of construction and services.

Simulating the impact of future reductions in robot prices offers several interesting insights, which are represented in Figure 3.2.2. As robot prices decline, producers in the North, who face higher wages, will adopt progressively more robots (Panel A). When prices decline even further it also becomes profitable for less developed countries, where producers face lower labour costs, to robotise production. As a result, robot adoption is associated with an initial reduction in the number of jobs in the automating sector (Panel B). Yet the impact of robot price reductions on employment is non-linear. Once all tasks that can be automated are performed by robots, further reductions in robot prices boost the demand for labour in the robotised sector, because

[9] We use the World Input Output Database (WIOD) to calibrate international trade, production functions and labour shares. In the baseline simulation, we use WIOD data for 2005 to calibrate initial trade patterns. We group countries into three broad categories, based on their income per capita, robot density and data availability. The group of countries in the North is composed of Belgium, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden and the United States. The group of countries in the South is composed of Brazil, China, India, Indonesia, Mexico, Turkey and Taiwan, China. Based on these two groupings, we construct the representative countries in the North and South. The group of other developed countries results from the aggregation of other OECD and EU countries for which data are available in WIOD. This group consists of Australia, Austria, Bulgaria, Canada, Czech Republic, Spain, the United Kingdom, Greece, Croatia, Hungary, Ireland, Portugal, the Slovak Republic, Poland, Norway and Switzerland. Various robustness checks in Artuc et al. (2018) find that results are qualitatively robust across a variety of alternative groupings.

[10] This setup is ideal for illuminating the relevant dynamics without losing tractability. If we were to aggregate within groups, rather than averaging to create representative countries, the North would account for more than 50% of world GDP, and the bulk of world trade would occur within the North. This setting would underrepresent the importance of North-South trade, and trade as share of GDP would be very small. To avoid this aggregation bias, we instead construct representative countries in the North and the South. Considering a relatively large group of other developed countries is also important to allow for the possibility that competitiveness gains associated with robot adoption in the North translate into higher demand for its final-goods exports.

they make workers in those sectors more productive. While industrial robots compete with workers in the early stages of adoption, they complement them in subsequent stages, since we assume that the range of automatable tasks is fixed. A U-shaped relationship appears between robot prices and labour demand (and, by implication, wages) in North and 'Other' (Panel C). Once again, robots initially substitute for labour, but later on are complements – as they increase the productivity of those workers performing tasks that cannot be automated.[11] Interestingly, lower robot prices also gradually raise the wages of workers in the South.[12] As robot prices fall, aggregate welfare increases in all countries, but more so in the countries that adopt more robots (Panel D). Finally, As Northern producers demand progressively more intermediate inputs to enable their expansion of production (shown in Panel E), their demand for Southern exports of intermediates surges (Panel F).[13]

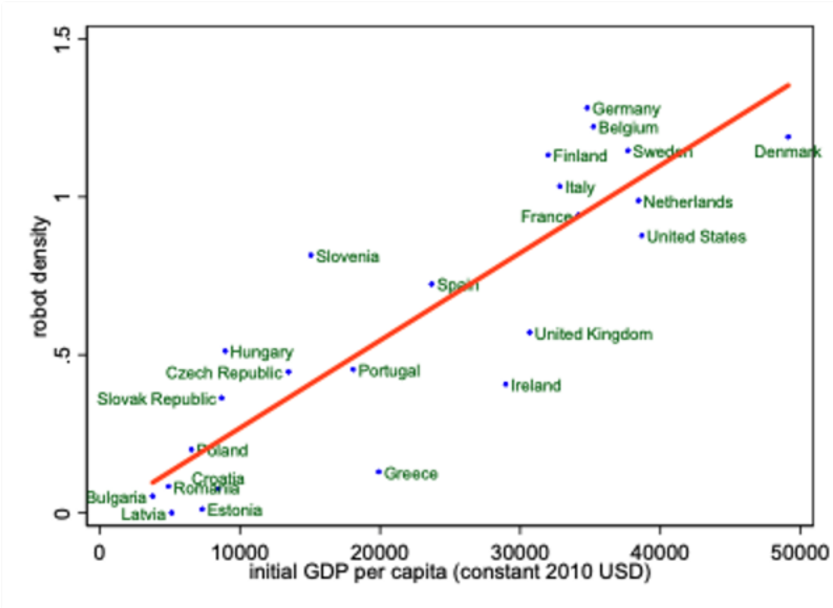
[11] Broadly, lower robot prices initially cause displacement of human labour at the 'extensive margin', but subsequently reduce costs and increase productivity at the 'intensive margin'. Such sequencing could help explain differing empirical findings on the impact of robots: countries in the displacement phase (e.g., the USA in Acemoglu & Restrepo 2020) may experience larger wage declines from additional robotisation than countries further ahead in the process of adoption (e.g., Germany in Dauth et al. 2021).

[12] However, for a sufficiently large reduction in robot prices (greater than 80% in Figure 3.2.2 Panel A) the South in turn adopts robots, lowering Southern wages (Panel C).

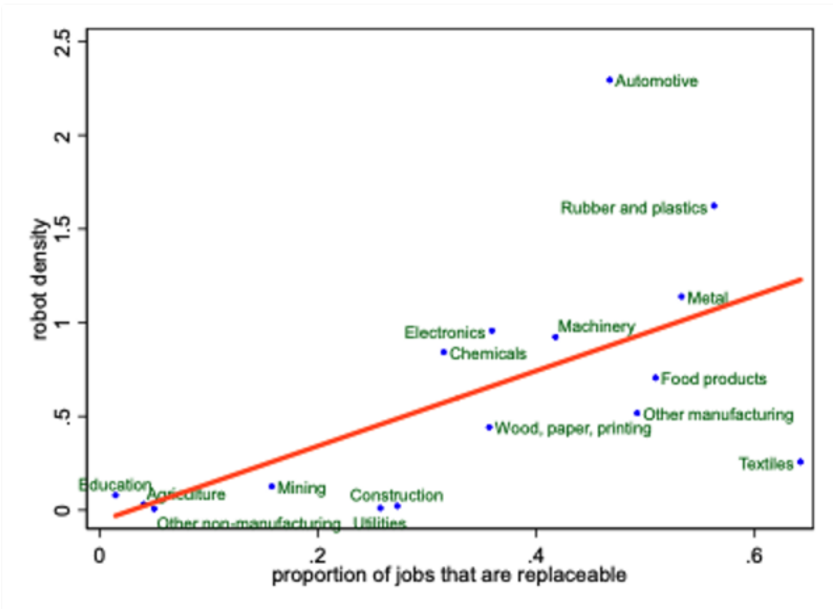
[13] Theoretically, cheaper robots in Northern production of intermediates could generate reshoring, by replacing previous demand for inputs imported from the South. This mechanism pushes against cheaper robots in Northern final goods production, which tends to increase scale and thus the demand for Southern inputs. In the calibrated model, North initially specialises heavily in production of final goods, so the latter effect dominates and we do not see reshoring. Future research with more granular data on robot use (i.e., distinguishing between robots used in the production of final vs. intermediate goods) could separate these effects empirically; here we focus on the net effect, which we observe.

Figure 3.2.1: Robotisation across countries and sectors

(a) Robot adoption is higher in richer countries



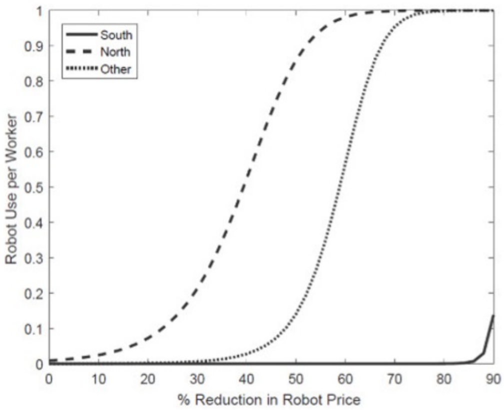
(b) Sectors in which automation is feasible adopt more robots



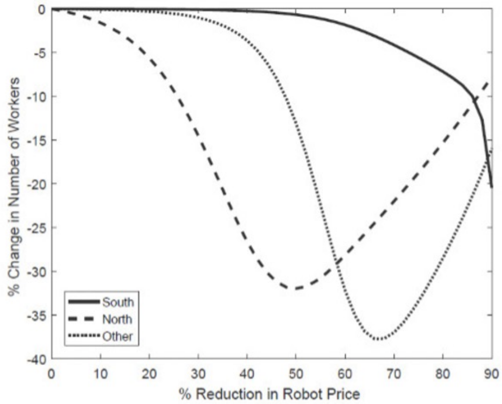
Notes: Panel A depicts the relationship between average robot density by country (averaged across years) and the initial GDP per capita. Panel B depicts the relationship between average robot density by sector (averaged across countries and years) and the share of replaceable jobs in the industry, as measured in Graetz & Michaels (2018). Robot density is defined as the log of one plus the number of robots in use per million worker-hours. *Source:* Artuc et al. (2018).

Figure 3.2.2: Effects of robot price reductions

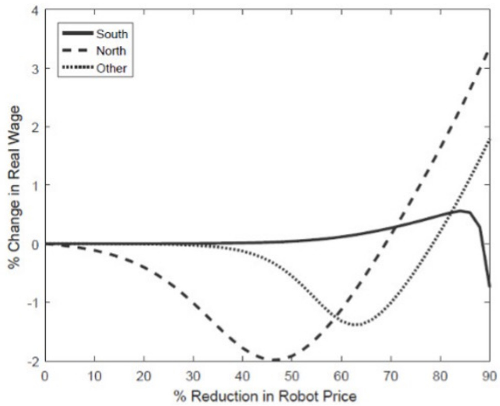
(a) Robot use



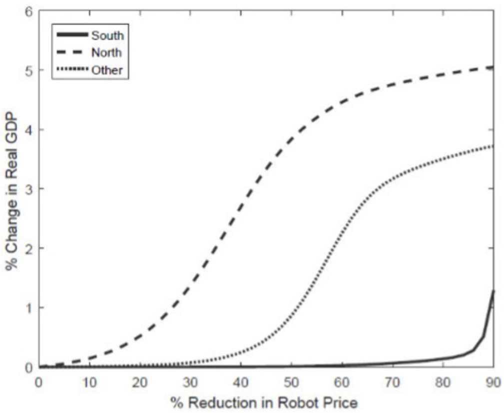
(b) Labour use in robotised industry



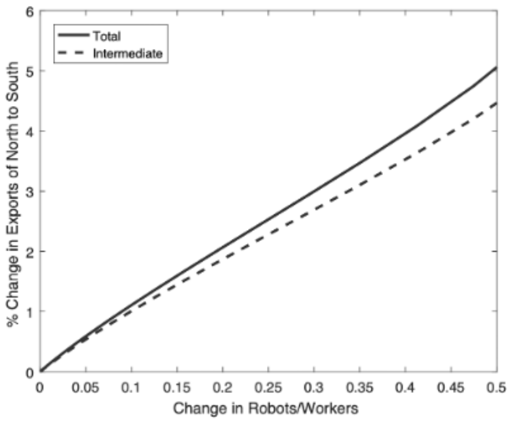
(c) Wages



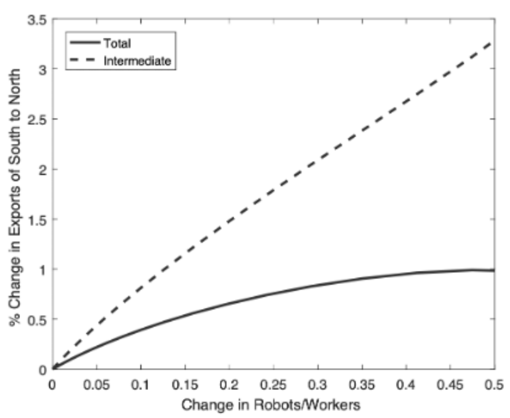
(d) Welfare



(e) Exports from North to South



(f) Exports from South to North



Notes: This figure presents results from simulations of the effects of lower robot prices (and increased robot density) on robot use, labour allocation, wages, welfare and North-South trade. As robot prices fall, initially only North and Other adopt robots (Panel A for a 0-80% reduction in robot price). Eventually these are fully robotised, and beyond 80% all effects are driven by Southern robotisation. *Source:* Artuc et al. (2018).

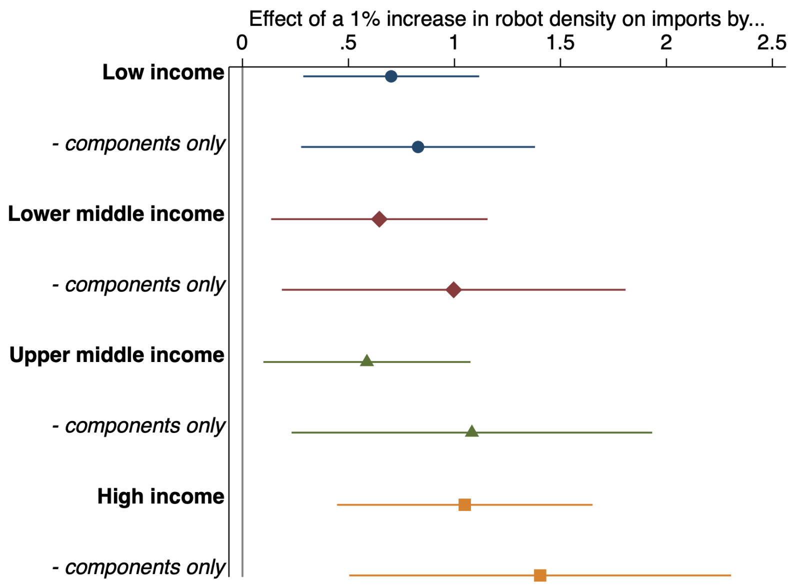
3.2.1 Heterogeneity across income levels and regions

How might these impacts vary across developing nations? Whilst the available input-output data used to quantify trade models does not make it possible to simulate fine-grained heterogeneity across a wide range of developing countries, we can use the empirical approach outlined above to make progress on such questions. In a new extension, we run the model above separately within sub-samples by income level and region.

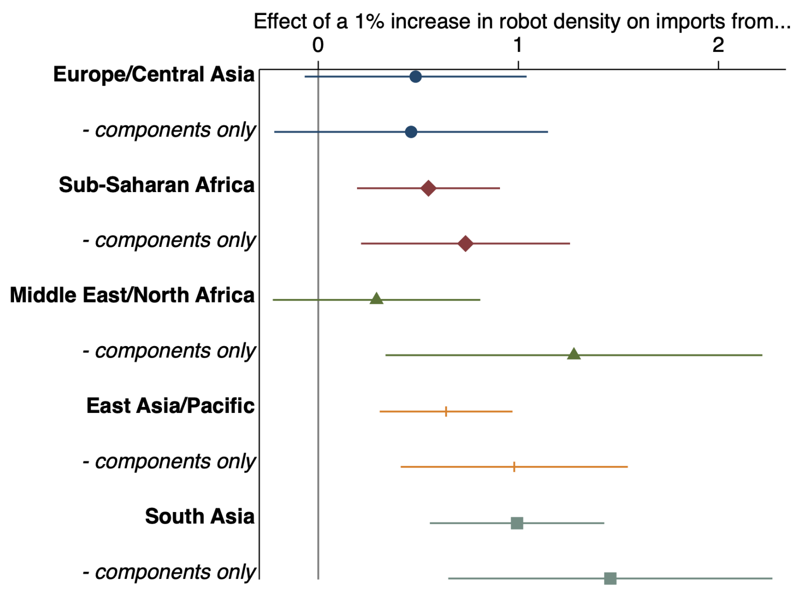
The results are shown in Figure 3.2.3. First, we find robust effects on imports at all income levels (Panel A): in each case, robotisation significantly raises both total imports and imports of parts and components from developing countries. The scale effect of robotisation on imports from developing countries thus appears to consistently outweigh the substitution effect within sectors. Second, we examine the effect of developed country robotisation on imports from developing countries in particular regions. We find that the effects are strongest in South Asia and East Asia/Pacific, with slightly less of an effect in Sub-Saharan Africa, a mixed picture in the Middle East/North Africa, and no effect in Europe and Central Asia. This points to factors beyond relative prices driving the heterogeneity – particularly regional trade linkages and global value chain participation, which are particularly strong in South and East Asia. These mechanisms are investigated in more detail in Section 3.5.

Figure 3.2.3: Heterogeneity of effects of Northern robotisation on North-South trade

(a) Heterogeneity across income levels of importers



(b) Heterogeneity across regions



Notes: This figure presents IV estimates of the heterogeneous effects of increased robot density in the OECD on imports from developing countries, using the empirical approach outlined in equation 3.2.1.

3.3 Implications of robotisation in China

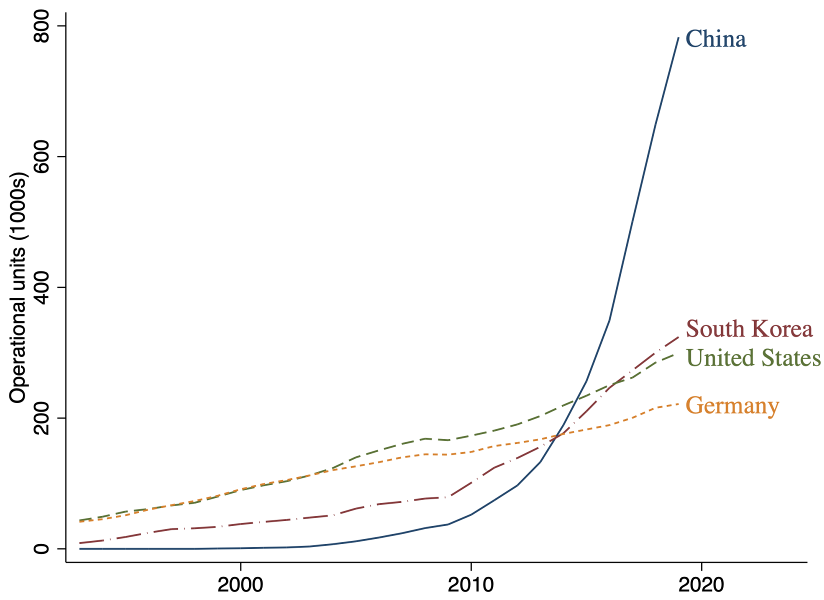
While global robot use has been increasing steadily, adoption of industrial robots has been especially rapid in China – particularly in the last few years (see Figure 3.3.1). This adds an extra dimension to the mechanisms described above. Rather than technological progress leading to an exogenous fall in robot prices, which encourages high-wage countries to automate, China's robotisation has been supported by large subsidies and a plethora of government programs. Faced with a rapidly ageing population, robotisation has been promoted by various levels of government (Cheng et al. 2019). The Ministry of Industry and Information Technology (MIIT) released its 'Guidance on the Promotion and Development of the Robot Industry' in 2013, which aimed for a robot density of 10 per 1000 workers in factories. Subsequently, the 2015 'Made in China 2025' program raised this to 15; the Robotics Industry Development Plan released in 2016 by the MIIT, National Development and Reform Commission, and Minister of Finance further encouraged robot use in a broader range of sectors, including services. At a regional level, examples of automation-promoting initiatives include the government of Guangdong Province's USD150 billion fund to invest in automation technology (Yang 2017).

To study the impact of automation subsidies in China, we use the framework of Artuc et al. (2018) with four countries.[14] The simulations include : (i) a representative country for the South (an average of Turkey, Taiwan, Mexico, Indonesia, India, Brazil, Mexico), (ii) a representative country for the North (an average of high automation counties, USA, Denmark, etc. excluding the outliers of Korea and Japan), (iii) the large 'Other' country, containing the totality of the OECD, and (iv) China. Everything in the model operates as before, except with a subsidy such that the robot price in China is $(1 - \mathit{subsidy}) \times \mathit{price}$.[15]

[14] Adding an additional country to the model, as opposed to re-calibrating South to represent China, allows us to consider the impact of subsidies on China's trade with both developed and developing countries.

[15] Analogous to the standard 'tariff revenue is burned' or 'iceberg trade costs melt away'

Figure 3.3.1: China's robot stock has grown rapidly



Notes: The figure shows the operational stock of robots over time for leading countries. China's robot stock has expanded rapidly, such that it is now the largest of any country. Note, however, that the robot stock per manufacturing worker in China continues to be considerably smaller than in the OECD. Source: International Federation of Robotics.

In the quantified model, China's robot subsidies now push them closer to the comparative advantage profile of developed countries, and away from that of developing countries. Specifically, we find that robotisation increases significantly with subsidies, so labour allocations in China initially decline as the robot subsidy rises (first part of Panel A).[16] Interestingly, other countries' wages seem hardly impacted by China's subsidies. As seen in the figures, the subsidy increases both total imports and exports of developing countries, which nets out the impact on wages. The impact on automatable sector labour

modelling assumptions, the subsidy does not carry a cost to modelled Chinese GDP.

[16]The strength of this effect depends on the level of initial robot prices. If robot prices are already low (so automation levels in the world are already high) then subsidies are more effective, as at this point even small subsidies tip robots into being the cheaper production option in China. This is the scenario shown in the graphs. Versions for a starting point of high robot prices and low automation levels are qualitatively similar, but with the impact of the subsidy only kicking in once it reaches a higher level (60%+) – effectively all the action in the graphs shifts rightwards.

allocation is noticeable, but small, since developing country labour markets are only indirectly exposed to robotisation in China through international trade. Therefore, the subsidy in China causes a modest labour shift in developing countries from automatable industries to non-automatable industries, with almost no impact on wages. In China, however, wages initially decline with subsidies as workers are replaced, but if initial automation is high wages can actually increase with the subsidy: once all automatable tasks are performed by robots, further robot subsidies simply lower production costs, expand output, increase labour demand (second part of Panel A) and thus raise wages (Panel B). In other words, there is a robotisation frontier beyond which further declines in robot prices are unambiguously beneficial for workers. Once all opportunities for substituting humans for robots have been exhausted, further subsidies for robots simply encourage further investment in a technology that is now complementary to the remaining human workers.[17] However, in the very long run, new tasks can be created and some of the existing tasks can be terminated thus the robotisation frontier can also move, which is an aspect omitted from our model. Depending on the direction of the shift of the robotisation frontier, labour demand can increase or decrease.

How do China's subsidies impact trade with other countries? In the calibrated model, exports by China's robotised sectors increase unambiguously with subsidies, while China's imports in those sectors decrease unambiguously. Trade of China with the South increases unambiguously (Panel C). This is because subsidies make China more different to other developing countries, as its comparative advantage moves to robot-intensive sectors.[18] China's trade

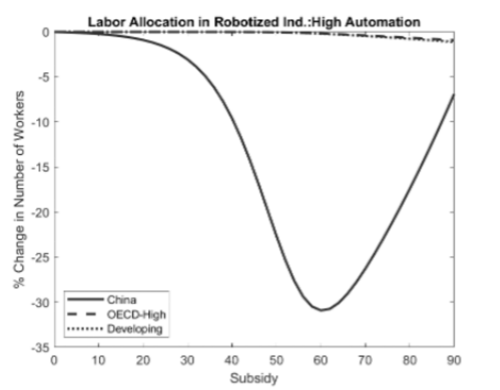
[17]In the case of low initial automation, where subsidies only impact robotisation at 60%+, the robotisation frontier is reached too late, such that even at a 90% robot subsidy wages remain below their initial level. In other words, wages are unambiguously lower with subsidies, if robot prices are initially high and automation is initially low.

[18]In the model, the effect of Chinese robotisation on imports from the South is ambiguous: robot subsidies in China could support production of intermediate goods (which would reduce offshoring to the South) or production of final goods (which would increase offshoring to the South, through scale effects). In the calibrated model, the former (i.e. the substitution effect) is outweighed by the latter. The dominant effect of Chinese robot subsidies is that China increases its scale of production, and so on net imports more intermediates from the South.

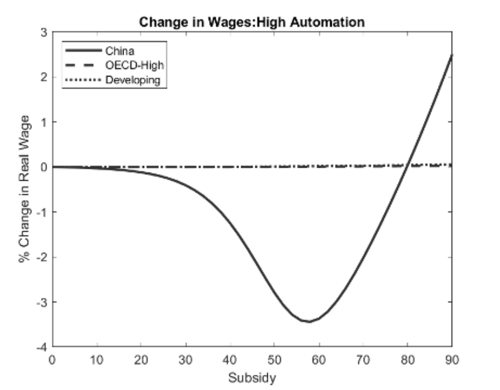
with the North may increase for lower subsidy levels, but it will probably decline over time as subsidies continue and China's specialisation patterns become more similar to those in the OECD (Panel D). In short, as China's robot subsidies push it closer to the relative productivity profile of high-income countries (and further away from that of low-income countries), classical comparative advantage discourages trade with high-income countries and encourages it with low-income countries.

Figure 3.3.2: Simulated effects of increased Chinese robot subsidies

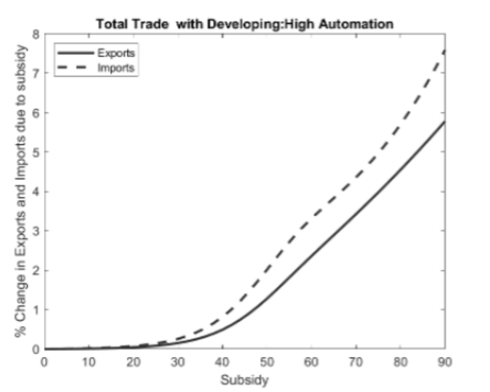
(a) Labour use in robotised industry



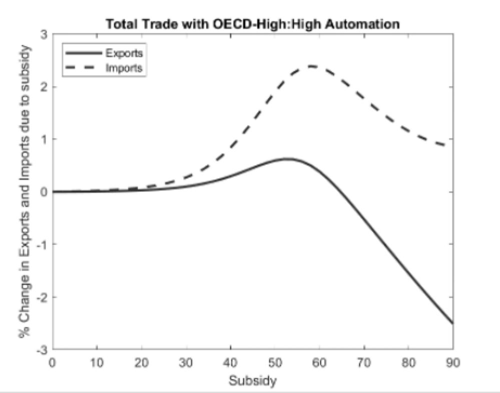
(b) Wages



(c) Trade with developing countries



(d) Trade with high income countries



Notes: The figure presents results from simulations of the effects of Chinese robot subsidies on labour use in the robotised industry, wages and trade. Everything in the model operates as before, except that there is now an extra country, calibrated to fit China, which subsidises robots such that the robot price there is $(1 - subsidy) \times price$.

3.4 Broader evidence: global value chains, frictions and de-industrialisation

These findings dovetail with empirical evidence from other recent studies. Robotisation by Spanish firms increased their demand for inputs from developing countries, and also led them to increase their number of affiliates in developing countries (Stapleton & Webb 2020).[19] Robot usage has also promoted greenfield FDI from high-income countries to low-income countries (Hallward-Driemeier & Nayyar 2019). This evidence is particularly informative on future trends because greenfield FDI decisions are a forward-looking indicator of where production is expected – unlike trade flows, which reflect past investment decisions. In contrast to fears of automation driving mass reshoring, there is reason to be cautiously optimistic that the positive scale/productivity effect of developed country automation on offshoring may outweigh the negative substitution effect.

However, the focus of our Ricardian model is on long run and aggregate effects. In the short run, workers cannot move freely across sectors or between sub-national regions. Frictions and sunk investments could drive transitional unemployment – some workers in robot-competing sectors and localities could lose out from Northern robotisation. Recent studies find evidence for such effects. To gauge the impact of US robots on employment in Colombia, Kugler et al. (2020) use employer-employee matched data from social security records. They measure exposure to US robotisation by combining baseline Colombian local labour market-industry employment shares with industry-time robot adoption in the US, and find that such exposure reduces employment and

[19] Interestingly, Stapleton & Webb (2020) illuminate a firm-level analogue of the contrasting forces in our model, finding that firm-level sequencing matters for the net impact of robotisation on offshoring. For firms that had not yet offshored any production, robotisation simply allowed them to expand, which caused them to begin new offshoring. In contrast, for firms that had already offshored some production, there was also a negative effect on offshoring – as robots allowed some previously-offshored production to be automated domestically. In the Spanish case they find that the effect for the former group dominates, with robotisation in the full sample having a net positive impact on imports from lower-income countries.

earnings in Colombia. Their estimates imply that, between 2011 to 2016, the known adoption of 70,000 new robots in the US led to the cumulative loss of between 63,000 and 100,000 Colombian jobs. The negative effects are largest for women, older and middle-aged workers, and those employed in small and medium-size businesses – groups which may be least mobile across locations or industries to find new employment.

Similarly, Faber (2020) examines the impact of US robotisation on employment in Mexican local labour markets between 1990 and 2015. He combines initial Mexican local labour market-industry employment shares with a measure of offshorability and changes in US robot intensity, and again finds a sizeable negative impact on Mexican employment. Although Mexico also automated industrial production in this period, and the coarse industry-level robots data make it difficult to distinguish between the effects of robotisation in the US and at home, he finds that the burden of robotisation fall most heavily on low-educated machine operators in the manufacturing sector – again, a group likely to be less mobile across locations and occupations. Also focusing on Mexico, but over 2004-2014 Artuc et al. (2019) find less of an effect of US robotisation on Mexican regional exports and local labour markets. They find evidence that the informal sector expands, acting as an 'employment buffer' as in Dix-Carneiro et al. (2021), but that automation is nonetheless relatively hardest on the unskilled and other disadvantaged workers. Wage inequality thus increases in the most exposed areas. Taken together, this evidence suggests that while robotisation could increase trade and real wages in developing countries in the medium and long run, in the short run governments will need to be attentive to those workers and regions that are most vulnerable in the transition.

Furthermore, long-run risks remain in the background. The model described above focuses on static gains from trade in a world with symmetric sectors and constant returns to scale. In reality, developed-country robotisation could also push developing economies to specialise in sectors with less potential for learning-by-doing or technology transfers. This in turn could push the minimum efficient scale in technology-intensive manufacturing even further out of reach.

We find some evidence of such robot-driven 'premature de-industrialisation', using data from World KLEMS (Rodrik 2016, Jorgenson 2017).[20] We regress industry i log employment or value added y_{mit} in developing country m on robot intensity in developed countries n, weighted by their share of m's baseline exports:

$$y_{mit} = \beta \cdot \ln \left(1 + \sum_{k \in n} \omega_{mkit_0} \cdot Robots_{kit} \right) + \Psi_{mt} + \Lambda_{it} + \epsilon_{mit} \tag{3.4.1}$$

where $\omega_(mkit_0)$ is baseline exports in industry i from m to k, out of total exports of i from m to all n, and $Robots_{kit}$ is the number of robots per million worker hours in country-industry ki. Table 3.4.1 shows weak evidence of a negative relationship between exposure to foreign robotisation and value added and employment, including when instrumenting with the log of the baseline-weighted product of replaceability, initial GDP per capita and the global robot stock (as described for regression 3.2.1 above). While data availability limits the sample substantially relative to the regressions with bilateral trade flows, these patterns are consistent with developed-country robotisation reducing developing countries' ability to compete in the global value chains of highly robotised sectors. Such dynamics could help explain the emergence of robot subsidies in some developing economies, particularly China.

[20]Specifically, we use an unbalanced panel of value added and employment data from Russia, China, India, Cyprus, Colombia, Costa Rica, El Salvador, Honduras, Peru and the Dominican Republic between 1980 and 2016.

Table 3.4.1: Foreign robotisation, employment and value added

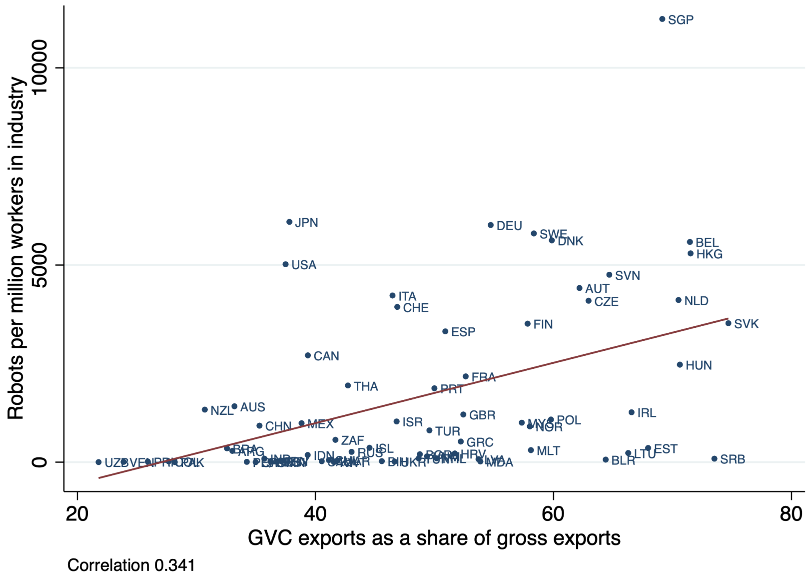
	ln Value Added				ln Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to developed-country robotisation	-0.103 (0.0802)	-0.103 (0.231)	-0.310* (0.170)	-0.310 (0.494)	-0.384* (0.217)	-0.384 (0.862)	-1.428*** (0.429)	-1.428 (1.802)
Fixed effects:								
– Country-Year	✓	✓	✓	✓	✓	✓	✓	✓
– Industry-Year	✓	✓	✓	✓	✓	✓	✓	✓
Clustering	Robust	Country-Industry	Robust	Country-Industry	Robust	Country-Industry	Robust	Country-Industry
First Stage F-Stat	OLS	OLS	208.702	14.218	OLS	OLS	208.702	14.218
Observations	1,676	1,676	1,169	1,169	1,676	1,676	1,169	1,169

Notes: Standard errors in parentheses, either robust or clustered at the country-industry level. (Insufficient variation to cluster at country- or industry-level alone.) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Unbalanced panel of industry-level data between 1980 and 2016.

3.5 Robot adoption in developing countries: beyond relative prices

The Ricardian model described above abstracts from firm-level heterogeneity in order to emphasise country- and sector-level effects. In reality, many factors beyond robot prices, wages and subsidies will influence the incentives to adopt robots. First, we can conceptualise robotisation as a one-off or per-period fixed cost that lowers marginal production costs. In this case, we might expect only larger, more productive, export-oriented firms to undertake such investment, in the spirit of Melitz (2003) and Bustos (2011). Alternatively, robotisation could be conceptualised as an upgrade to product quality – for instance, by allowing higher precision and reliability, as discussed in Verhoogen (2008) and Rodrik (2018). These attributes may be most valued by firms that are tightly integrated into complex production networks, involving the coordination and assembly of many interdependent components (Kremer 1993, Verhoogen 2008, Demir et al. 2021). The cost of producing a defective widget compounds rapidly if its failure negates all the other inputs into a complex final product. By this reasoning, we might then expect more automation in firms that are tightly integrated into global value chains, where the costs of errors (or the payoffs to quality) are highest. Such mechanisms will drive some robot adoption within developing countries, despite the availability of cheap labour. A first glance at high-level cross-country correlations do indeed point to a positive association between GVC participation and robot adoption (Figure 3.5.1).

Figure 3.5.1: Robot use and participation in global value chains



Notes: This graph shows the correlation between robot density and GVC participation in 2015, using the data and methodology outlined in the World Development Report 2020 (Bank 2020). GVC exports are defined as those crossing more than one border. One outlier (Republic of Korea) is excluded from the graph for clarity, but is included in the correlation calculation.

To investigate such relationships further, we use the near-universe of firm-level trade transactions from ten developing countries, identifying automation events from imports of industrial robots.[21] The shares of firms which have ever imported robots are shown in Figure 3.5.2. Consistent with the patterns presented in Section 3.2, the electronics and automotive sectors have the highest shares of robot use. We regress ever-robotiser status on a range of

[21]Source: The World Bank's Exporter Dynamics Database, which covers all trade transactions except those of oil and arms. We use data from importer-exporters in Bangladesh, Chile, China, Colombia, Ecuador, Egypt, Mexico, Peru, Romania and South Africa, which contain 10,312 separate robot purchases by 4646 distinct firms.

firm characteristics, using only observations prior to the first observed robot purchase by each firm.[22] The resulting ex-ante correlations are shown in Figure 3.5.3.[23] Firms adopting robots are larger, more diversified across products (yet simultaneously more specialised in their core products), and more integrated with GVCs. This resonates with the literature on technology adoption. Firms adopting robots in developed countries are generally larger, more productive and growing faster (Humlum 2019, Koch et al. 2019, Acemoglu, Lelarge & Restrepo 2020, Bonfiglioli et al. 2020, Kariel 2021). In China firms that adopt robots also tend to be larger, have more capital per worker, pay higher wages, and are less likely to be state-owned (Cheng et al. 2019).

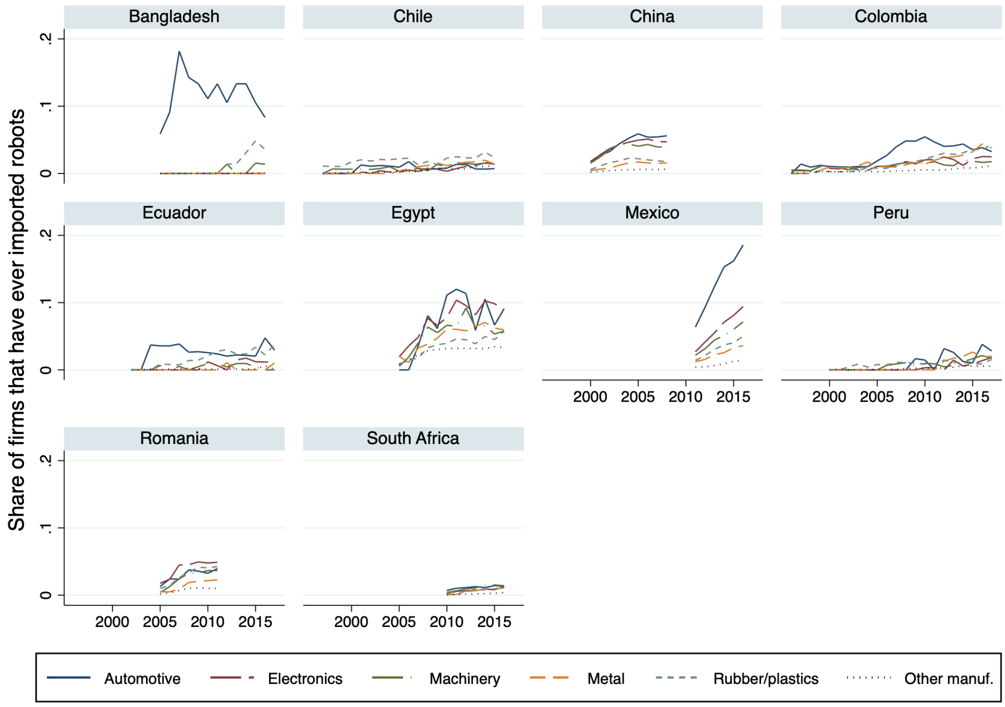
We supplement this evidence with detailed firm-level data from the Vietnam Technology and Competitiveness Surveys 2010-14. These data record explicitly whether a firm uses computer-operated machines, and are also not restricted to firms that trade internationally. Table 3.5.1 shows summary statistics for automating vs. non-automating firms. The patterns are similar: in general, automators are larger, pay higher wages, are more likely to export and to be foreign-owned. Moving to partial correlations in Table 3.5.2, and accounting for province, industry and year fixed effects, we find that automators have more assets, earn higher revenues, pay higher wages and are more likely to be foreign-owned.

Surveying this evidence, it seems likely that domestic robot adoption will primarily help the largest, most productive and most globally-integrated firms in developing countries. Smaller and less productive firms miss out, in line with Rodrik (2018) and Goger et al. (2014). What are the impacts of this skewed

[22]We also include industry-year and country-year fixed effects and cluster at the firm level.

[23]Concentration is measured by a Herfindahl index of export sales, using each firm-product's share of total firm exports. Market shares are the firm's share of total sales from the home country to each given export destination, which are then averaged across all of the firm's export dyads. Offshoring is the sum of imports in the same HS4 category as goods sold by the firm, following the 'narrow' measure of Hummels et al. (2014). Roundtripper is a dummy that takes value one only for firms which export and import the same HS6 product to the same partner in a given year. Relationship stickiness is a weighted average across either exports or imports of the measure of Martin et al. (2020).

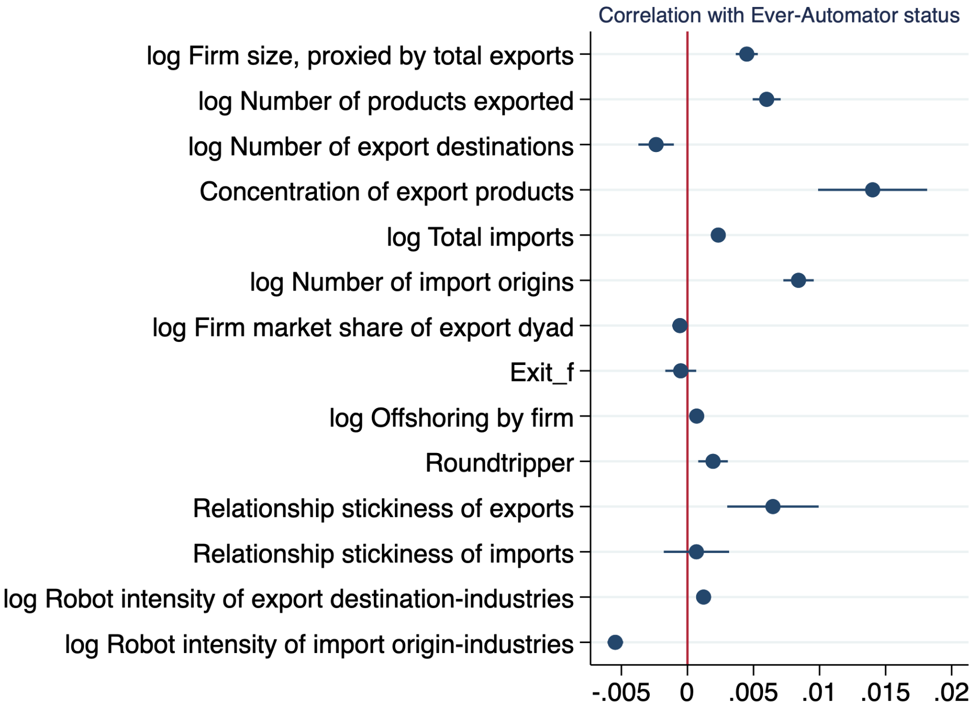
Figure 3.5.2: Share of firms that imported robots by country and industry



Notes: The figure draws on data from the World Bank's Exporter Dynamics Database, which covers all trade transactions except those of oil and arms. We use data from importer-exporters in Bangladesh, Chile, China, Colombia, Ecuador, Egypt, Mexico, Peru, Romania and South Africa, which contain 10,312 separate robot purchases by 4,646 distinct firms. Note that the range of years displayed for each country varies, according to the current availability of customs data in the EDD.

adoption, and what are the implications for policy? We turn to these questions in the next section.

Figure 3.5.3: Ex-ante correlates of automation



Notes: Confidence intervals shown for 95% significance level. Fixed effects: industry-year, country-year. Standard errors clustered at the firm level.

Table 3.5.1: Descriptives for automating vs. non-automating firms in Vietnam

	Non-Automators				Automators				(1)-(2)	
	Mean	SD	Min	Max	Mean	SD	Min	Max	Diff	S.E.
log employment	4.092	1.367	0.693	10.091	4.907	1.413	0.693	9.429	-0.814***	(0.027)
log avg. wage	3.401	0.632	0.000	10.085	3.736	0.599	0.065	8.405	-0.335***	(0.011)
Exporter	0.391	0.488	0.000	1.000	0.609	0.488	0.000	1.000	-0.218***	(0.009)
log revenues	9.580	1.989	0.000	16.604	10.952	2.046	0.000	16.952	-1.372***	(0.038)
log leverage	0.420	0.194	0.000	0.693	0.430	0.179	0.000	0.693	-0.010**	(0.003)
log fixed assets	8.363	2.073	0.000	17.279	9.990	2.134	0.000	16.395	-1.627***	(0.040)
State-owned	0.435	0.496	0.000	1.000	0.330	0.470	0.000	1.000	0.105***	(0.009)
Privately-owned	0.370	0.483	0.000	1.000	0.265	0.441	0.000	1.000	0.105***	(0.008)
Foreign-owned	0.195	0.396	0.000	1.000	0.405	0.491	0.000	1.000	-0.210***	(0.009)
Observations	28097				3141				31238	

Notes: Standard errors in parentheses clustered by firm. * p <0.10, ** p <0.05, *** p <0.01. Data for the 2010-2013 period. Leverage normalised to lie between 0 and 1.

Table 3.5.2: Firm-level correlates of automation in Vietnam

	$\mathbb{1}$(Automator) (1)	(2)
log employment	-0.001	0.003
	(0.003)	(0.004)
log avg. wage	0.025***	0.017***
	(0.004)	(0.004)
Exporter	0.014	0.012
	(0.007)	(0.008)
log revenues	0.008***	0.007**
	(0.002)	(0.002)
log leverage	-0.041**	-0.039**
	(0.013)	(0.013)
log fixed assets	0.022***	0.022***
	(0.002)	(0.002)
State-owned	0.006	0.001
	(0.005)	(0.005)
Foreign-owned	0.031**	0.030**
	(0.010)	(0.011)
Fixed effects:		
– Province-Industry		✓
– Industry	✓	
– Year	✓	✓
R^2	0.077	0.145
F-stat	72.458	59.066
Observations	31233	31109

Notes: Standard errors in parentheses clustered by firm. * p <0.10, ** p <0.05, *** p <0.01. Firm-level data for the 2010-2013 period. Leverage normalised to lie between 0 and 1.

3.6 Firm-level implications

Larger, internationally active firms are more likely to adopt robots. How do they change ex-post? Drawing on firm-level data for ten developing countries, we address this question using an event study approach following Bessen et al. (2020). We estimate:[24]

$$\ln Y_{ft} = \sum_{s \neq -1, s=-2}^{2} \beta_s \times AutoEvent_{ft-s} + \alpha \cdot X_{ft} + \alpha_{ct} + \alpha_{it} + \alpha_f + \epsilon_{ft} \tag{3.6.1}$$

where X_{ft} controls for firm age. An automation event is defined as a period in which the firm spends more than three times its average cost-share on robots, not including robot purchases in the current period. Specifically:

$$AutoEvent_{f\tau} = \mathbf{1}\left\{ \frac{RobotPurchases_{f,t=\tau}}{TotalNonRobotImports_f} \geq 3 \times \frac{\overline{RobotPurchases_{f,t=\tau}}}{TotalNonRobotImports_f} \right\} \tag{3.6.2}$$

To mitigate selection effects, e.g. automators being particularly well-managed, we restrict our primary sample to only firms that do, at some point, automate. Thus β's counterfactual is the trend in firms that do automate, but not in the same period as the firm under consideration. We find that, after adopting robots, firms increase their exports and market share, and expand their range of export products and destinations (Figure 3.6.1). Robotising firms are not only larger ex-ante; their adoption of robots also coincides with a further expansion ex-post.[25]

In other words, we have early evidence consistent with robotisation boosting

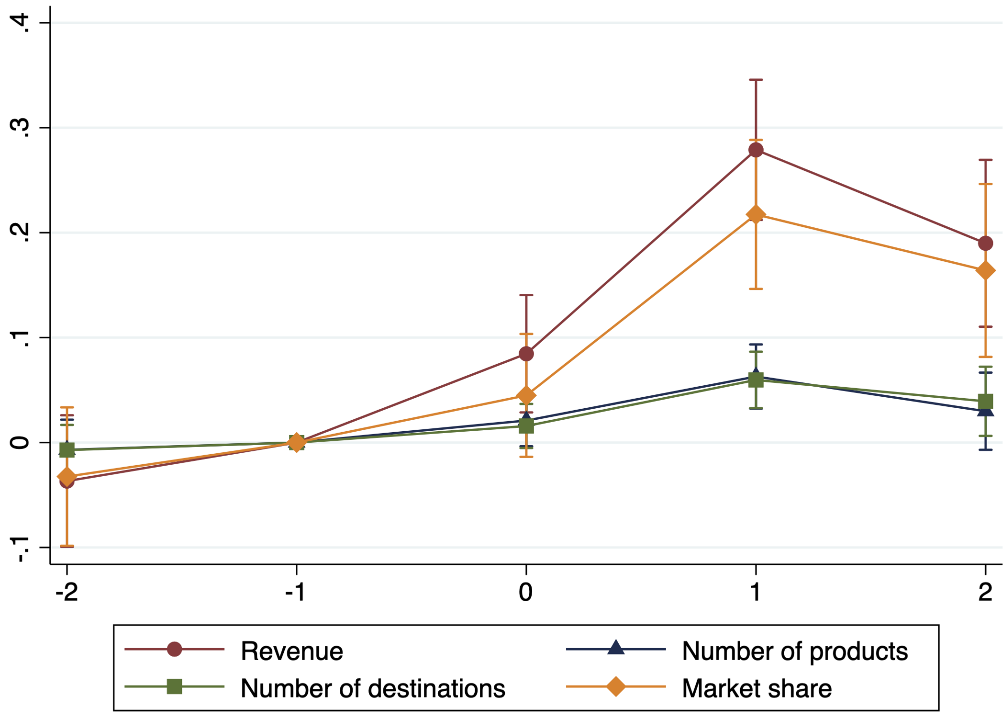
[24] We use a four-year window to maximise the number of automation events for which pre- and post-trends can be detected, given the short panel lengths in some of our countries. Results are qualitatively robust to using a longer window and fewer observations.

[25] If we expand the sample to include never-adopters, rather than only not-now-adopters, the relative post-adoption expansion is even larger.

the growth of initially larger firms in developing countries. Robotisation could thus contribute to increasing the average firm size in developing countries, and thereby raise aggregate productivity Hsieh & Klenow (2014). Yet this evidence also adds a firm-side element to the earlier distributional concerns: it is not just more disadvantaged workers who are most threatened by robotisation, but also smaller, less productive, less internationally active firms.[26] Given that low-skilled workers are also more likely to work at such firms, this dual threat is a key issue for policymakers to consider. As Rodrik (2018) notes, a key objective will be to 'disseminate throughout the rest of the economy the capabilities already in place in the most advanced parts of the productive sector'. In the meantime, robot adoption may place temporary support systems – whether state welfare systems, social networks or the informal sector (Dix-Carneiro et al. 2021, Dix-Carneiro & Kovak 2019) – under increasing strain. Reaping the benefits of robot adoption at home and abroad, whilst mitigating the downsides, will be a key policy challenge.

[26]This aligns with findings from developed countries that firms adopting robots expand at the expense of more labour-intensive competitors (Koch et al. 2019, Acemoglu, Lelarge & Restrepo 2020). Smaller and less productive firms may also be more vulnerable to automation-driven business-stealing from abroad Aghion et al. (2020).

Figure 3.6.1: Impact of robot adoption on firm export outcomes



Notes: All variables in logs. Confidence intervals shown for 95% significance level. Standard errors clustered at the firm level.

3.7 Conclusion

Industrial robots will likely place conflicting pressures on developing countries. In the long run, robot adoption in developed countries will most probably catalyze international trade and enhance global welfare. This conclusion is likely to be reinforced by the fact that other new technologies – such as high-speed internet and digital platforms – will further reduce the costs of trading and coordinating across borders (Brynjolfsson et al. 2019, Freund & Weinhold 2002, 2004) and will create entirely new products and tasks (Acemoglu & Restrepo 2018, Nakamura & Zeira 2018). Furthermore, while China's growing robotisation (driven in part by subsidies) might reduce inter-industry productivity differences with advanced economies (and thereby the scope for trade with them), it need not hinder future prospects for industrialisation and export-led growth in lower-income countries.

At the same time, trade and technological change will necessitate labour market adjustment and may create severe distributional tensions both during and after the transition to automated production. Robot adoption in developing countries could exacerbate disparities between, on the one hand, the more advanced internationally active firms which account for a large share of exports, and on the other hand the small-scale, informal firms which account for a large share of low-skilled and manual employment. These firm-level disparities may also accentuate income disparities across households in developing countries. Furthermore, rich-world automation could lock some developing countries out of sectors with high growth potential, exacerbating problems of 'premature de-industrialisation' (Rodrik 2016). Weighing these risks against the potential gains from specialising in labour-intensive exports will be a difficult balancing act. Informing policies that harness the growth potential of globalisation and technological progress while ensuring the attendant gains are equitably shared is thus an important task for future research.

3.A Theoretical Appendix

This section provides a high-level overview of the model; further details can be found in Artuc et al. (2018). The task-based Ricardian framework combines several ideas from the literature: productivity differences across countries and sectors (Eaton & Kortum 2002), two-stage production with trade in intermediates and final goods (Yi 2003, Caliendo & Parro 2015) and feasible robotisation of some tasks previously performed by humans (Acemoglu & Restrepo 2020).

We denote countries by m and n, sectors by i, and production stages by s, where $s = 1$ refers to intermediate inputs (first stage) and $s = 2$ refers to final goods (second stage). Workers are mobile across stages and sectors, but not across countries. Robots are equally available in all countries, at the same (exogenous) rental rate, and are owned by residents of the country that robotises production. The representative household in country n maximises Cobb-Douglas utility

$$U^n = \prod_i \left(Q_2^{n,i}\right)^{\gamma^{n,i}} \tag{3.A.1}$$

where $Q_2^{n,i}$ is the amount of composite final good from sector i demanded by consumers in country n, and $\gamma^{n,i}$ is a constant with $\sum_i \gamma^{n,i} = 1$. The composite final good $Q_2^{n,i}$ results from the aggregation of final stage varieties by consumers, as described in detail below.

A continuum of varieties $\omega \in [0, 1]$ is produced in each sector i of country n. These varieties can be produced either as intermediate inputs in the first stage or as final goods in the second stage. We define the set of first and second stage varieties in industry i respectively as S_1^i and S_2^i, such that $S_1^i \cup S_2^i = \{0, 1\}$. The production function for varieties ω is:

$$q^{n,i}(\omega) = z^{n,i}(\omega) \left(F_s^{n,i}(\omega)\right)^{\alpha_F^{n,i}} \left(Q_1^{n,i}(\omega)\right)^{\alpha_M^{n,i}} \left(T^{n,i}(\omega)\right)^{\alpha_T^{n,i}} \tag{3.A.2}$$

where $Q_1^{n,i}$ is a first stage composite, $F_s^{n,i}(\omega)$ is a fixed factor specific to the industry-stage, $T^{n,i}(\omega)$ is a composite task input, and $z^{n,i}(\omega)$ is productivity drawn from a Frechet distribution with shape parameter θ. Aggregation of stage s varieties $\omega \in S_s^i$ then yields the stage s composite good $Q_s^{n,i}$.

The production of the composite task input $T^{n,i}$ for variety ω requires performing a range of tasks $k \in [0, 1]$. We assume that tasks from 0 to K^i can be performed by robots or humans, while tasks between K^i and 1 can only be performed by workers. In some industries, robotisation is not feasible, and hence $\exists i \,:\, K^i = 0$. The subset of tasks that can be robotised is thus given by K^i, while the subset of tasks that cannot be robotised is given by $1 - K^i$. The robotisation frontier and the productivity of robots are assumed to be industry specific, but not stage specific.

To perform 1 unit of task k of variety ω within industry i, $\phi_L^i \zeta_L(k)$ labour units are required. If $k < K^i$, $\phi_R^i \zeta_{\mathrm{R}}(k)$ robot units can perform the same task. $\zeta_R(k)$ and $\zeta_L(k)$ are distributed Weibull with shape parameter ν. Thanks to the distributional assumptions, the optimal set of tasks performed by robots is then given by the simple expression

$$K_R^{n,i} = \frac{\left(\phi_R^i w_R\right)^{-\nu}}{\left(\phi_R^i\ w_R\right)^{-\nu} + \left(\phi_L^i\ w_L^n\right)^{-\nu}} K^i \tag{3.A.3}$$

and depends upon the automation frontier K^i, the elasticity of substitution between robots and workers $1 + \nu$, and the productivity-adjusted relative price of workers versus robots $\frac{\phi_L^i w_L^n}{\phi_R^i w_R}$. The average unit cost of tasks from 0 to K^i is given by the standard CES function

$$w_{T_A}^{n,i} = \psi_3^i\ \left(\left(\phi_R^i w_R\right)^{-\nu} + \left(\phi_L^i w_L^n\right)^{-\nu}\right)^{-\frac{1}{\nu}} \tag{3.A.4}$$

and depends on wages w_L^n, the unit cost of robots $w_R$and the elasticity of substitution between robots and workers.[27] Similarly, the unit cost of tasks

[27]Parameters ψ throughout denote various constants.

from K^i to 1 is $w_{T_N}^{n,i} = \psi_3^i \phi_L^i w_L^n$. Combining these expressions, the cost of producing a task with robots, relative to the cost of producing it without robots, is:

$$\Omega^{n,i} = 1 - K^i + K^i \left(1 - \frac{K_R^{n,i}}{K^i}\right)^{\frac{1}{\nu}} \tag{3.A.5}$$

Intuitively, robots bring no cost benefit (i.e. $\Omega^{n,i}$=1) if there is no potential for robotisation in an industry ($K_i = 0$), while the relative cost is minimised (i.e. $\Omega^{n,i}$ is close to zero) if robots are free to rent ($w_R = 0$) and can be used for all tasks ($K_i = 1$). Analogously, labour demand per task is

$$\Xi^{n,i} = 1 - K^i + K^i \left(1 - \frac{K_R^{n,i}}{K^i}\right)^{1+\frac{1}{\nu}} \tag{3.A.6}$$

such that labour demand is lower when robots (i) are cheaper, or (ii) can be used more widely.

We can use $\Omega^{n,i}$ to express the unit price of output under robotisation:

$$c_s^{n,i} = \psi_4^{n,i} \left(r_{s,F}^{n,i}\right)^{\alpha_F^{n,i}} \left(P_1^{n,i}\right)^{\alpha_M^{n,i}} \left(\Omega^{n,i} w_L^n\right)^{\alpha_T^{n,i}} \tag{3.A.7}$$

where $P_1^{n,i}$ is the price of (first-stage) inputs. A larger cost reduction from robotising (i.e. $\Omega^{n,i}$ closer to zero) lowers output prices. This in turn raises the probability that country n is the lowest-priced provider of a stage s variety to country m:

$$\pi_s^{m,n,i} = \left(\frac{\psi_{s,4}^{n,i}\ \tau^{m,n,i} \left(\ r_{s,F}^{m,i}\right)^{\alpha_{s,F}^{m,i}} \left(P_1^{n,i}\right)^{\alpha_{s,M}^{n,i}}\ \left(\Omega^{n,i}\ w_L^n\right)^{\alpha_{s,T}^{n,i}}}{P_s^{m,i}/\psi_2^i}\right)^{-\theta} \tag{3.A.8}$$

In other words, robotisation at home increases exports to other countries. In the calibrated model, initial higher wages lead the richer Northern countries n to adopt more robots than Southern countries m. Declines in robot prices then induce further robotisation, which disproportionately lowers production costs in the North and so increases their exports to the South.

In contrast, the effect of Northern robotisation on imports sourced from the South is theoretically ambiguous. On the one hand, robotisation makes Northern producers more competitive at home (i.e. $\pi_s^{n,n,i}$ is larger), which implies that some varieties that were previously imported from the South are now sourced domestically. On the other hand, robotisation leads to an expansion in the scale of production, which raises demand for first-stage varieties sourced from the South (i.e. $Q_1^{m,i}$ is larger).

Chapter 4

Market structure, timing and VAT pass-through*

with **Matthieu Bellon**

We examine the role of market structure and announcement timing in explaining observed heterogeneity in VAT pass-through. We first extend existing theory to characterise the roles of imperfect competition and product differentiation, then investigate these relationships empirically using a panel of 14 Eurozone countries between 1999 and 2013. We find important roles for product market regulation and product quality, and little impact of advance announcement of reforms. Our findings have important implications for policy-makers considering VAT rate adjustments, by illuminating which of the consumers or the producers would experience the brunt of a reform across different settings.

Keywords: *VAT, pass-through, competition, product differentiation*
JEL Classification Codes: *D43, H22, H25*

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4.1 Introduction

Value added taxes raise about a fifth of total tax revenues both worldwide and among the members of the OECD (OECD 2018*a*). Given the relative ease of modifying the rates, they are frequently at the centre of policy debates during economic crises – whether for fiscal stimulus (as in the 2009 VAT reform in China) or for domestic revenue mobilisation (as in Europe in the 2010s). How the impact of a VAT change will be divided between firms and consumers is critical for policymakers aiming to target their support or to minimise the tax burden for one group relative to the other. Who bears the consequences of a VAT reform is governed by the key parameter of 'pass-through' – the elasticity of consumer prices with respect to the VAT rate (Weyl & Fabinger (2013)).

There is a vast literature estimating the impact of VAT changes on prices. Yet, estimates of VAT pass-through to consumer prices can vary greatly across studies.[1] This paper builds on the recent empirical methodology of Benedek, De Mooij, Keen & Wingender (2020, hereafter BDKW) to explain how differences in VAT pass-through can be related to differences in market characteristics. Specifically, we examine the role of market competition, product differentiation and timing in explaining heterogenous VAT pass-through. We find that VAT pass-through is greater for products requiring inputs produced more competitively and for products with greater scope for vertical differentiation, namely quality. We do not find any significant difference in pass-through for reforms announced more in advance.

We start by extending existing theory to identify how supply and demand features can influence the degree of VAT pass-through under different market structures. We develop four simple partial equilibrium models. We first consider equally productive firms competing on price under monopolistic competition. Building on Dierickx et al. (1988), the next two consider VAT changes in a

[1] From, for instance, full pass-through (100%) of a cut in the Norwegian VAT on food (Gaarder 2018) to 9.7% for a cut in the French VAT on sit-down restaurants (Benzarti & Carloni 2017).

market with heterogeneous firms where the downstream and upstream sectors in turn produce under Cournot competition. In the three cases, we find that the effect of competition intensity on pass-through depends on whether producers have increasing or decreasing marginal costs. In the intuitive case of increasing marginal costs, pass-through increases with competition because greater competition prevents producers from realising and passing on savings from scaling down in response to a tax hike.

The fourth model generalises the ‘quality ladder’ model in Khandelwal (2010) to allow for substitution or complementarity effects between consumer valuation of affordability and quality. We find that variation in pass-through depends on price-quality complementarity. For products with longer ‘quality ladders’, where differences in quality are starkest, we show that pass-through is larger when there is a high enough degree of price-quality complementarity. In this case, consumers faced with higher prices from higher taxes ask for objects of greater quality, resulting in even higher prices. With less complementarity, consumers prefer lower quality and a lower price increase.

We then investigate empirically the relationships between market characteristics and pass-through using a panel of 14 Eurozone countries between 1999 and 2013. We follow closely the methodology developed in BDKW to systematically quantify the effects of VAT reforms in Europe over time, at the product and country levels. We enrich their specification by interacting VAT reforms with measures of competition and scope for quality. We also examine the role of different varieties of VAT reform (e.g. reforms announced well in advance vs. surprise reforms, or tax hikes vs. tax cuts) in explaining some of the pass-through heterogeneity.

Firstly, we find that changes in regulation in supplier markets play a substantial role, with a one standard deviation rise in the competition-friendliness of regulation (roughly equal to the difference between Austria and relatively uncompetitive Italy in 2013) increasing pass-through by up to 55%. We benchmark this effect against other supply-side characteristics, and find that it is more significant and more important. These results are also significant in a historical context. Liberalising reforms over the last thirty years have substantially increased the competition-friendliness of regulation in European product markets, so our findings imply that VAT cuts today will be passed on to consumers substantially more than in the past.

Secondly, we investigate the role of product differentiability, and find that the greater the scope for quality differentiation the larger is pass-through. Our empirical results are consistent with our theoretical framework and suggest the existence of complementarity between preferences for quality and price.

Many recent VAT policy changes have been announced significantly before they come into effect.[2] This constitutes a form of 'fiscal forward guidance' (see e.g. Fujiwara & Waki 2019), which could have real effects (Leeper et al. 2013, Mertens & Ravn 2010, 2011, 2012). Even outside times of crisis, fiscal policy uncertainty is large, so it is important to understand the effects of advance communication by policymakers.[3] We therefore match data on VAT changes to the Tax Policy Reform Database (Amaglobeli et al. 2018) to create the first cross-sector database of VAT reforms including announcement dates, and use it to provide the first systematic assessment of announcement effects across many product categories.[4] We find little overall support for 'anticipation' or 'total effect' hypotheses.

Together our results imply that market structure should be an important consideration when reforming VAT. For a government seeking to mobilise revenue through raising VAT (e.g. Saudi Arabia in May 2020), a greater share of the burden of higher taxes will fall on consumers relative to firms for products with higher upstream competition or for products characterised by a wider

[2]For instance, the German standard rate VAT cut announced on June 4 took effect on July 1.

[3]E.g. Baker et al. (2016) note that "fiscal matters, especially tax policy, stand out... as the largest source of policy uncertainty, especially in recent years."

[4]Buettner & Madzharova (2017) also construct a dataset of VAT reforms with announcement dates, but only include specific durable 'white goods' (cookers, dishwashers etc.).

quality range. For a government using a VAT cut to stimulate consumption (e.g. Germany in June 2020), or to support firm profits, the effects are opposite. Firms will retain more of the VAT cut in higher markups, and consumers will experience smaller price reductions, the less competitive the upstream sector or the narrower the range of product quality.

The rest of this paper proceeds as follows. The next section provides a review of the literature. Section 4.3 outlines the theoretical motivation, then Section 4.4 describes the data and outlines the empirical strategy. Section 4.5 presents the results, and Section 4.6 addresses their robustness. Section 4.7 concludes. The Appendix surveys related literature, provides detailed theoretical derivations, and presents additional results and robustness checks.

4.2 Literature

A substantial literature exists estimating the effects of specific tax changes. Carbonnier (2007) considers the impact of decreasing VAT on cars and housing repairs in France; Benzarti & Carloni (2017) consider a VAT cut for French restaurants, Mariscal & Werner (2018) consider the impact of differences in VAT for Mexican border cities, and Gaarder (2018) considers a cut in the VAT on food in Norway. A few studies consider effects across multiple countries: while Benzarti et al. (2017) focus on changes in the VAT on hairdressing in Finland, they also consider all VAT changes across EU member states, and Andrade et al. (2015) consider the impact on French export prices of VAT changes in several destination markets. This paper builds primarily on the work of Benedek et al. (2015), who constructed the core dataset of European VAT rates used in this paper. Like BDKW, in estimating VAT pass-through across a broad range of countries and consumption categories we aim to provide more general results than can be reached in studies of a small number of countries, sectors or reforms. We also use the same identification strategy and a product-country panel which, by comparing products across countries and countries across products, provides better controls than product-specific studies or economy-wide cross-country studies.

To measure the impact of upstream regulation on a sector, we use the *Regimpact* indicator developed by the OECD (Conway & Nicoletti 2006, Égert & Wanner 2016, Koske et al. 2015). This has been widely used to study the impacts of regulation on productivity (Amable et al. 2007, Arnold et al. 2008, Bourlès et al. 2013, Cette et al. 2013, 2014, Copenhagen Economics 2013, European Commission 2007, Havik et al. 2008, International Monetary Fund 2015, Yahmed & Dougherty 2012), and to a lesser extent to study the impacts on competitiveness (Braila et al. 2010) and firms' input sourcing decisions (Di Ubaldo & Siedschlag 2018). These studies generally find a positive effect of deregulation on productivity, competitiveness, and the propensity of firms to purchase inputs rather than source them intra-firm through FDI. To the best of our knowledge the *Regimpact* indicator has not previously been used to investigate VAT pass-through.

Other studies of upstream service sector reform have found substantial downstream effects on firms. Arnold et al. (2016) construct a measure of services liberalisation in India, and find a strong positive effect on the productivity of manufacturing firms intensive in the liberalising services. Bertrand et al. (2007) find similar effects on French manufacturing firms of banking deregulation in the 1980s. Our finding that features of the upstream market have substantial downstream effects also parallels an established result from the trade literature that input tariffs can have major effects in output markets (e.g. Amiti & Konings 2007, De Loecker et al. 2016, Goldberg, Khandelwal, Pavcnik & Topalova 2010*a*, Topalova & Khandelwal 2010).

To measure the degree of quality differentiation, we use the 'quality ladder' measure derived in Khandelwal (2010). While this method requires assumptions on the structure on demand, it has the advantage of producing estimates of the quality range for a broad class of consumption categories. In contrast, papers using directly observed quality measures tend to be confined to a limited range of products (e.g. rugs, wine or coffee respectively in Atkin et al. 2017, Chen & Juvenal 2016, Macchiavello & Miquel-Florensa 2017), so cannot be used to study VAT reforms which affect a wide range of products simultaneously.

Several previous studies consider the impact of anticipated fiscal shocks on aggregate economic variables, both in theory and empirically (Bi et al. 2013, Fujiwara & Waki 2019, Mertens & Ravn 2012, 2011, Ramey 2011). To the best of our knowledge this is the first study to consider product-level announcement effects across many different VAT reforms. In using the Tax Policy Reform Database (Amaglobeli et al. 2018) to identify announcement effects of VAT reforms on consumer prices, our paper also parallels the work of Pallan (2019), who considers the impact on stock prices.

4.3 Theoretical Motivation

We examine the role of market structure and consumer preferences in determining pass-through by considering four specific cases, building on earlier work by Dierickx et al. (1988) and Delipalla & Keen (1992). Consider a good i, with consumer price p_i and producer price $\widetilde{p}_i$ subject to ad valorem tax-exclusive rates τ_i, meaning that $p_i = \widetilde{p}_i(1 + \tau_i)$. As is standard, we define the degree of pass-through to the consumer as the proportionate response of the consumer price to an increase in the tax factor:

$$\gamma^i = \frac{\partial \ln p_i}{\partial \ln (1 + \tau_i)} \tag{4.3.1}$$

We investigate the factors determining γ^i in the following settings. All proofs are in the Theory section in Appendix.

4.3.1 Imperfect competition in a downstream sector

We consider a single-good market in which there are N producers. We infer the role of greater competition by studying the impact of having more producers.

Every firm indexed by n produces a quantity q_n under the cost function

$$C_n(q_n) = a + c_n q_n + \frac{b}{2} q_n^2 \quad \text{with } a > 0;\ c_n > 0; \tag{4.3.2}$$

where $b < 0$ corresponds to decreasing marginal costs and $b > 0$ corresponds to increasing marginal costs. We examine two different market structures in turn.

First, we consider the case of monopolistic competition where each firm produces a different variety of the good and competes on price. To keep the problem tractable, we assume in this case that all firms are equally productive ($c_n = c$ for all n). Preferences over the different varieties follow the standard Dixit-Stiglitz form and we assume that aggregate demand $Q = \left(\int_1^N q_n^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ is isoelastic, implying that $q_n = \left(\frac{p_n}{P}\right)^{-\sigma} \frac{A}{P}$, with $A > 0$, the elasticity of substitution across varieties $\sigma > 1$ and P the price index which takes the form $P = \left(\int_1^N p_n^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$.[5] Thus, each firm chooses its price $\widetilde{p}_n$ to maximise profits $\pi_n = \widetilde{p}_n q_n - C(q_n)$ subject to the demand for their variety. Because all firms are identical, the prices they choose are identical and we can drop the subscript n for prices. We also show in the appendix that tax pass-through is the same whether it is computed at the individual or aggregate price level.

Second, we consider a more general case with heterogeneous firms that have different production costs. In this case, there is no differentiation and firms are competing in quantities at a common price $\widetilde{p}$ under Cournot competition as described in Dierickx et al. (1988). Total demand $Q = \sum_n q_n$ is assumed to be isoelastic and such that $p(Q) = A'Q^{-\beta}$, with parameters $A' > 0$ and $\beta > 0$ and such that the demand function is steep enough ($\frac{\partial \widetilde{p}}{\partial q} - b < 0$) and concave enough ($\frac{\partial p}{\partial q} + \frac{\partial^2 p}{\partial q^2} q_n < 0$).[6][7] Each firm n chooses its output q_n independently to maximise profits $\widetilde{p}_n(q_n)q_n - C_n(q_n)$.

[5] As we show in the appendix, this demand function stems from a simple utility maximisation problem.

[6] Dierickx et al. (1988) shows that these conditions ensure the existence, stability and uniqueness of the Cournot-Nash equilibrium.

[7] See footnote 5.

Proposition 1 *In the Monopolistic competition and Cournot competition cases, pass-through respectively takes the form*

$$\gamma^{Monopolistic} = 1 - \frac{bA}{(1+\tau)N\widetilde{p}\left(2\frac{\sigma-1}{\sigma}\widetilde{p} - c\right)}\ ; \qquad \textit{and} \tag{4.3.3}$$

$$\gamma^{Cournot} = \left[1 + \frac{bA'^{\frac{1}{\beta}}}{(1+\tau)^{\frac{1}{\beta}}(N-\beta)\beta\widetilde{p}^{\frac{\beta+1}{\beta}}}\right]^{-1}. \tag{4.3.4}$$

In both cases, pass-through increases with the number of firms N only when $b > 0$, when marginal costs are increasing. Otherwise, pass-through decreases with N if $b < 0$ and is independent of N if costs are linear $b = 0$.

Proxying 'competitiveness' by the number of firms in the market, we thus show that the impact of competition on pass-through depends on the cost functions. For any cost function, lower demand resulting from higher taxes induces producer to scale back production. With increasing marginal costs, a reduction in scale implies some savings on production costs which, in turn, allows for lower producer prices.[8] Greater competition dampens producer costs adjustment. With few large firms with stretched production capacities and increasing marginal costs, a reduction in scale yields large savings. With many smaller firms competing, savings from scaling down are smaller and producers are less able to lower their prices in compensation for higher VAT. Therefore, greater competition with increasing marginal costs implies a greater pass-through.

Conversely, in the case of decreasing marginal costs, the reduction in demand induced by a higher VAT rate has a different effect on producers. Faced with higher marginal costs, producers choose to sell at higher producer prices and pass-through is greater than one ($\gamma > 1$ when $b < 0$). Once again, greater competition dampens producer price adjustments. Thus, greater competition with decreasing marginal costs implies a lower pass-through.

We investigate in the empirical section whether the impact of competition

[8]This can be seen because $\gamma < 1$ when $b > 0$ (see the Theoretical Appendix for details).

on pass-through is consistent with increasing or decreasing marginal costs.

4.3.2 Imperfect competition in the upstream sector

We now examine the case of two sectors, with perfect competition in the downstream sector selling the final good and with Cournot competition in the upstream sector. Demand for the final good is characterised by $p_F(Q_F) = A'Q_F^{-\beta}$ and is the same as in the previous case with Cournot competition. Assuming perfect competition in the downstream sector allows us to consider a representative final good producer which maximises profits $\widetilde{p}_F Q_F - p_I Q_I$ by choosing a quantity Q_F to produce given the input cost function $Q_I = d(1-\rho)Q_F^{\frac{1}{1-\rho}}$ with $0 < \rho < 1$ and $d > 0$. Final good producers take the producer price $\widetilde{p}_F = \frac{p_F}{1+\tau}$ as given.

Solving the final good producer maximisation problem to get input demand, we show in the appendix that the demand function is isoelastic and a function of the final good price: $p_I = \widetilde{p}_F d^{\rho-1}(1-\rho)^{\rho} Q_I^{-\rho}$. We impose the same concavity conditions on this function as in the previous case under Cournot competition to ensure the existence and uniqueness of an equilibrium solution.

For the sake of clarity, we assume that inputs Q_I produced in the upstream sector are only consumed by final good producers and that inputs are not taxed (producer and consumer prices are then the same, meaning that $\widetilde{p}_I = p_I$). Each input producer n chooses quantity $q_{I,n}$ independently to maximise profits $\widetilde{p}_I(Q_I)q_{I,n} - C_n(q_{I,n})$ subject to the isoelastic input demand function. As before, upstream firms internalise their impact on total production $Q_I = \sum_n q_{I,n}$ and the cost function follows equation 4.3.2. Consequently, operations in the upstream sector are very similar to those described in the single sector case under Cournot competition presented in the previous section.

Proposition 2 *In the 2-sector case with Cournot competition in the upstream sector and perfect competition in the final good sector, pass-through in the final* *good sector takes the form*

$$\gamma^F = \left[1 + \frac{\rho}{\beta(1-\rho)} + \frac{bd^2(1+\tau)^{-\frac{1+\rho}{\beta(1-\rho)}} A'^{\frac{1+\rho}{\beta(1-\rho)}}}{\beta(N-\rho)\widetilde{p}_F^{\,1+\frac{1+\rho}{\beta(1-\rho)}}}\right]^{-1} \tag{4.3.5}$$

Furthermore, the pass-through increases with the number of firms N only when $b > 0$, when marginal costs are increasing. Otherwise, pass-through decreases with N if $b < 0$ and is independent of N if costs are linear $b = 0$.

We obtain the same result as in the previous section. An increase in VAT lowers demand for the final good, and now also reduces demand for upstream inputs. In the case of increasing marginal costs ($b > 0$), a reduction in scale for input producers means lower cost, which are then passed through to input prices. Cheaper input costs allow for lower producer prices in the downstream sector. As in the previous case, greater competition dampens the variation in producer costs in response to VAT rate changes. With more firms competing, production capacities are not overly stretched, implying smaller savings from scaling down, and a lower reduction in producer prices. The results are the same as in the single sector case: pass-through increases (decreases) with competition when marginal costs are increasing (decreasing). We investigate in the empirical section whether the impact of competition in upstream sectors on pass-through is consistent with increasing or decreasing marginal costs.

4.3.3 Differences in scope for quality in the final good

We now examine a sector in which consumers make 'discrete choices', meaning that they choose at most one of the competing products. There are many varieties indexed by n that differ along a horizontal and a vertical dimension as in Khandelwal (2010).

Horizontal differentiation is assumed to randomly appeal more to some consumers than others and to be costless, implying that all varieties are consumed in equilibrium.[9] Following standard practice in the discrete choice literature, horizontal characteristics denoted ξ_{nk} are assumed to be distributed i.i.d. type-I extreme value with mean zero.

By contrast, vertical differentiation, i.e. 'quality', is costly to produce but is regarded by all consumers as superior: holding prices fixed, all consumers would prefer higher quality objects. Each consumer k knows her valuation of horizontal (ξ_{nk}) and vertical (λ_n) characteristics of every variety and chooses the variety n that gives her the highest indirect utility.

$$V_{nk} = \delta_n + \xi_{nk}, \qquad \text{with } \delta_n \equiv \left(\theta\lambda_n^{\psi} - p_n^{\psi}\right)^{1/\psi} \qquad \text{and } \psi < 1 \quad (4.3.6)$$

where δ_n represents the mean consumer valuation of variety n. δ_n increases with quality and decreases with price.[10] The parameter ψ controls the degree of substitution between price and quality, with higher ψ indicating the two characteristics are more easily substituted – i.e. consumers are happy to sacrifice quality for a lower price – while a lower, possibly negative, ψ indicates greater complementarity. In other words and as we show in the appendix, the marginal willingness to pay for quality increases with the quality-price ratio when ψ is positive while it decreases with the quality-price ratio when ψ is negative. Greater values of the parameter θ indicate a longer 'quality ladder', as defined in Khandelwal (2010), and imply that firms have incentives to produce higher quality.

Each firm n produces a variety subject to a marginal cost function that is increasing with quality, $w + \frac{\lambda_n}{Z}$. Under the distributional assumption, the market share of variety n is given by the familiar logit formula $m_n = \frac{e^{\delta_n}}{\sum_m e^{\delta_m}}$. We assume that the market is characterised by monopolistic competition with a sufficiently large number of firms so that no one firm can influence the market

[9]Costless horizontal differentiation means that varieties differ on some characteristics, like color, that appeal more to some consumers than others while having no impact on production costs and no relation to prices.

[10] Equation 4.A.30 is a generalisation of the specification in Khandelwal (2010) which would be obtained when $\psi \to 1$.

equilibrium prices and qualities. A firm n maximises profits by choosing the price and quality.

$$\max_{\widetilde{p}_n,\lambda_n}\left[\widetilde{p}_n - w - \frac{\lambda_n}{Z}\right]\frac{e^{\delta_n}}{\sum_m e^{\delta_m}} \tag{4.3.7}$$

Proposition 3 *In the case of discrete choices with monopolistic competition, pass-through takes the form*

$$\gamma = 1 + \frac{-\psi/(1-\psi)}{\theta^{\frac{1}{\psi-1}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{\psi-1}} - 1} - \frac{1}{1-\theta^{\frac{1}{1-\psi}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}} + w(1+\tau)\left(1-\theta^{\frac{1}{1-\psi}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}}\right)^{\frac{1}{\psi}}} \tag{4.3.8}$$

Furthermore, the pass-through decreases with the length of the quality ladder θ when $0 < \psi < 1$, in the substitution case when the marginal willingness to pay for quality increases with the quality-price ratio. Conversely, pass-through increases with θ when ψ is negative enough, for example when $\psi < -\frac{1}{w(1+\tau)}$

Thus, the effect of quality on VAT pass-through depends on ψ, the degree of substitution-complementarity between consumer valuations of price and quality. In the substitution case when $\psi > 0$ (as in Khandelwal (2010)), for a given increase in consumer price resulting from a tax hike, consumers prefer a mitigation in the price increase at the expense of lower quality. Producers respond accordingly and pass-through is lower. The opposite is true in the complementarity case when $\psi < 0$ is negative enough: consumers prefer to tolerate a larger price increase and to be compensated with relatively higher quality. Those effects are magnified by the scope for quality, or 'quality ladder', θ. Therefore, pass-through decreases with the quality ladder in the substitution case, while the opposite is true in the complementarity case. We investigate in the empirical section whether the effect of the scope for quality on pass-through is consistent with price-quality complementarity or substitution.

4.3.4 Early Announcement

Early announcement can, in theory, generate anticipation and smoothing effects, i.e. an early and/or prolonged increase in pass-through. On the supply side, the presence of menu costs or Calvo pricing (Calvo 1983) encourages firms to smooth the price response to an announced VAT change to save on adjustment costs. As discussed in Buettner & Madzharova (2017), for durables there is an extra effect through the demand channel: consumers aware of a future tax fall will defer consumption, reducing demand before the reform and hence lowering prices. Conversely, for an anticipated tax hike, consumers raise pre-reform demand, thereby contributing to higher prices before the rate increase – as observed before the German VAT increase in January 2007 (Danninger et al. 2008). Lastly, in a situation of information overload and rational inattention (Sims 2003), early announcement may increase the salience of a particular reform to consumers and firms, increasing total pass-through. We investigate these 'anticipation' and 'total effects' in the empirical section.

4.4 Data and Empirical Specification

We use data on monthly VAT rates across European countries and consumption categories constructed by BDKW from the European Commission publication *VAT Rates Applied in the Member States of the European Union* and from additional publications by the International Bureau for Fiscal Documentation. The distribution and characteristics of VAT reforms across countries are summarised in Tables 4.B.1 and 4.B.2 in the Appendix.[11] All the countries studied are in the Eurozone, reducing distortions due to differing exchange rates or monetary policies.[12] Data on monthly prices are from Eurostat's Harmonised Index of Consumer Prices, categorised according to the 'Classification of Individual Consumption According to Purpose' (COICOP). We follow BDKW in limiting our sample to those categories for which prices are sufficiently market-driven – excluding, for example, rental accommodation, electricity and healthcare.

[11] There are no reclassifications or other rate changes among the small number of products at the zero rate in our sample, but we retain these observations to improve precision.

[12] For instance, the influence of common monetary policy changes on pass-through will be removed by time fixed effects in the regressions.

We measure the competition-friendliness of regulation in upstream non-manufacturing industries using the annual *Regimpact* indicator from the Organisation for Economic Co-operation and Development (Conway & Nicoletti 2006, Égert & Wanner 2016, Koske et al. 2015). This uses country-specific input-output weights w_{jk} to combine survey-based measures of anti-competitive regulation in several upstream non-manufacturing industries ($REGNMI_{jt}$), producing a measure of the degree of regulation affecting final output sectors:[13][14]

$$Regimpact_{ikt} = \sum_{j=1}^{J} REGNMI_{jt} \cdot w_{jk} \tag{4.4.1}$$

where k denotes the output sectors of interest and j denotes upstream non-manufacturing sectors. The distribution in product market regulation across consumption categories is shown in Figure 4.B.1 in the Appendix. The trends in regulation are shown in Figure 4.B.3 in the Appendix; in general regulation became much more pro-competitive over the period.

We construct two measures of market competitiveness in the downstream sectors affected by the VAT change, using annual trade data from UN Comtrade.[15] Firstly, we use the sum of imports and exports over total consumption as a measure of openness to trade:

$$Openness_{ikt} = \frac{Imports_{ikt} + Exports_{ikt}}{Consumption_{ikt}} \tag{4.4.2}$$

[13] We use the 'wide' version of the *Regimpact* indicator, which contains the broadest range of upstream non-manufacturing industries. The precise industries that it covers, and the categories upon which they are scored to generate the aggregate REGNMI indicator, are shown in Figure 4.B.4 in the Appendix. We use the version with country-specific weights to account for differences in input-output patterns across countries.

[14] The lower the score, the more competition-friendly the regulatory environment. For instance, one question on 'entry regulation' for the electricity industry sub-indicator is: "What is the minimum consumption threshold that consumers must exceed in order to be able to choose their electricity supplier?" (Conway and Nicoletti, 2006). The lack of any threshold scores zero, a threshold less than 250 gigawatts scores one, 250-500 gigawatts scores two, etc.

[15] We use the BACI refinement of the Comtrade database, compiled by CEPII, which cleans and harmonises the data through a series of procedures described in Gaulier & Zignago (2010).

where consumption data are drawn from Eurostat at the 3-digit sector level (rather than the 4-digit level for which VAT rates are available). Secondly, we construct a Herfindahl-Hirschman Index based on import origins to proxy for market concentration:

$$ImportConcentration_{ikt} = \sum_{c=1}^{N} s_{ickt}^2 \tag{4.4.3}$$

where:

$$s_{ickt} = \frac{M_{ickt}}{\sum_{c=1}^{N} M_{ickt}} = \frac{\text{Imports into } i \text{ from } c}{\text{Total imports into } i} \tag{4.4.4}$$

Both of these are imperfect measures of competitiveness, but serve in the absence of relevant firm-level data. Assuming that firms are evenly distributed across producing countries, a high degree of concentration observed among import origins is a necessary consequence of high market concentration among firms, though not sufficient to guarantee it.[16]

We use the scope for product differentiability derived in Khandelwal (2010). The scope for quality, or 'quality ladder', is backed out from price and quantity data. High market share conditional on price suggests that a product is high quality and long quality ladders correspond to products with a large dispersion in estimated quality. Khandelwal constructs his product-level measure using trade data on goods, which means 'quality ladder' estimates are only available for the subset of good industries and do not vary across countries.[17] This prevents us from using the full price and VAT dataset, and some controls, with this measure – so we also perform several robustness checks to verify that our results are not driven by the restrictions related to these data limitations. The

[16] For instance, a market dominated by a single foreign firm producing in one country would have $ImportConcentration_{ikt} = 1$, yet having $ImportConcentration_{ikt} = 1$ is also compatible with there being substantial competition in the supply of the good – if all those firms competing are located in the same country.

[17] Given the lack of quantity data over our whole period, we use only cross-sectional product-wise variation in quality.

distribution of quality scope across consumption categories is shown in Figure 4.B.2 in the Appendix.

We standardise all four measures (*Regimpact*, trade openness, import concentration and quality ladder length) so that their impacts are comparable. The four measures are only weakly correlated, as shown in Table 4.B.3 in the Appendix. We also match VAT reforms in the BDKW data to the IMF's new Tax Policy Reform Database (Amaglobeli et al. 2018), which contains announcement dates. Summary statistics for those VAT changes that we can match to announcement dates are shown in Appendix Table 4.B.5. Lastly, we use consumption data from Eurostat to weight observations by their consumption share, and total value added from EU KLEMS in a robustness check. Overall, we use an unbalanced panel of approximately 110k observations spanning January 1998 to December 2013. The variables are summarised in Table 4.B.4 in the Appendix.

Our empirical approach builds on BDKW, estimating pass-through from VAT changes to price rates by regressing country-product prices on taxes:[18]

$$\begin{aligned}\Delta \ln(p_{ikt}) = \beta_0 &+ \sum_{j=-6}^{6} \beta_{1j} \cdot \Delta \ln(1+\tau_{ikt+j}) \\ &+ \sum_{j=-6}^{6} \boldsymbol{\beta}_{2j} \cdot \Delta \ln(1+\tau_{ikt+j}) \cdot \mathbf{X}_{ikt} \\ &+ \boldsymbol{\beta}_3 \cdot \mathbf{X}_{ikt} + \varphi_{it} + \varphi_{kt} + \varphi_{ik} + \epsilon_{ikt} \qquad (4.4.5)\end{aligned}$$

where p_{ikt} denotes the price of product k in country i in month t and τ_{ikt+j} represents the VAT rate in country i for product k in month t. The coefficients of interest β_{1j} capture the average pass-through across products at different horizons j, while $\boldsymbol{\beta}_{2j}$ measures deviations from the mean pass-through across several covariates. Specifically, the sequences of β_{1j} and $\boldsymbol{\beta}_{2j}$ capture the magnitude of pass-through adjustments at different times around the reform

[18]BDKW in turn follow Poterba (1996) and Besley & Rosen (1999), who consider city-level sales taxes in the USA.

dates, i.e. at a number of months j before and after the reform date.[19] The coefficients φ_{it}, φ_{kt} and φ_{ik} are country-time, product-time, and country-product fixed effects, and ϵ_{ikt} is the error term.[20] $\mathbf{X}_{ikt}$ denotes country-product-time covariates of interest, specifically product market regulation, quality range, openness to trade, and import concentration. In our main specification we de-seasonalise and de-trend all price indices, weight observations by their consumption share, and cluster standard errors at the country-product level to account for possible autocorrelation in the error term.[21]

To investigate the effects of early announcement, we run a similar specification with the change in VAT also interacted with a dummy for whether the announcement-to-implementation lag for a particular reform is above or below the median. In this case the interaction of the dummy with the sum of pre-reform coefficients $\sum_{j=1}^{6} \boldsymbol{\beta}_{2j}$ tests for an anticipation effect, and the interaction of the dummy with the cumulation of all the $\boldsymbol{\beta}_{2j}$ terms across the whole window $j \in \{-6, ..., 6\}$ tests for a total effect.

4.5 Results

This section presents our three main results. The first part, on product market regulation, tests the theory of Sections 4.3.1 and 4.3.2, as summarised in Propositions 1 & 2. The second part, on quality scope, tests the theory of section 4.3.3, as summarised in Proposition 3. The third part investigates potential mechanisms by which early announcement could impact pass-through, as

[19]In this paper we focus on the medium-run, i.e. a 12-month window centred on the date of the reform, as we do not find significant effects outside this window.

[20]We also report results using separate country, product and time fixed effects, and no fixed effects, as in BDKW. Our preferred specification includes all three interaction fixed effects, as shown, since this accounts for all industry trends and country-specific macroeconomic conditions.

[21]We de-seasonalise and de-trend because, as in BDKW, our time-indexed fixed effects only remove trends in the first difference of prices, not the levels of prices. Specifically, we regress log prices on month-of-year dummies and linear to quartic time trends, then substitute raw prices with the predicted values. Our main results are very similar when using raw prices, but with slightly larger standard errors.

outlined in Section 4.3.4. Various robustness checks are included in Section 4.6, and the Appendix contains additional results, for example on the heterogeneity of announcement effects.

4.5.1 Product market regulation

Table 4.5.1 shows results from the main specification in the full dataset; column (1) shows results with no fixed effects, column (2) shows results with individual fixed effects, and column (3) uses interaction fixed effects. The first four estimates correspond to β_1 in the main estimating equation above – they estimate the relationship between changes in the VAT rate and changes in prices, i.e. baseline pass-through. 'Pre-Reform' refers to the total effect across the six months preceding the VAT change, and 'Post-Reform' refers to that across the six months afterwards; 'Contemporaneous' refers to effects in the month of the reform, and 'Total' is the sum of effects over the whole window. The remaining estimates correspond to different elements of $\boldsymbol{\beta}_2$, and in turn reflect the impact of variation in the elements of $\boldsymbol{X}_{ikt}$ – specifically, $Openness_{ikt}$, $ImportConcentration_{ikt}$ and $Regimpact_{ikt}$ – on pass-through.[22]

Average baseline pass-through of a VAT rise to prices is 31% in column (3).[23] As in BDKW's estimates, this effect is almost entirely driven by the contemporaneous pass-through effect – i.e. by the impact on prices in the month that the reform is introduced. A one standard deviation fall in *Regimpact* (i.e. a one standard deviation rise in the competition-friendliness of upstream regulation, equivalent to the gap between Italy and relatively competitive Austria in 2013) raises pass-through by a further 18 percentage points, a 56

[22]Pre-Reform, Contemporaneous, Post-Reform and Total effects are estimated for each of Openness, Concentration and *Regimpact*. Across the first three the lowest p-value for either Openness or Concentration is 0.236, for the Post-Reform effects of Openness in model (1), so these rows are omitted from the results tables for brevity. Indeed, under the tighter fixed effects of model (3) the strongest effect corresponds to Pre-Reform Concentration, with a p-value of 0.336 – i.e. only extremely weak evidence of any effect.

[23]This is close to BDKW's main estimate of 25%; it differs slightly because (i) we use only the subset of their observations for which measures of regulation, openness and concentration are available, and (ii) they sum over a 24-month window around the reform.

percent increase in pass-through.

Table 4.5.1: Estimates of pass-through heterogeneity

		Dependent variable: change in log prices		
		No FEs	Individual FEs	Interaction FEs
Baseline β_1:	Pre-Reform	0.193	0.181*	0.0247
	– i.e. $\sum_{j=1}^{6} \beta_{1j}$	(0.152)	(0.056)	(0.640)
	Contemporaneous	0.331***	0.325***	0.257***
	– i.e. β_{10}	(0.000)	(0.000)	(0.001)
	Post-Reform	0.156	0.114	0.0267
	– i.e. $\sum_{j=-6}^{-1} \beta_{1j}$	(0.142)	(0.226)	(0.712)
	Total	0.681***	0.620***	0.309***
	– i.e. $\sum_{j=-6}^{6} \beta_{1j}$	(0.000)	(0.000)	(0.001)
Openness:	Total	0.638	0.522	0.00263
		(0.172)	(0.377)	(0.995)
Concentration:	Total	-0.0209	-0.00425	-0.0351
		(0.896)	(0.977)	(0.754)
Regimpact:	Pre-Reform	-0.0553	-0.0188	0.0639
		(0.430)	(0.724)	(0.289)
	Contemporaneous	-0.157***	-0.180***	-0.228***
		(0.005)	(0.001)	(0.002)
	Post-Reform	-0.0172	-0.00685	-0.0123
		(0.798)	(0.897)	(0.783)
	Total	-0.229**	-0.206**	-0.177*
		(0.041)	(0.038)	(0.052)
FEs		None	i,k,t	it,kt,ik
Clustering		None	ik	ik
N		100,983	100,983	100,983

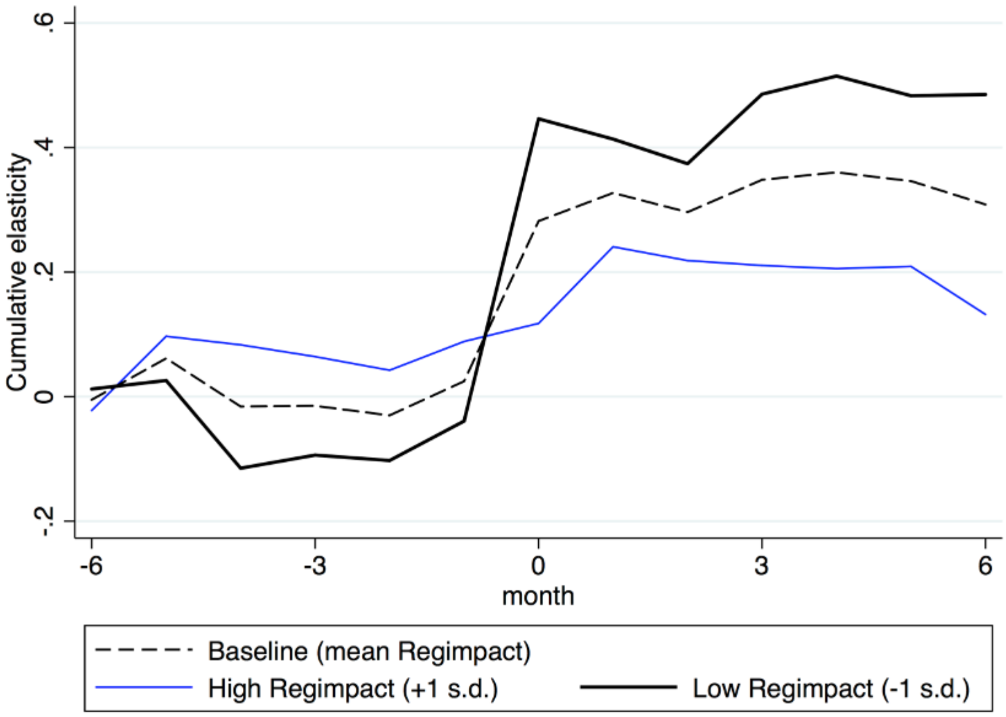
Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption. *Regimpact*, openness and market concentration are standardised so the coefficients can be interpreted as the impact on pass-through of a one-standard-deviation rise in the regressor. Pre-Reform, Contemporaneous and Post-Reform effects are also estimated for Openness and Concentration, but are not significant so omitted for conciseness.

These effects are more significant and more important than the other supply-side competition measures of openness to trade and import concentration. To the extent that openness and concentration proxy for the competitiveness of the downstream sector, this suggests that the theoretical mechanism outlined in Section 4.3.2 is stronger than that in Section 4.3.1. As discussed further in the Appendix, this result aligns with findings elsewhere that upstream reforms affecting inputs can have substantial downstream effects (e.g. Amiti & Konings

2007, Arnold et al. 2016, Bertrand et al. 2007). A full analysis of the conditions under which such upstream effects can amplify further downstream, rather than decay into insignificance, is beyond the scope of this paper (for details, see e.g. Acemoglu et al. 2012).

Figure 1 plots the cumulated values of the estimated coefficients β_{1r} for the 12 months surrounding a VAT change for the specification with the most complete set of fixed effects. The dashed line shows pass-through over time for a consumption category with exactly average levels of upstream product market regulation, openness to trade, and market concentration. There is little pass-through prior to the change, then most of the total effect comes within the first month of the reform. The black line illustrates the marginal impact of upstream regulation on these dynamics: it plots the marginal impact on pass-through of having upstream regulation that is one standard deviation more competition-friendly than the average. Again, most of the marginal impact occurs in the month of the VAT reform, with some additional impact in the six months after the reform. This is consistent with the purchaser-supplier relationships described in Section 4.3 adjusting to the change reasonably quickly. The extent to which forewarning of the reform speeds up such processes is examined in Section 4.5.3 below.

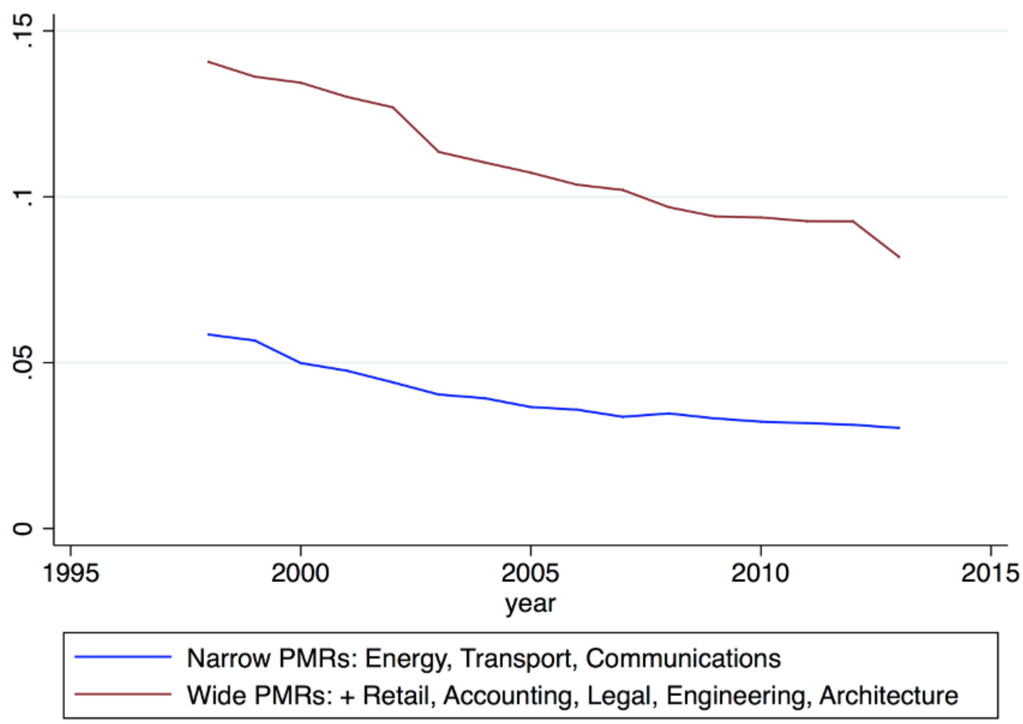
Figure 4.5.1: Cumulative effect of upstream regulation on pass-through



Notes: This graph shows cumulative baseline pass-through and the impact upon this of upstream regulation. The black (blue) lines show cumulative pass-through in a country-product pair with regulation that is exactly one standard deviation more (less) competition-friendly.

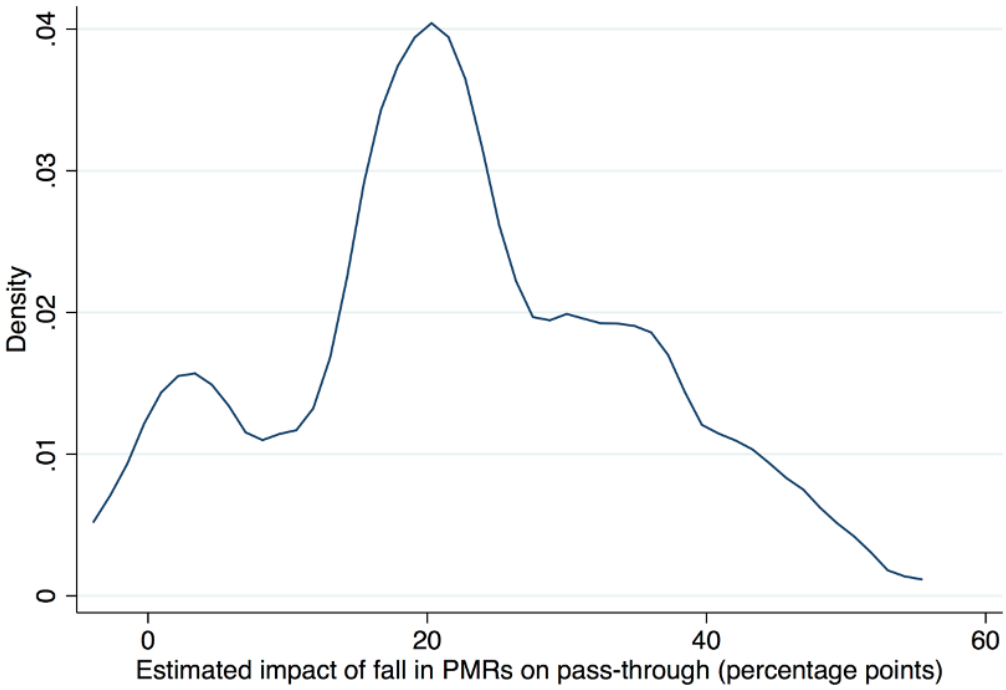
Reforms over the last thirty years have substantially increased the competition-friendliness of regulation in European product markets (Égert & Wanner 2016). The overall median value of the *Regimpact* measure since 1999 is shown in Figure 4.5.2, while the trends in each country and consumption category are shown in Figure 4.B.3 in the Appendix. A back-of-the-envelope calculation takes the observed changes in the *Regimpact* index for each country-product category over the observed period and multiplies them by the coefficient on the VAT-PMR interaction term in Table 4.5.1. The smoothed distribution of these estimated changes in VAT pass-though is shown in Figure 4.5.3. Because regulations were loosened almost everywhere, our results imply that VAT pass-through increased practically everywhere for all products. The median estimated impact of the large increase in the competition-friendliness of regulation since 1999 is an increase in pass-through of approximately 21 percentage points, while the vast majority of the distribution has an increase in pass-through of more than 10 percentage points. This is a direct extrapolation of our results without proper identification, but this illustrates that changes in upstream regulation are likely to have substantially affected the consequences of most VAT reforms in recent history.

Figure 4.5.2: Median index of regulation over time



Notes: This graph shows the trends over time in the median value, across all countries and products, of the 'wide' and 'narrow' *Regimpact* indices of product market regulation. A lower value of the index reflects a more competition-friendly regulatory stance in upstream non-manufacturing industries.

Figure 4.5.3: Distribution of estimated impact of regulation on pass-through



Notes: This graph shows the smoothed distribution across country-product categories of the estimated increase in pass-through resulting from changes in regulation between 1999 and 2013. It applies the main estimate from Table 4.5.1 to the observed change in the *Regimpact* indicator across the period observed, using only those country-product categories with observations spanning at least ten years.

4.5.2 Scope for quality

Table 4.5.2 repeats the analysis for those products for which measures of the scope for quality are available.[24] Since the 'quality ladder' data only vary across products, not across countries, we cannot include product-time fixed effects as these would remove all variation. We therefore include only country-product, country-time, product and time fixed effects in the 'Interaction FEs' quality specification. This slight loosening has little impact on the *Regimpact* results, which remain consistent across columns, suggesting that the 'lighter'

[24] All variables are re-standardised for the regressions on this smaller quality-inclusive sample, so that each estimated coefficient retains the interpretation as 'the impact on pass-through of a one-standard deviation rise in the variable'.

specification still provides informative estimates for the effect of quality range.

The results in Table 4.5.2 show that a one standard deviation increase in the length of the 'quality ladder' of a product can raise pass-through by more than 40 percentage points. This fits the theory in Section 4.3 in the case that demand for quality is relatively more important to consumers when prices are higher – i.e. in the 'complementarity' case. In this scenario, firms opt to pass on more of a VAT rise rather than reduce quality to dampen the impact on prices; the greater the scope for quality differentiation, the stronger this effect, so the higher is pass-through.

Considering Table 4.5.1 and Table 4.5.2 together, the regulation and quality effects have comparable magnitudes, while the regulation effect is somewhat more robust across different specifications. Figure 4.B.5 in the Appendix below shows the dynamics of the quality scope effect. While there is again a significant effect in the month of the reform, the effect also continues to grow over the six months following the reform.

Table 4.5.2: Estimates of pass-through heterogeneity, including quality range

		Dependent variable: change in log prices		
		No FEs	Individual FEs	Interaction FEs
Baseline β_1:	Pre-Reform	0.191	0.226**	0.116
		(0.565)	(0.045)	(0.429)
	Contemporaneous	0.234	0.201**	0.0169
		(0.192)	(0.019)	(0.891)
	Post-Reform	-0.0381	-0.000174	-0.067
		(0.889)	(0.999)	(0.468)
	Total	0.387	0.427***	0.066
		(0.384)	(0.009)	(0.764)
Openness:	Total	-0.573	-0.409	-0.551
		(0.572)	(0.485)	(0.433)
Concentration:	Total	-0.152	-0.202	-0.153
		(0.692)	(0.220)	(0.398)
Regimpact:	Pre-Reform	-0.0558	-0.0466	0.122
		(0.676)	(0.559)	(0.450)
	Contemporaneous	-0.212***	-0.278***	-0.444***
		(0.003)	(0.000)	(0.003)
	Post-Reform	-0.0853	-0.0897**	-0.0945*
		(0.461)	(0.016)	(0.075)
	Total	-0.353*	-0.414***	-0.416**
		(0.067)	(0.002)	(0.029)
Quality range:	Pre-Reform	-0.0838	-0.0996	-0.0368
		(0.829)	(0.384)	(0.754)
	Contemporaneous	0.213	0.228**	0.256***
		(0.326)	(0.041)	(0.009)
	Post-Reform	0.268	0.256**	0.268***
		(0.401)	(0.033)	(0.003)
	Total	0.397	0.385**	0.487**
		(0.440)	(0.025)	(0.010)
FEs		None	i,k,t	it,k,t,ik
Clustering		None	ik	ik
N		49,598	49,598	49,598

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption.

4.5.3 Early announcement

To investigate the role of early announcement empirically, we consider the dynamics of those cases where we can match a VAT change to an announcement date in the TPRD. We create a dummy *AnnouncedEarly* that equals one if the lag between announcement and implementation is greater than the median implementation lag of 32 days. Interacting this with the pass-through term in the baseline dynamic regression finds that there is no significant anticipation effect in the six months before the reform, as shown in Table 4.5.3, though there may be some small cumulative effect over the whole one year window. The full dynamics are illustrated in Figure 4.5.4.

To check whether this null result is driven by the above/below median specification, in Table 4.B.7 in the Appendix we also present results using a continuous implementation lag variable. We find that an additional month of implementation lag is weakly associated with up to 6% additional total pass-through, but there is again no significant anticipation effect. Anticipation effects through the demand channel may be particularly strong for durables, as noted in Section 4.3.4, since they offer greater opportunity to expedite or defer consumption in response to future price changes. We therefore also split the results between durables and non-durables, shown in Table 4.B.8 in the Appendix, and again find no evidence for anticipation effects.[25] Lastly, a positive result may be obscured by variation in market competitiveness, which we know plays a role as discussed above. Therefore in Table 4.B.9 in the Appendix we also include regulation, quality, openness and concentration in the specification, but again find no evidence for announcement effects.

Overall, while there is some weak evidence that reforms announced earlier tend to have slightly larger pass-through, there is no strong support for either

[25] This contrasts, for instance, with the work of Buettner & Madzharova (2017), who find a large anticipatory demand effect for eight categories of 'white goods' (e.g. dishwashers, refrigerators). Our results likely differ due to the broader range of goods in our dataset – we include other durables such as carpets, furniture, IT equipment, jewellery etc.

the 'anticipation' or 'total effect' hypotheses.[26] We consider this null result a useful and constructive contribution to the literature. To the best of our knowledge this is the first study to systematically match broad country-product VAT reform data to announcement dates – and thus we are able to examine a potential 'missing variable' in important works such as BDKW and Benzarti et al. (2017). Our null result thus reinforces the findings of these papers, by suggesting that, in aggregate, announcement effects are unlikely to be playing a substantial confounding role.

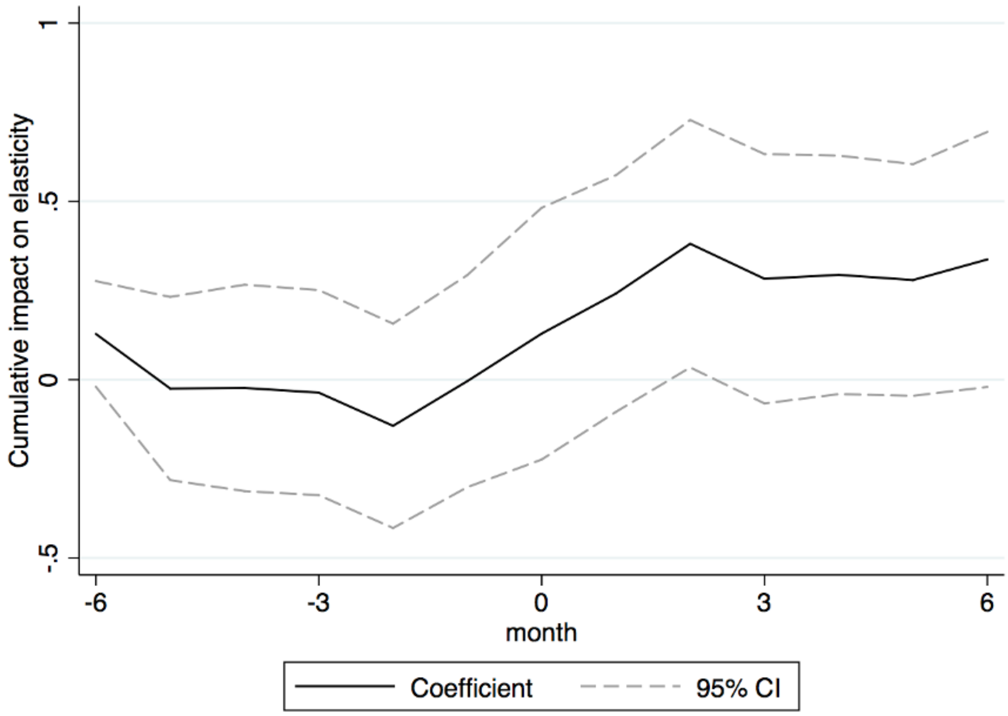
Table 4.5.3: Impact of early announcement on pass-through

		Dependent variable: change in log prices		
		No FEs	Individual FEs	Interaction FEs
Baseline:	Pre-Reform	0.163*	0.171*	0.0571
		(0.0885)	(0.0818)	(0.466)
	Contemporaneous	0.244**	0.214*	0.0848
		(0.017)	(0.0541)	(0.527)
	Post-Reform	0.0532	0.0632	-0.0377
		(0.546)	(0.388)	(0.443)
	Total	0.460***	0.448**	0.104
		(0.005)	(0.0272)	(0.375)
Announced Early:	Pre-Reform	-0.0633	-0.051	-0.00404
		(0.853)	(0.748)	(0.979)
	Contemporaneous	0.0609	0.0794	0.133
		(0.737)	(0.573)	(0.408)
	Post-Reform	0.247	0.12	0.208
		(0.326)	(0.593)	(0.161)
	Total	0.244	0.149	0.337*
		(0.589)	(0.663)	(0.0646)
# of VAT changes:		564	564	564
FEs		None	i,k,t	it,kt,ik
Clustering		None	ik	ik
N		100,983	100,983	100,983

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption.

[26] There is, however, substantial heterogeneity across reforms, as discussed in Appendix 4.B.

Figure 4.5.4: Marginal effect on pass-through of early announcement



Notes: This graph shows the cumulative marginal impact on baseline pass-through of having an implementation lag (announcement date minus implementation date) above the median.

4.6 Robustness Checks

To reduce the influence of regulatory outliers, Table 4.B.10 in the Appendix replaces *Regimpact* with $RegimpactHML$, which takes value 1 if the observation is in the top quartile of the *Regimpact* distribution, value -1 if in the bottom quartile, and zero otherwise. Results remain similar, with a strong negative relationship between $RegimpactHML$ and pass-through.

Secondly, we check whether pass-through heterogeneity depends on the direction of the VAT change, following recent work on asymmetric pass-through (e.g. Benzarti et al. 2017, Carbonnier 2007, Politi & Mattos 2011). Pass-through heterogeneity for increases and decreases are estimated by $\boldsymbol{\beta}_{2j}^{(inc)}$ and $\boldsymbol{\beta}_{2j}^{(dec)}$ in:

$$\begin{aligned}\Delta \ln(p_{ikt}) = \beta_0 &+ \sum_{d\in\{inc,dec\}} \sum_{j=-6}^{6} \beta_{1j}^{(d)} \cdot \Delta \ln(1+\tau_{ikt+j}^{(d)}) \\ &+ \sum_{d\in\{inc,dec\}} \sum_{j=-6}^{6} \boldsymbol{\beta}_{2j}^{(d)} \cdot \Delta \ln(1+\tau_{ikt+j}^{(d)}) \cdot \mathbf{X}_{ikt} \\ &+ \boldsymbol{\beta}_3 \cdot \mathbf{X}_{ikt} + \varphi_{it} + \varphi_{kt} + \varphi_{ik} + \epsilon_{ikt} \qquad (4.6.1)\end{aligned}$$

Results comparing pass-through across products impacted differently by regulation are shown in Table 4.B.11 in the Appendix. The previous literature has found evidence for greater price rigidity with respect to decreases than increases; however, like BDKW, we find little evidence of this in our data – the final column of Table 4.B.11 show few significant differences between the coefficients on increases and decreases. As discussed in BDKW, the mostly insignificant differences are likely due to substantial heterogeneity across product categories in our dataset, without direct association with the reform type (a VAT hike or cut).

Table 4.B.12 in the Appendix repeats this exercise for those observations with quality data. In this case, greater pass-through for products with a longer 'quality ladder' as estimated in Section 4.5.2 appears to be essentially driven by reforms with VAT increases. According to our theoretical framework, the result would suggest that producers respond to a VAT hike by increasing quality, while they choose to leave quality unchanged in the case of VAT cuts.

Thirdly, we use a similar method to investigate whether pass-through varies with the business cycle. We use recession indicators from the OECD (Federal Reserve Bank of St. Louis 2020, OECD 2020), constructed by using statistical methods to identify turning points in the time series of industrial output and

GDP. We run:

$$\Delta \ln(p_{ikt}) = \beta_0 + \sum_{d\in\{exp,rec\}} \sum_{j=-6}^{6} \beta_{1j}^{(d)} \cdot \Delta \ln(1 + \tau_{ikt+j}^{(d)}) \tag{4.6.2}$$

$$+ \sum_{d\in\{exp,rec\}} \sum_{j=-6}^{6} \boldsymbol{\beta}_{2j}^{(d)} \cdot \Delta \ln(1 + \tau_{ikt+j}^{(d)}) \cdot \mathbf{X}_{ikt} \tag{4.6.3}$$

$$+ \boldsymbol{\beta}_3 \cdot \mathbf{X}_{ikt} + \varphi_{it} + \varphi_{kt} + \varphi_{ik} + \epsilon_{ikt} \tag{4.6.4}$$

where $\beta_{1j}^{(rec)}$ and $\beta_{1j}^{(exp)}$ reflect baseline pass-through in recessionary and expansionary periods respectively, and $\boldsymbol{\beta}_{2j}^{(rec)}$ and $\boldsymbol{\beta}_{2j}^{(exp)}$ reflect heterogeneity likewise. The results are shown in Table 4.B.13 in the Appendix. We find some evidence that pass-through effects are stronger in expansions, possibly because prices are more flexible when inflation is higher, but ultimately cannot reject equality of pass-through coefficients across expansionary/contractionary periods.

In additional specifications (available on request) we allow for differential effects of regulation and quality across types of VAT change – specifically standard rate changes, reduced rate changes and reclassifications, as discussed in detail in BDKW. However, with current data we cannot make clear inferences about the triple interaction between reform, regulation/quality and reform-type, as our results may simply be driven by the composition of reforms in our dataset. For instance, the vast majority of reforms in our data our standard rate changes, affecting relative standard errors in estimates across the varieties. The average sizes of the reforms also vary substantially across type, as shown in Table 4.B.5, which could affect the estimated coefficients if the relationship between reform size and pass-through is non-linear. We therefore focus on the pooled effects, but also note that Figure 2 of BDKW shows similar effects across reform types – particularly once the reform is introduced, i.e. in the period for which we find regulation and quality to be important.[27]

[27] Noting that VAT changes due to reclassification are of a different character to changes in the standard or reduced rate, we also run our main specification excluding reclassification reforms, and find very similar results.

Lastly, we also repeat the main specifications using country-level clustering and product-level clustering in turn. Results are similar with product-level clustering, while with country-level clustering the contemporaneous effect of *Regimpact* remains significant while the total effect is marginally insignificant.

4.7 Conclusion

This paper investigates the role of market structure and timing in pass-through heterogeneity. We extend existing theory by modelling four different settings in which market competitiveness can influence pass-through. We test these relationships empirically using a consumption panel across 14 Eurozone countries, and find that upstream product market regulation and quality have a substantial impact – both in absolute terms and relative to other market characteristics. Our results indicate that pass-through to consumer prices is greater the more competitive the upstream sector or the wider the quality range of the taxed product.

Extending such analysis beyond pricing behaviour – e.g. to direct observation of firm markups and marginal costs – is likely to be a fruitful area for future research. We model imperfect competition in upstream and downstream sectors independently and in a partial equilibrium framework, so future work could also extend the theory to a GE setting – allowing for broader linkages between sectors.

The substantial loosening in regulations to encourage greater competition in upstream sectors at the beginning of the century suggests that there has been a substantial decrease in pass-through in recent history. We also provide the first systematic evidence on 'fiscal forward guidance' with respect to VAT reforms, finding that early announcement is unlikely to have large anticipation or total effects.

Together our results are relevant for governments considering VAT reforms with the view of stimulating demand, supporting supply or protecting either side of the market. Because pass-through affects whether supply or demand is more affected by a VAT reform (Weyl & Fabinger 2013), policy-makers should factor in market characteristics. A greater or smaller VAT rate change may be needed to achieve a certain price variation objective depending on market characteristics. In the cases where pass-through is such that producer or consumer prices are unresponsive to VAT change, policymakers willing to achieve some targeted support could look for more cost-effective instruments than VAT changes.

4.A Theoretical Appendix

We examine the four separate case studies presented in the main text one at a time. For every case, we find it is convenient to use an expression of the degree of pass-through based on producer prices that can be derived from definition 4.3.1 above:

$$\begin{aligned}\gamma - 1 &= \frac{\partial \ln p}{\partial \ln \widetilde{p}} . \frac{\partial \ln \widetilde{p}}{\partial \widetilde{p}} . \frac{\partial \widetilde{p}}{\partial \tau} . \frac{\partial \tau}{\partial \ln (1+\tau)} - 1 \\ \gamma - 1 &= \frac{\partial \ln \widetilde{p}}{\partial \tau} . \frac{(1+\tau)}{\widetilde{p}} \end{aligned} \tag{4.A.1}$$

4.A.1 Monopolistic Competition in the Downstream Sector

We focus on a good with horizontal differentiation where each of the N firm in this market sells a quantity q_n of its own variety at a price p_n. Preferences over the different varieties follow the standard Dixit-Stigliz form and we assume that aggregate demand $Q = \left(\int_1^N q_n^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ with $\sigma > 1$ is associated with price index P which takes the form $P = \left(\int_1^N p_n^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. We assume that there are other goods that we represent with an outside good Q_o and its price P_o. A representative consumer chooses consumption q_n and Q_o to buy to maximise a CES utility function

$$U = \left(aQ^{1-\beta} + (1-a)Q_o^{1-\beta}\right)^{\frac{\nu}{1-\beta}} \tag{4.A.2}$$

with parameters $1 > a > 0$, $\nu > 0$, $1 > \beta > 0$ and under the budget constraint $\int_1^N p_n q_n + P_o Q_o = I$ where I is aggregate income.

The first order conditions (FOC) of the consumer problem are:

$$\nu U^{\frac{\nu/(1-\beta)-1}{\nu/(1-\beta)}} a Q^{\frac{(1-\beta)\sigma/(\sigma-1)-1}{(1-\beta)\sigma/(\sigma-1)}} q_n^{\frac{\sigma-1}{\sigma}-1} = \eta p_n \tag{4.A.3}$$

$$\nu(1-a) Q_o^{-\beta} U^{\frac{\nu/(1-\beta)-1}{\nu/(1-\beta)}} = \eta P_o \tag{4.A.4}$$

Where η is the Lagrange multiplier associated to the budget constraint. By using the FOC (equation 4.A.3) for any two goods n and m to eliminate η, we obtain that $q_m = q_n \left(\frac{p_m}{p_n}\right)^{-\sigma}$. After multiplying both sides by p_m, summing up over m and using the budget constraint, we obtain $I - P_o Q_o = q_n p_n^{\sigma} P^{1-\sigma}$. We obtain the demand curve introduced in the main text after reordering the different terms and introducing the parameter $A = I - P_o Q_o$

$$q_n = \left(\frac{p_n}{P}\right)^{-\sigma} \frac{A}{P} \tag{4.A.5}$$

In what follows, our partial equilibrium approach assumes that variations in the tax rate applied to the varieties q_n affect neither aggregate income nor the amount spend on the outside good. Hence, A is assumed to be exogenous.

On the supply side, we assume that firms compete in price under monopolistic competition. Every firm has the same cost function given by equation 4.3.2 in the main text: $C_n(q_n) = a + c_n q_n + \frac{b}{2} q_n^2$ with $a > 0$, $c_n = c > 0$ for all n, and where $b < 0$ corresponds to decreasing marginal costs and $b > 0$ corresponds to increasing marginal costs.

Each firm chooses its price $\widetilde{p}_n$ to maximise profits $\pi_n = \widetilde{p}_n q_n - C(q_n)$. The first order condition of the maximisation problem is $q_n + (\widetilde{p}_n - c - bq_n)\frac{\partial q_n}{\partial \widetilde{p}_n} = 0$ and the second order equation is $\frac{\partial q_n}{\partial \widetilde{p}_n} + (1 - b\frac{\partial q_n}{\partial \widetilde{p}_n})\frac{\partial q_n}{\partial \widetilde{p}_n} + (\widetilde{p}_n - c - bq_n)\frac{\partial^2 q_n}{\partial \widetilde{p}_n^2} < 0$. The derivatives of q_n are obtained using the demand function (equation 4.A.5).[28] We get $\frac{\partial q_n}{\partial \widetilde{p}_n} = -\sigma \frac{q_n}{p_n}(1+\tau)$ and $\frac{\partial^2 q_n}{\partial \widetilde{p}_n^2} = \sigma(\sigma+1)(1+\tau)^2 \frac{q_n}{p_n^2}$.

Because all firms are equally productive, all firm prices and quantities are identical and, from now on, we can drop the subscript n for conciseness. This also implies that $Q = qN^{\frac{\sigma}{\sigma-1}}$, $P = pN^{\frac{1}{1-\sigma}}$. The latter entails that $\gamma = \frac{\partial \ln P}{\partial \ln (1+\tau)} = \frac{\partial \ln p}{\partial \ln (1+\tau)}$. We also obtain that demand for a single variety is given by $q = \frac{A}{\widetilde{p}(1+\tau)N}$.

[28]Note that monopolistic firms ignore the impact of their pricing decisions on the aggregate price index P.

We can then express the system of the first and second order conditions as:

$$\frac{\sigma-1}{\sigma}\widetilde{p}^2 - c\widetilde{p} - \frac{bA}{(1+\tau)N} = 0 \tag{4.A.6}$$

$$c - \frac{\sigma-1}{\sigma}\frac{\sigma+1}{\sigma}\widetilde{p}^2 < 0 \tag{4.A.7}$$

This system of equations admits a unique positive solution $\widetilde{p} = \frac{c+\sqrt{c^2+\frac{4bA(\sigma-1)}{(1+\tau)N\sigma}}}{2\frac{\sigma-1}{\sigma}}$. This implies

$$2\frac{\sigma-1}{\sigma}\widetilde{p} - c > 0 \tag{4.A.8}$$

We take the derivative of equation 4.A.6 with respect to N and obtain

$$2\frac{\sigma-1}{\sigma}\frac{\partial\widetilde{p}}{\partial N}\widetilde{p} - c\frac{\partial\widetilde{p}}{\partial N} - \frac{bA}{(1+\tau)N^2} = 0$$

After some manipulations, we can solve for $\frac{\partial\widetilde{p}}{\partial N}$:

$$\frac{\partial\widetilde{p}}{\partial N} = -\frac{bA}{(1+\tau)N^2\left(2\frac{\sigma-1}{\sigma}\widetilde{p} - c\right)} \tag{4.A.9}$$

As a result, we found that prices are decreasing with the number of firms N if and only if $b > 0$.

To obtain an expression for the degree of pass-through, we start with equation 4.A.6, take the derivative with respect to τ and multiply by $\frac{1+\tau}{\widetilde{p}}$. In what follows, we make use of equation 4.A.1 to introduce $(\gamma - 1)$. We get

$$\begin{aligned}
0 &= 2\left(\frac{\partial\widetilde{p}}{\partial\tau}\frac{1+\tau}{\widetilde{p}}\right)\frac{\sigma-1}{\sigma}\widetilde{p} - c\left(\frac{\partial\widetilde{p}}{\partial\tau}\frac{1+\tau}{\widetilde{p}}\right) + \frac{bA}{(1+\tau)^2N}\left(\frac{1+\tau}{\widetilde{p}}\right) \\
0 &= 2\frac{\sigma-1}{\sigma}(\gamma-1)\widetilde{p} - c(\gamma-1) + \frac{bA}{(1+\tau)N\widetilde{p}}
\end{aligned}$$

After some more algebra where we make use of equation 4.A.6 to substitute for

$\widetilde{p}^2$, we get equation 4.A.10 as reported in **Proposition 1**:

$$\gamma = 1 - \frac{bA}{(1+\tau)N\widetilde{p}\left(2\frac{\sigma-1}{\sigma}\widetilde{p}-c\right)} = 1 - \frac{bA}{(1+\tau)N\left(2c\widetilde{p}+\frac{2bA}{(1+\tau)N}-c\widetilde{p}\right)}$$

$$\gamma = 1 - \frac{1}{\frac{(1+\tau)c}{bA}N\widetilde{p}+2} \tag{4.A.10}$$

We take the derivative of the above equation 4.A.10 with respect to N and use equation 4.A.9 to obtain:

$$\begin{aligned}
\frac{\partial\gamma}{\partial N} &= \frac{\frac{(1+\tau)c}{bA}\widetilde{p}+\frac{(1+\tau)c}{bA}N\frac{\partial\widetilde{p}}{\partial N}}{\left(\frac{(1+\tau)c}{bA}N\widetilde{p}+2\right)^2} = \frac{\frac{(1+\tau)c}{bA}\widetilde{p}-\frac{c}{N\left(2\frac{\sigma-1}{\sigma}\widetilde{p}-c\right)}}{\left(\frac{(1+\tau)c}{bA}N\widetilde{p}+2\right)^2} \\
&= c.\frac{(1+\tau)\widetilde{p}N\left(2\frac{\sigma-1}{\sigma}\widetilde{p}-c\right)-bA}{bAN\left(2\frac{\sigma-1}{\sigma}\widetilde{p}-c\right)\left(\frac{(1+\tau)c}{bA}N\widetilde{p}+2\right)^2} \\
&= c(1+\tau)N.\frac{2\frac{\sigma-1}{\sigma}\widetilde{p}^2-c\widetilde{p}-\frac{bA}{(1+\tau)N}}{bAN\left(2\frac{\sigma-1}{\sigma}\widetilde{p}-c\right)\left(\frac{(1+\tau)c}{bA}N\widetilde{p}+2\right)^2} \\
&= \frac{(1+\tau)c\frac{\sigma-1}{\sigma}\widetilde{p}^2}{bA\left(2\frac{\sigma-1}{\sigma}\widetilde{p}-c\right)\left(\frac{(1+\tau)c}{bA}N\widetilde{p}+2\right)^2} \qquad (4.A.11)
\end{aligned}$$

Using inequality 4.A.8, we find that the terms in brackets in the denominator are positive as well as all the terms in the numerator. Hence, we find that the degree of pass-through increases if and only if $b > 0$, that is when firm production is characterised by decreasing returns to scale. This proves that pass-through variations with N under monopolistic competition are as described in **Proposition 1**.

4.A.2 Cournot competition in the downstream sector

We now assume that the first good Q is homogeneous but produced by heterogeneous firms that differ in productivity and who compete in quantities under Cournot competition. Total demand is the sum of every firm's production, $Q = \sum_{n=1}^{N} q_n$. Aggregate consumer preferences are characterised by the same utility function (equation 4.A.2) as before.

The first order condition of the consumer problem with respect to the first good yields $\nu a Q^{-\beta} U^{\frac{\nu/(1-\beta)-1}{\nu/(1-\beta)}} = \eta p$. We combine it with the other FOC (equation 4.A.4) to eliminate η and get the aggregate demand curve introduced in the main text

$$p(Q) = A' Q^{-\beta} \tag{4.A.12}$$

where $A' = P_o Q_o^{\beta} \frac{a}{(1-a)}$. As in the previous case, we adopt a partial equilibrium approach and we here assume that variations in the tax rate applied to the first good Q affect neither the price nor the quantity of the outside good. Hence, A' is assumed to be exogenous. As described in Dierickx et al. (1988), we also assume that the demand function is steep enough ($\frac{\partial \widetilde{p}}{\partial Q} - b < 0$) and concave enough ($\frac{\partial p}{\partial Q} + \frac{\partial^2 p}{\partial Q^2} q_n < 0$ for all q_n) because these conditions ensure the existence, stability and uniqueness of the Cournot-Nash equilibrium. In the present setting, these conditions become

$$-\beta \frac{\widetilde{p}}{Q} - b < 0 \tag{4.A.13}$$

$$-\beta \frac{p}{Q} + \beta(\beta+1) \frac{p}{Q^2} q_n < 0 \tag{4.A.14}$$

After summing up the second inequality for all n, we get that it implies $(\beta + 1) < N$.

Each firm n facing the cost function 4.3.2 chooses its output q_n independently to maximise profits $\widetilde{p}(q_n) q_n - C_n(q_n)$ and, while doing so, firms internalise their impact on total output. In equilibrium, the first order condition of the profit maximisation problem is

$$\widetilde{p}(q_n) + \frac{\partial \widetilde{p}}{\partial q_n} q_n - c_n - b q_n = 0 \text{ for all } n \tag{4.A.15}$$

Summing equation 4.A.15 across firms and then using demand function 4.A.12 rewritten as $Q = \left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}$ and the associated derivative $\frac{\partial \widetilde{p}}{\partial q_n} = -\beta \frac{\widetilde{p}}{Q}$, yields

$$N\widetilde{p}-\beta\widetilde{p}-N\bar{c}-b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}=0 \tag{4.A.16}$$

where $\bar{c}=\sum_n c_n/N$. Note that we assumed that the mean of the cost distribution is fixed and independent from N. Together with inequality 4.A.13, this implies that $\widetilde{p}-\bar{c}>0$.

We can examine how producer prices vary with competition by differentiating equation 4.A.16 with respect to N:

$$\begin{aligned}
0 &= \widetilde{p}+(N-\beta)\frac{\partial\widetilde{p}}{\partial N}-\bar{c}+\frac{1}{\beta}\frac{\partial\widetilde{p}}{\partial N}\frac{b}{\widetilde{p}}\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta} \\
\frac{\partial\widetilde{p}}{\partial N} &= \frac{\bar{c}-\widetilde{p}}{(N-\beta)+\frac{b}{\beta\widetilde{p}}\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}}=-\frac{\widetilde{p}(\widetilde{p}-\bar{c})}{N\bar{c}+\frac{\beta+1}{\beta}b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}} \qquad (4.A.17)
\end{aligned}$$

We can find out the sign of the above derivative by examining the denominator:

$$\beta\widetilde{p}(N-\beta)+b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}=[\beta\widetilde{p}(N-1-\beta)]+[\beta\widetilde{p}+bQ]>0$$

which is positive because both terms in square brackets turns out to be positive after comparing them to conditions 4.A.13 and 4.A.14 respectively. The numerator is negative as noted in the previous paragraph. Therefore, prices decline with the number of competing firms.

The pass-through is obtained once again using equation 4.A.1. We differentiate equation 4.A.16 with respect to τ and multiply it by $\frac{1+\tau}{\widetilde{p}}$ to introduce $(\gamma-1)$. We recover one of the central results in Dierickx et al. (1988) and equation 4.A.18 in **Proposition 1**:

$$\begin{aligned}
0 &= (N-\beta)(\gamma-1)+\frac{b}{\beta}A'^{1/\beta}\left(\widetilde{p}^{-\frac{1}{\beta}-1}(1+\tau)^{-\frac{1}{\beta}}(\gamma-1)+\widetilde{p}^{\frac{1}{\beta}-1}(1+\tau)^{-\frac{1}{\beta}}\right) \\
\gamma &= \left[1+\frac{bA'^{\frac{1}{\beta}}}{(1+\tau)^{\frac{1}{\beta}}(N-\beta)\beta\widetilde{p}^{\frac{\beta+1}{\beta}}}\right]^{-1}=\frac{1}{1+\frac{b(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}}{(N-\beta)\beta\widetilde{p}^{\frac{\beta+1}{\beta}}}}
\end{aligned}$$

We examine how pass-through vary with competition by deriving the variations of γ with respect to the number of firms.

$$\begin{aligned}
\frac{\partial\gamma}{\partial N} &= \frac{\left[\widetilde{p}+\frac{\beta+1}{\beta}\frac{\partial\widetilde{p}}{\partial N}(N-\beta)\right]\frac{b}{\beta}(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}(N-\beta)^{-2}\widetilde{p}^{-\frac{2\beta+1}{\beta}}}{\left[1+\frac{b(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}}{(N-\beta)\beta p^{\frac{\beta+1}{\beta}}}\right]^2} \\
&= \left[1-\frac{(N-\beta)}{N}\frac{(\beta+1)\widetilde{p}+\frac{\beta+1}{\beta}b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}}{N\bar{c}+\frac{\beta+1}{\beta}b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}}\right]*\frac{\frac{b}{\beta}(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}(N-\beta)^{-2}\widetilde{p}^{-\frac{\beta+1}{\beta}}}{\left[1+\frac{b(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}}{(N-\beta)\beta p^{\frac{\beta+1}{\beta}}}\right]^2} \\
&= \left[\frac{N^2\bar{c}-(N-\beta)(\beta+1)\widetilde{p}+(\beta+1)b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}}{N^2\bar{c}+N\frac{\beta+1}{\beta}b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}}\right]*\frac{\frac{b}{\beta}(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}(N-\beta)^{-2}\widetilde{p}^{-\frac{\beta+1}{\beta}}}{\left[1+\frac{b(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}}{(N-\beta)\beta p^{\frac{\beta+1}{\beta}}}\right]^2} \\
&= \left[\frac{(N-\beta-1)\bar{c}}{N\bar{c}+\frac{\beta+1}{\beta}b\left(\frac{A'}{\widetilde{p}(1+\tau)}\right)^{1/\beta}}\right]*\frac{\frac{b}{\beta}(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}(N-\beta)^{-2}\widetilde{p}^{-\frac{\beta+1}{\beta}}}{\left[1+\frac{b(1+\tau)^{-\frac{1}{\beta}}A'^{\frac{1}{\beta}}}{(N-\beta)\beta p^{\frac{\beta+1}{\beta}}}\right]^2} \qquad (4.A.18)
\end{aligned}$$

By comparing the first term in squared bracket with equation 4.A.17, we deduct that the term is positive. Therefore the derivative $\partial\gamma/\partial N$ has the sign of b and this proves that pass-through variations with N under Cournot competition with heterogeneous firms are as described in **Proposition 1**.

4.A.3 Cournot competition in the upstream sector

We examine the case of two sectors, with perfect competition in the downstream sector and Cournot competition in the upstream sector. For clarity purpose, we assume that inputs q_I produced in the upstream sector are only consumed by producers of the final good and that inputs q_I are not taxed. The representative consumer as the same aggregate utility function 4.A.2 as in the previous section. This implies that aggregate demand for the final good Q_F is given by $Q_F = \left(\frac{p_F}{A'}\right)^{-\frac{1}{\beta}}$ as in equation 4.A.12.

Taking prices as given because of perfect competition, the representative producer of the final good maximises profits $\widetilde{p}_F Q_F - p_I Q_I$ by choosing the quantity Q_F to produce given the cost function $Q_I = d(1-\rho)Q_F^{\frac{1}{1-\rho}}$ with $0 < \rho < 1$ and $d > 0$. The first order condition of the profit maximisation problem yields the input demand function:

$$p_I = \frac{\widetilde{p}_F}{d} Q_F^{\frac{-\rho}{1-\rho}} \tag{4.A.19}$$

$$p_I = \widetilde{p}_F d^{\rho-1}(1-\rho)^{\rho} Q_I^{-\rho} \tag{4.A.20}$$

Similarly to the previous section, the existence and uniqueness of a solution in the upstream sector requires the following two constraints on input demand:

$$\frac{\partial p_I}{\partial Q_I} - b < 0$$
$$\frac{\partial p_I}{\partial Q_I} + \frac{\partial^2 p_I}{\partial Q_I^2} q_{I,n} < 0$$

which imply

$$-\frac{\rho}{d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}} \widetilde{p}_F^{\,1+\frac{\rho}{\beta(1-\rho)}} - bd(1-\rho)\left(\frac{A'}{\widetilde{p}_F(1+\tau)}\right)^{\frac{1}{\beta(1-\rho)}} < 0 \tag{4.A.21}$$

$$-N + (\rho+1) < 0 \tag{4.A.22}$$

In the upstream sector, each firm n chooses output independently to maximise profits $\widetilde{p}_I(Q_I)q_{I,n} - C_n(q_{I,n})$ subject to 4.A.20 as upstream firms internalise their impact on total production $Q_I = \sum_n q_{I,n}$. In equilibrium, the first order conditions of the profit maximisation problem for all upstream firms is such that

$$\widetilde{p}_I(Q_I) + \frac{\partial \widetilde{p}_I}{\partial q_{I,n}} q_{I,n} - c_n - bq_{I,n} = 0 \tag{4.A.23}$$

Summing equation 4.A.23 across firms, noting that $\widetilde{p}_I = p_I$, and using demand function 4.A.20 yields

$$(N-\rho)p_I - N\bar{c} - b(1-\rho)d^{(\rho-1)/\rho}\left(\frac{\widetilde{p}_F}{p_I}\right)^{1/\rho} = 0 \tag{4.A.24}$$

where $\bar{c} = \sum_n c_n/N$. We can use the demand equation (equation 4.A.19) and the above supply equation 4.A.24 to solve for the input price and obtain the final good supply function:

$$\begin{aligned}
0 &= (N-\rho)\frac{\widetilde{p}_F}{d}Q_F^{\frac{-\rho}{1-\rho}} - N\bar{c} - b(1-\rho)d^{(\rho-1)/\rho}\left(dQ_F^{\frac{\rho}{1-\rho}}\right)^{1/\rho} \\
\widetilde{p}_F &= \frac{N\bar{c}dQ_F^{\frac{\rho}{1-\rho}} + b(1-\rho)d^2Q_F^{\frac{1+\rho}{1-\rho}}}{(N-\rho)} \qquad (4.A.25)
\end{aligned}$$

We combine the above supply side equation 4.A.25 with the final good demand equation 4.A.12 to obtain the equation that pins down the final good price:

$$\begin{aligned}
\widetilde{p}_F &= \frac{N\bar{c}A'^{\frac{\rho}{\beta(1-\rho)}}\left((1+\tau)\widetilde{p}_F\right)^{-\frac{\rho}{\beta(1-\rho)}} + b(1-\rho)dA'^{\frac{1+\rho}{\beta(1-\rho)}}\left((1+\tau)\widetilde{p}_F\right)^{-\frac{1+\rho}{\beta(1-\rho)}}}{(N-\rho)/d} \\
0 &= \frac{N-\rho}{d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}} - N\bar{c} - b(1-\rho)d\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}} \\
& \qquad (4.A.26)
\end{aligned}$$

We can examine how producer prices vary with competition by differentiating equation 4.A.26 with respect to N:

$$\begin{aligned}
0 &= \left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\frac{\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}}}{d}\left(1+(N-\rho)\frac{\rho+\beta(1-\rho)}{\beta(1-\rho)\widetilde{p}_F}\frac{\partial\widetilde{p}_F}{\partial N}\right) - \bar{c} + \frac{bd}{\beta\widetilde{p}_F}\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}\frac{\partial\widetilde{p}_F}{\partial N} \\
\frac{\partial\widetilde{p}_F}{\partial N} &= \frac{\bar{c} - \left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\frac{\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}}}{d}}{(N-\rho)\frac{\rho+\beta(1-\rho)}{\beta(1-\rho)d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{\frac{\rho}{\beta(1-\rho)}} + \frac{bd}{\beta\widetilde{p}_F}\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}} \qquad (4.A.27)
\end{aligned}$$

The same logic as in the previous section applies and condition 4.A.21 together with equation 4.A.26 implies that the numerator is negative. The denominator can be expressed as

$$\frac{\left[(N-\rho)\frac{\rho+\beta(1-\rho)}{d} - \frac{\rho}{d}\right]\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}} + \left[\frac{\rho}{d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}} + bd(1-\rho)\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}\right]}{\beta\widetilde{p}_F(1-\rho)}$$

where we can see that the two terms in square brackets are positive because of conditions 4.A.21 and 4.A.22. Hence, the price of inputs decreases with N.

The pass-through is again obtained using equation 4.A.1. We differentiate equation 4.A.16 with respect to τ and multiply it by $\frac{1+\tau}{\widetilde{p}_F}$ to introduce $(\gamma^F - 1)$.

We obtain the expression for the pass-through reported in **Proposition 2**.

$$
\begin{aligned}
0 &= \frac{N-\rho}{d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{\frac{\rho}{\beta(1-\rho)}}\left(\frac{\rho}{\beta(1-\rho)}+\left(1+\frac{\rho}{\beta(1-\rho)}\right)(\gamma^F-1)\right)...\\
&\quad +\frac{b(1-\rho)d}{\beta(1-\rho)}\left(\frac{A'}{1+\tau}\right)^{\frac{1}{\beta(1-\rho)}}\widetilde{p}_F^{-\frac{1}{\beta(1-\rho)}-1}\left(1+(\gamma^F-1)\right)\\
\gamma^F &= \frac{1}{1+\frac{\rho}{\beta(1-\rho)}+\frac{bd^2(1+\tau)^{-\frac{1+\rho}{\beta(1-\rho)}}A'^{\frac{1+\rho}{\beta(1-\rho)}}}{\beta(N-\rho)\widetilde{p}_F^{1+\frac{1+\rho}{\beta(1-\rho)}}}}
\end{aligned}
\tag{4.A.28}
$$

The sign of $\frac{\partial\gamma^F}{\partial N}$ is the same as the sign of $\partial\left[\frac{\beta(N-\rho)}{b}\widetilde{p}_F^{1+\frac{1+\rho}{\beta(1-\rho)}}\right]/\partial N$.

$$
\begin{aligned}
\frac{\partial\left[\frac{\beta(N-\rho)}{b}\widetilde{p}_F^{1+\frac{1+\rho}{\beta(1-\rho)}}\right]}{\partial N} &= \frac{\beta}{b}\widetilde{p}_F^{1+\frac{1+\rho}{\beta(1-\rho)}}+\frac{1+\rho+\beta(1-\rho)}{b(1-\rho)}(N-\rho)\widetilde{p}_F^{\frac{1+\rho}{\beta(1-\rho)}}\frac{\partial\widetilde{p}_F}{\partial N}\\
&= \frac{\beta}{b}\widetilde{p}_F^{\frac{1+\rho}{\beta(1-\rho)}}\left(\frac{[denominator]\widetilde{p}_F+\frac{1+\rho+\beta(1-\rho)}{\beta(1-\rho)}(N-\rho)\left(\bar{c}-\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\frac{\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}}}{d}\right)}{(N-\rho)\frac{\rho+\beta(1-\rho)}{\beta(1-\rho)d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{\frac{\rho}{\beta(1-\rho)}}+\frac{bd}{\beta\widetilde{p}_F}\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}}\right)\\
&= \frac{\beta}{b}\widetilde{p}_F^{\frac{1+\rho}{\beta(1-\rho)}}\left(\frac{\frac{bd}{\beta}\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}+\frac{1+\rho+\beta(1-\rho)}{\beta(1-\rho)}(N-\rho)\bar{c}-\frac{(N-\rho)}{\beta(1-\rho)d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{1+\frac{\rho}{\beta(1-\rho)}}}{(N-\rho)\frac{\rho+\beta(1-\rho)}{\beta(1-\rho)d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{\frac{\rho}{\beta(1-\rho)}}+\frac{bd}{\beta\widetilde{p}_F}\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}}\right)\\
&= \frac{[(\rho+\beta(1-\rho))N-(1+\rho+\beta(1-\rho))\rho)]\frac{\bar{c}}{b(1-\rho)}\widetilde{p}_F^{\frac{1+\rho}{\beta(1-\rho)}}}{(N-\rho)\frac{\rho+\beta(1-\rho)}{\beta(1-\rho)d}\left(\frac{1+\tau}{A'}\right)^{\frac{\rho}{\beta(1-\rho)}}\widetilde{p}_F^{\frac{\rho}{\beta(1-\rho)}}+\frac{bd}{\beta\widetilde{p}_F}\left(\frac{A'}{(1+\tau)\widetilde{p}_F}\right)^{\frac{1}{\beta(1-\rho)}}}
\end{aligned}
\tag{4.A.29}
$$

The denominator is positive as was shown for equation 4.A.27. Using inequality 4.A.22, we find that

$$(\rho+\beta(1-\rho))N-(1+\rho+\beta(1-\rho))\rho) > (\rho+\beta(1-\rho))(\rho+1)-(1+\rho+\beta(1-\rho))\rho) \geq 0$$

In equation 4.A.29, this implies that the term in square brackets is positive and therefore that $\frac{\partial\gamma^F}{\partial N}$ has the sign of b as stated in **Proposition 2**.

4.A.4 Differences in scope for quality in the final good

We examine a sector characterised by 'discrete choices', meaning that consumers can decide to purchase at most one variety of the product. For any consumer, not buying any variety and spending all her income on an outside good is always an option. We consider a partial equilibrium in which income and the outside good are unaffected by changes in the tax rate in the sector that we examine. N homogeneous firms compete by manufacturing horizontally and vertically distinct varieties as in Khandelwal (2010). Horizontal differentiation is assumed to be costless, implying that in equilibrium, all firms produce horizontally distinct varieties.

Consumer k observes all varieties and chooses the variety n with price p_n and quality λ_n that provides her with the highest indirect utility

$$V_{nk} = \delta_n + \xi_{nk}, \quad \text{with } \delta_n \equiv \left(\theta\lambda_n^{\psi} - p_n^{\psi}\right)^{1/\psi} \quad \text{and } \psi < 1 \tag{4.A.30}$$

Quality is defined as an attribute whose valuation is agreed upon by all consumers: holding prices fixed, all consumers would prefer higher quality objects. The "quality ladder" parameter θ reflects the consumers' valuation for quality.

The price-quality indifference curves are given by $p_n = \left(\theta\lambda_n^{\psi} - \delta_n^{\psi}\right)^{1/\psi}$. The marginal willingness to pay $\frac{\partial \ln p_n}{\partial \ln \lambda_n} = \theta\left(\frac{p_n}{\lambda}\right)^{\psi}$ is increasing in the quality-price ratio if $\psi > 0$ and decreasing with the the quality-price ratio if $\psi < 0$. In other words in the case when $\psi < 0$, consumers demand cheaper quality when quality increases.

Horizontal product differentiation is introduced in equation 4.A.30 through the consumer-variety-specific term, ξ_{nk}. Following standard practice in the discrete choice literature, ξ_{nk} is assumed to be distributed i.i.d. type-I extreme value. Unlike the vertical attribute, the horizontal attribute has the property that some people prefer it while others do not, and on average, it provides zero utility. Therefore, the mean valuation for variety n is δ_n. Under the distributional assumption, the market share of variety n is given by the familiar logit formula $m_n = \frac{e^{\delta_n}}{\sum_m e^{\delta_m}}$.

Each firm n produces a variety subject to a marginal cost function that is increasing with quality, $w + \frac{\lambda_n}{Z}$. We assume that the market is characterised by monopolistic competition with a sufficiently large number of firms so that no one firm can influence the market equilibrium prices and qualities. A firm n maximises profits by choosing the price and quality.

$$\max_{\widetilde{p}_n, \lambda_n} \left[\widetilde{p}_n - w - \frac{\lambda_n}{Z} \right] \frac{e^{\delta_n}}{\sum_m e^{\delta_m}} \tag{4.A.31}$$

The two first order conditions are

$$0 = e^{\delta_n} - \left(\widetilde{p}_n - w - \frac{\lambda_n}{Z} \right) (1+\tau)^{\psi} \widetilde{p}_n^{\psi-1} \left(\theta \lambda_n^{\psi} - (\widetilde{p}_n(1+\tau))^{\psi} \right)^{\frac{1-\psi}{\psi}} e^{\delta_n} \tag{4.A.32}$$

$$0 = -\frac{1}{Z} e^{\delta_n} + \left(\widetilde{p}_n - w - \frac{\lambda_n}{Z} \right) \theta \lambda_n^{\psi-1} \left(\theta \lambda_n^{\psi} - (\widetilde{p}_n(1+\tau))^{\psi} \right)^{\frac{1-\psi}{\psi}} e^{\delta_n} \tag{4.A.33}$$

We obtain quality and mean valuation as functions of price by combining the first order conditions.

$$\lambda_n^{1-\psi} = \frac{\theta Z}{(1+\tau)^{\psi}} \widetilde{p}_n^{1-\psi} \tag{4.A.34}$$

$$\begin{aligned} \delta_n &= \left(\theta \left(\frac{\theta Z}{(1+\tau)^{\psi}} \right)^{\frac{\psi}{1-\psi}} \widetilde{p}_n^{\psi} - (\widetilde{p}_n(1+\tau))^{\psi} \right)^{\frac{1}{\psi}} \\ &= \left(\theta^{\frac{1}{1-\psi}} Z^{\frac{\psi}{1-\psi}} (1+\tau)^{\frac{\psi}{\psi-1}} - 1 \right)^{\frac{1}{\psi}} (1+\tau) \widetilde{p}_n \end{aligned} \tag{4.A.35}$$

We solve for prices by substituting quality and mean valuation using equations

4.A.34 and 4.A.35 in the first order condition (equation 4.A.32).

$$
\begin{aligned}
0 &= 1-\left(\widetilde{p}_n - w - \frac{\lambda_n}{Z}\right)(1+\tau)^{\psi}\widetilde{p}_n^{\psi-1}\left(\theta^{\frac{1}{1-\psi}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}}-1\right)^{\frac{1-\psi}{\psi}}((1+\tau)\widetilde{p}_n)^{1-\psi}\\
0 &= 1-\left(\widetilde{p}_n - w - \frac{\widetilde{p}_n}{Z}\left(\frac{\theta Z}{(1+\tau)^{\psi}}\right)^{\frac{1}{1-\psi}}\right)\left(\theta^{\frac{1}{1-\psi}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}}-1\right)^{\frac{1-\psi}{\psi}}(1+\tau)\\
\widetilde{p}_n &= w\left(1-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-1}+\frac{1}{(1+\tau)}\left(1-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}}
\end{aligned}
\tag{4.A.36}
$$

The existence of a positive price solution therefore requires that $\theta < \left(\frac{1+\tau}{Z}\right)^{\psi}$.

We obtain pass-through as stated in **Proposition 3** by taking the derivative of the equation 4.A.36 and multiplying by $\frac{(1+\tau)}{\widetilde{p}_n}$.

$$
\begin{aligned}
(\gamma-1) = &-w\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}\frac{\psi}{1-\psi}\frac{(1+\tau)^{\frac{\psi}{\psi-1}}}{\widetilde{p}_n}\left(1-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-2}\\
&-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}\frac{1}{1-\psi}\frac{(1+\tau)^{\frac{\psi}{\psi-1}}}{\widetilde{p}_n}\frac{1}{(1+\tau)}\left(1-Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}-1}\\
&-\frac{1}{\widetilde{p}_n}\frac{1}{(1+\tau)}\left(1-Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}}\\
(\gamma-1) = &-w\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}\frac{\psi}{1-\psi}\frac{(1+\tau)^{\frac{\psi}{\psi-1}}}{\widetilde{p}_n}\left(1-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-2}\\
&-\frac{1}{\widetilde{p}_n}\frac{1}{(1+\tau)}\left(1-Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}-1}\left(1+\frac{\psi}{1-\psi}Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)\\
= &-\frac{\psi}{1-\psi}\frac{Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}}{\left(1-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)}-\frac{1}{\widetilde{p}_n}\frac{1}{(1+\tau)}\left(1-Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}-1}\\
= &-\frac{\psi}{1-\psi}\frac{Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}}{\left(1-\theta^{\frac{1}{1-\psi}}Z^{\frac{\psi}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)}-\frac{\frac{1}{(1+\tau)}\left(1-Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}}}{w+\frac{1}{(1+\tau)}\left(1-Z^{\frac{\psi}{1-\psi}}\theta^{\frac{1}{1-\psi}}(1+\tau)^{\frac{\psi}{\psi-1}}\right)^{-\frac{1}{\psi}+1}}\\
= &\frac{-\psi/(1-\psi)}{\theta^{\frac{1}{\psi-1}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{\psi-1}}-1}-\frac{1}{1-\theta^{\frac{1}{1-\psi}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}}+w(1+\tau)\left(1-\theta^{\frac{1}{1-\psi}}\left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}}\right)^{\frac{1}{\psi}}}
\end{aligned}
\tag{4.A.37}
$$

We take the derivative of the above with respect to θ to examine the variations of pass-through with respect to the scope for quality.

$$\frac{\partial \gamma}{\partial \theta} = -\frac{\psi}{(1-\psi)^2} Z^{\frac{\psi}{\psi-1}} \theta^{\frac{\psi}{1-\psi}} (1+\tau)^{\frac{\psi}{1-\psi}} \left(\theta^{\frac{1}{\psi-1}} Z^{\frac{\psi}{\psi-1}} (1+\tau)^{\frac{\psi}{1-\psi}} - 1 \right)^{-2}$$
$$- \frac{\frac{\theta^{\frac{\psi}{1-\psi}}}{1-\psi} \left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}} \left[1 + \frac{w(1+\tau)}{\psi} \left(1 - \theta^{\frac{1}{1-\psi}} \left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}} \right)^{\frac{1}{\psi}-1} \right]}{\left[1 - \theta^{\frac{1}{1-\psi}} \left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}} + w(1+\tau) \left(1 - \theta^{\frac{1}{1-\psi}} \left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}} \right)^{\frac{1}{\psi}} \right]^2} \tag{4.A.38}$$

When $0 < \psi < 1$, the above is negative. When $\psi < 0$, the above is positive when ψ is negative enough, for example when $\psi < -\frac{1}{w(1+\tau)} < -\frac{1}{w(1+\tau)} \left(1 - \theta^{\frac{1}{1-\psi}} \left(\frac{Z}{1+\tau}\right)^{\frac{\psi}{1-\psi}} \right)^{\frac{1-\psi}{-\psi}}$.

The above proves the remaining results in **Proposition 3**. A tax hike implies higher consumer prices. Note that the marginal cost of increasing quality does not depend on price. Quality adjustments by producers crucially depends on changes in consumers' valuation for quality which are characterised by the degree of substitution/complementarity. If substitution dominates (as in Khandelwal (2010)) consumers faced with a higher price prefer a reduction in quality as it allows producers to reduce prices. If complementarity dominates, consumers would rather get higher quality when they pay more, and producers will increase prices at the expense of a lower reduction in producer prices (possibly an increase in producer prices). Those effects are magnified by the scope for quality. Therefore, pass-through decreases with the quality ladder in the substitution case, while the opposite is true in the complementarity case.

4.B Empirical Appendix

This Appendix presents a series of additional descriptives, figures and results, as referenced in the main text. First, Tables 4.B.1 to 4.B.6 and Figures 4.B.1 to 4.B.4 provide more detail on the variables used in the analysis, including the characteristics of the reforms and the composition of the *Regimpact* indicator.

Second, Figures 4.B.5 to 4.B.7 and Tables 4.B.7 to 4.B.9 provide supplementary figures and tables referenced in the main text. Notably, 4.B.7 explores heterogeneity in the effects of early announcement. The top-left panel shows contemporaneous pass-through by implementation lag for all country-product pairs for which we have data on announcement dates. The specific cases highlighted illustrate the heterogeneity: the bottom-left panel shows a relatively large possible announcement effect for a rise in VAT on package holidays in Luxembourg, while the bottom-right panel shows no announcement effect for a rise in VAT on restaurants and cafés in Portugal. Table 4.B.9 considers the interaction between early announcement and openness, concentration, regulation and quality. Once again there is no evidence of an anticipation or total effect. The impact of regulation is driven by reforms which were announced fewer than 32 days in advance, but this is likely driven by the composition of that group – it contains a substantially higher share of changes to the reduced rate, which have the strongest effects as discussed above. The quality range effect is similar across implementation lag groups. Future research to gather more complete data on announcement dates will allow systematic evaluation of the factors determining whether advance announcement impacts pass-through.

Finally, Tables 4.B.10 to 4.B.13 show results from the various robustness checks described in Section 4.6.

Table 4.B.1: Summary of VAT Reforms by Country

	First year in data	Number of reforms	Products affected	Product-Months affected
Austria	1998	1	1	1
Finland	1998	2	48	59
France	1998	3	35	36
Germany	1998	2	36	72
Greece	2000	3	48	144
Ireland	1998	7	34	153
Italy	1998	2	36	36
Luxembourg	2003	1	1	1
Netherlands	1998	1	29	29
Portugal	1998	7	49	193
Slovakia	2008	1	45	45
Slovenia	2006	1	1	1
Spain	1998	2	38	76
Total		33	401	846

Table 4.B.2: Summary of Observed VAT Rates and Prices

		Obs	Mean	S.D.	Min	Max
VAT levels	Reduced rate	31,147	0.075	0.033	0.021	0.17
	Standard rate	74,010	0.194	0.02	0.15	0.23
	Zero rate	2,393	0	0	0	0
VAT changes	All	846	0.01	0.02	-0.15	0.17
	Standard	722	0.01	0.01	-0.01	0.03
	Reduced	116	0.01	0.02	-0.05	0.07
	Reclassification	8	-0.03	0.12	-0.15	0.17
	VAT decrease	143	-0.02	0.03	-0.15	-0.01
	VAT increase	703	0.02	0.01	0.01	0.17
Price levels		108,000	102.5	19.9	18.8	527.6

Table 4.B.3: Pairwise correlation between competitiveness variables

	(1)	(2)	(3)	(4)
(1) Openness	1.000			
(2) *Regimpact*	-0.122*	1.000		
(3) Concentration	0.022*	-0.045*	1.000	
(4) Quality range	0.050*	0.029*	-0.054*	1.000

* shows significance at the 5% level

Table 4.B.4: Summary statistics for main variables

Variable	Obs	Mean	S.D.	Min	Max
Δ ln(Price)	107,550	.001	.024	-.414	.415
Δ ln(1 + VAT)	107,550	0	.002	-.134	.149
Regimpact	107,550	.112	1.005	-2.098	3.774
Quality range	52,970	.052	.996	-1.933	1.785
Openness	107,550	.026	1.149	-.224	92.187
Concentration	107,550	-.024	.987	-1.263	5.997
TAX_package	107,550	.005	.069	0	1
Consumption	107,550	1.19e+08	3.35e+08	1456.954	1.67e+09
ValueAdded	106,542	18207.45	45043.92	.4	559000

Table 4.B.5: VAT changes for which announcement dates are observed

		Obs	Mean	S.D.	Min	Max
VAT changes	All	565	0.01	0.02	-0.15	0.17
	Standard	489	0.01	0.01	-0.01	0.03
	Reduced	71	0.01	0.01	-0.05	0.02
	Reclassification	5	-0.01	0.14	-0.15	0.17
	VAT decrease	101	-0.01	0.02	-0.15	-0.01
	VAT increase	464	0.02	0.01	0.01	0.17

Table 4.B.6: Correlation among other market structure variables

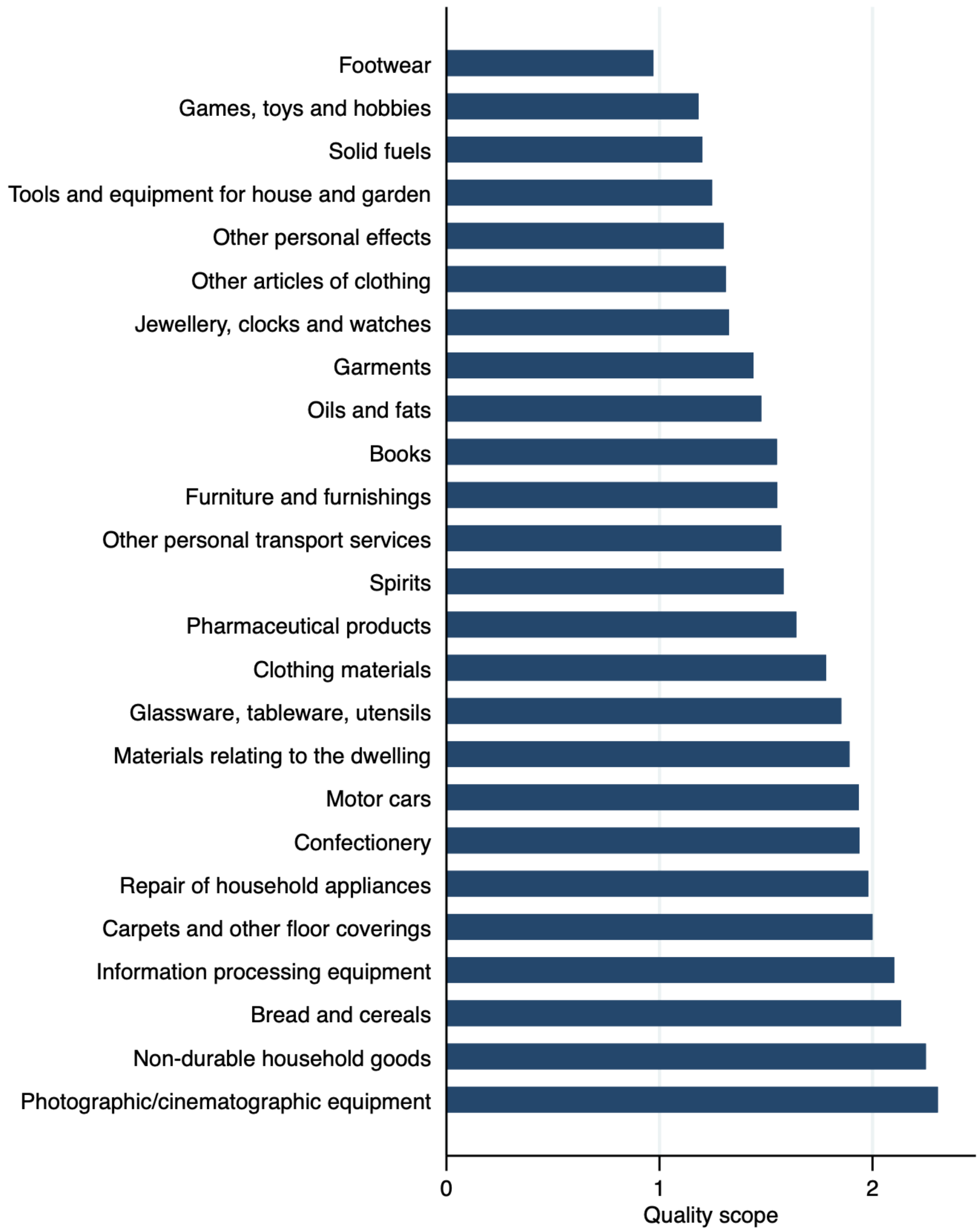
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Openness	1.000						
(2) Concentration	0.013*	1.000					
(3) *Regimpact*	-0.104*	-0.038*	1.000				
(4) Quality ladder	0.055*	-0.072*	0.031*	1.000			
(5) Dependence on external finance	0.022*	-0.042*	0.072*	0.147*	1.000		
(6) Export elasticity	0.044*	0.013*	0.022*	-0.216*	0.132*	1.000	
(7) Import elasticity	-0.029*	-0.013*	0.076*	0.133*	0.016*	0.020*	1.000

* shows significance at the 0.05 level

Figure 4.B.1: Distribution of regulation across consumption categories

Notes: These plots summarise the distribution of the *Regimpact* measure across consumption categories. A lower value of the indicator reflects a more competition-friendly regulatory stance among input industries. Each box depicts the 25th, 50th and 75th percentiles, with extending lines to the minimum and maximum values, excluding outliers (defined as 1.5IQR below/above the lower/upper quartile).

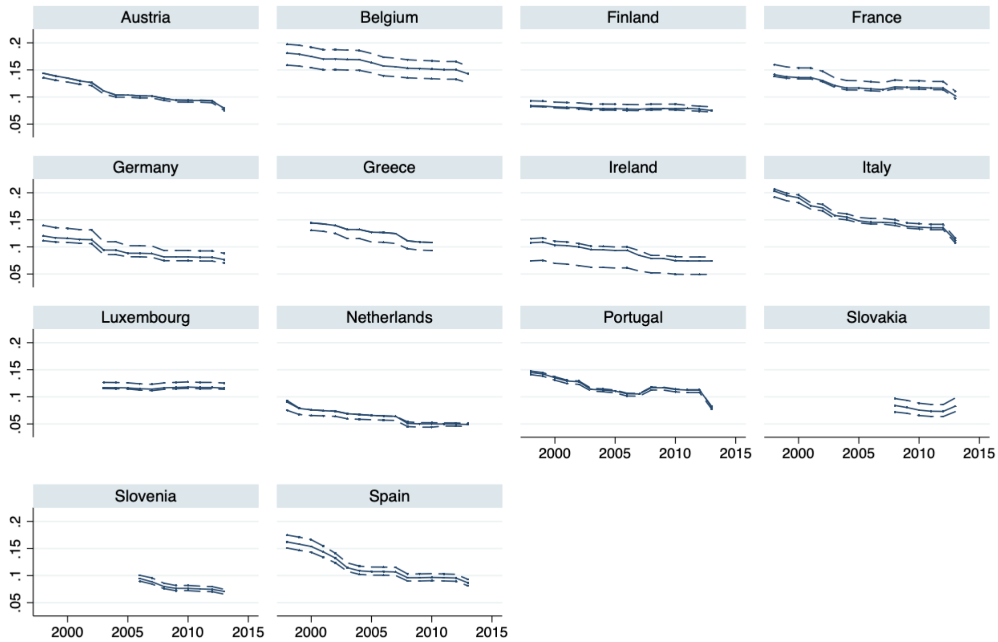
Figure 4.B.2: Distribution of quality scope across consumption categories



Notes: This graph depicts the estimated quality range across different consumption categories. A higher value of the indicator reflects a longer average 'quality ladder' (Khandelwal 2010).

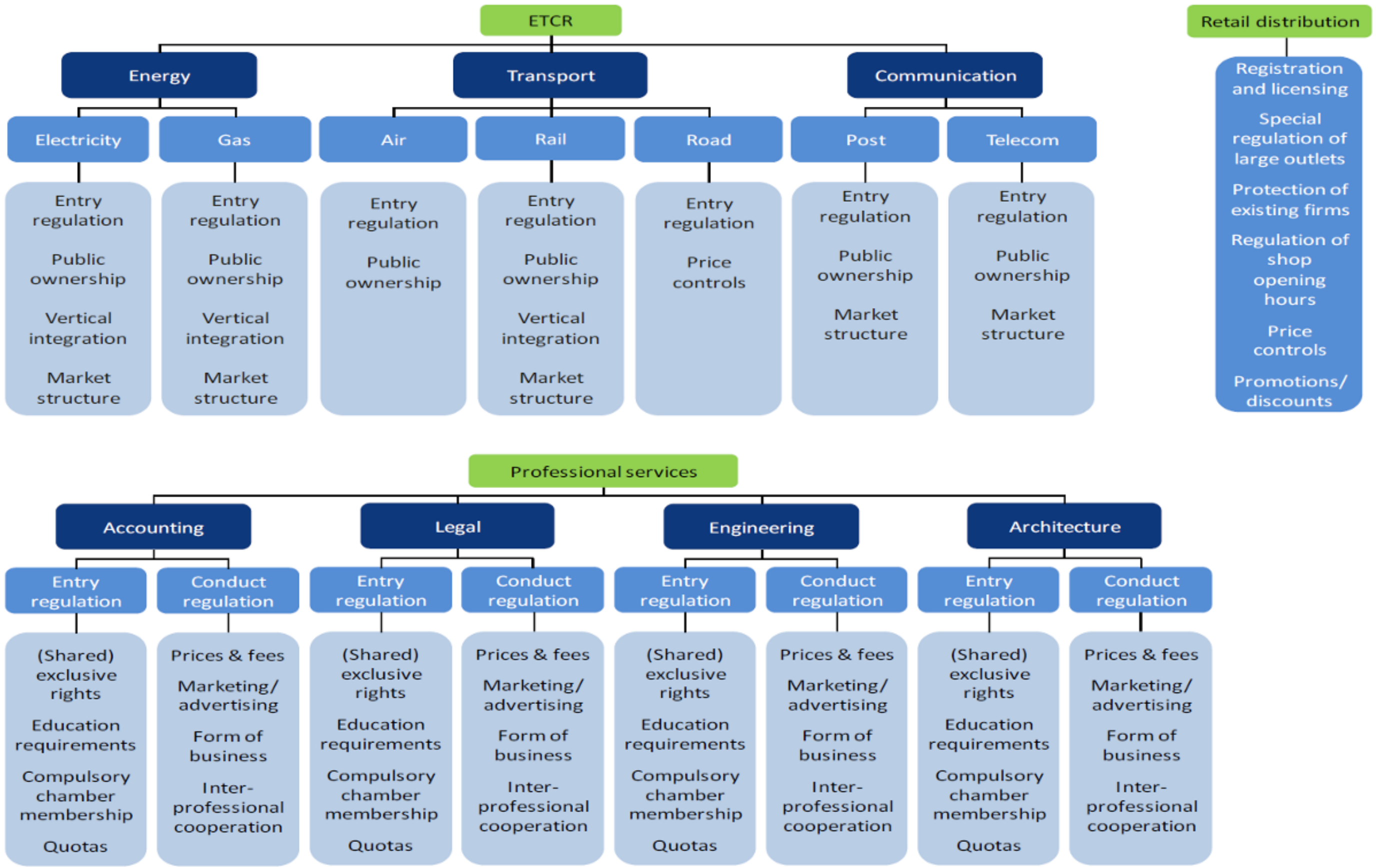
Figure 4.B.3: Changes in upstream regulation by country and consumption category

(a) Median *Regimpact* by country over time – 25th, 50th and 75th percentiles



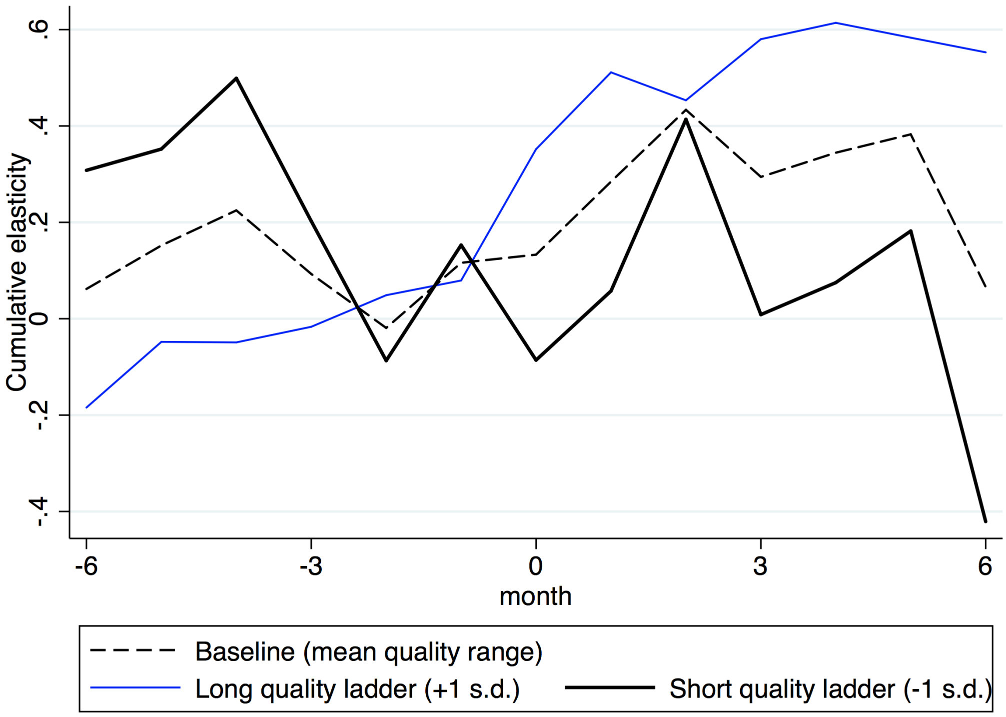
(b) Median *Regimpact* by consumption category over time – 25th, 50th and 75th percentiles

Figure 4.B.4: Upstream industries included in *Regimpact* indicator, and the categories upon which they are scored



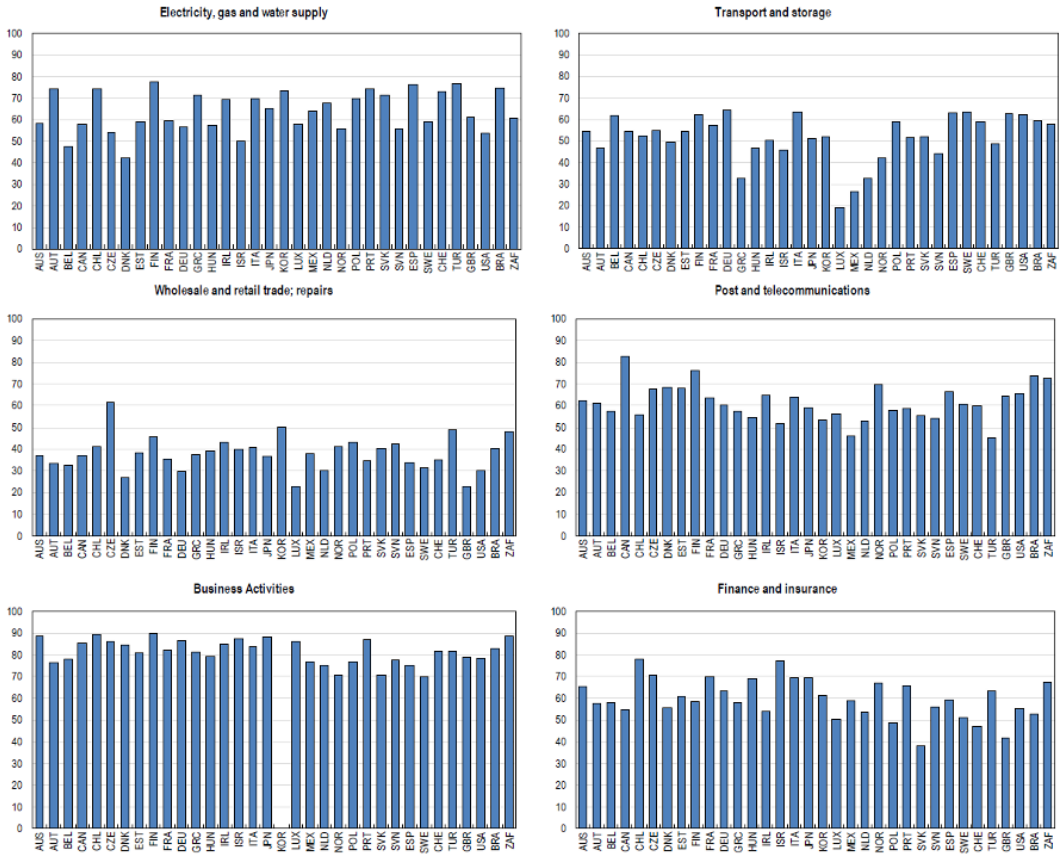
Notes: The *Regimpact* measure is the average score of the pro-competitiveness of regulation in the upstream services sectors (shown above), weighted by the proportions in which they are used in a given industry (from input-output tables). For example, one question used for 'entry regulation' in the electricity sector is: "What is the minimum consumption threshold that consumers must exceed in order to be able to choose their electricity supplier?" (Conway & Nicoletti 2006). The lack of any threshold scores zero, a threshold less than 250 gigawatts scores one, 250-500 gigawatts scores two, etc. *Source:* Égert & Wanner (2016)

Figure 4.B.5: Cumulative effect of quality scope on pass-through



Notes: This graph shows cumulative baseline pass-through and the impact upon this of quality scope. The blue (black) lines show cumulative pass-through in a country-product pair with a quality ladder that is exactly one standard deviation longer (shorter) than the mean.

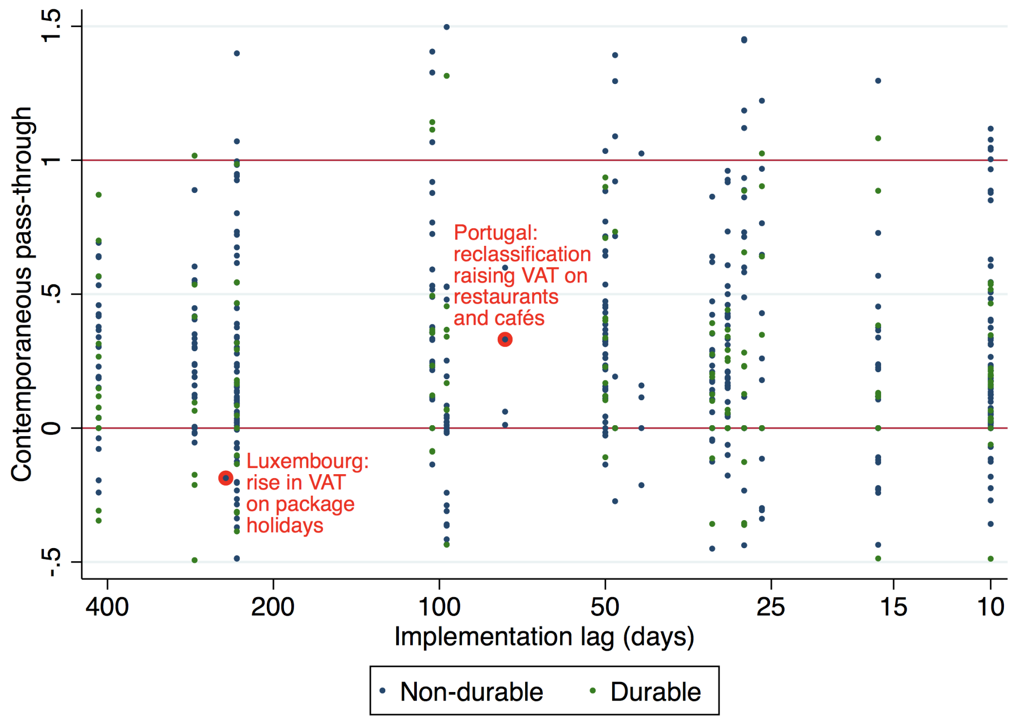
Figure 4.B.6: Share of intermediate demand in gross output of non-manufacturing sectors



Notes: These graphs show the share of intermediate demand in gross output of non-manufacturing sectors across countries in the mid-2000s. The ‘wide’ *Regimpact* measure includes the first five sectors, while the ‘narrow’ measure includes only ‘Electricity, gas and water supply’, ‘Transport and storage’, and ‘Post and telecommunications’. *Source:* Égert & Wanner (2016).

Figure 4.B.7: Heterogeneity in announcement effects

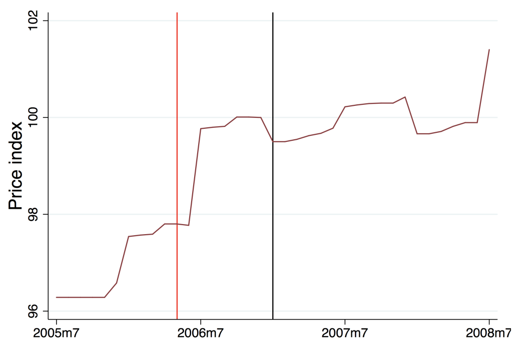
(a) Heterogeneity of pass-through by implementation lag



Notes: This graph shows the distribution of contemporaneous pass-through by implementation lag, across reforms for which announcement date data is available. The vertical spread illustrates the substantial heterogeneity in pass-through, even after controlling for implementation lags. The two reform episodes circled in red are shown in detail below.

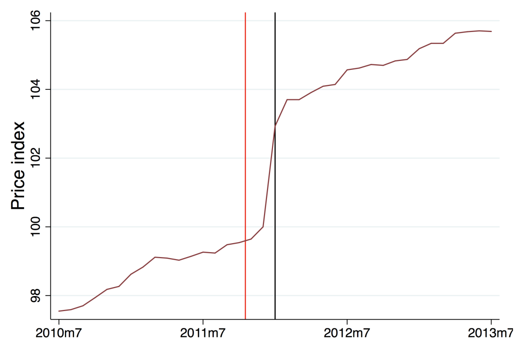
(b) Possible announcement effect:

Package holidays in Luxembourg



(c) No announcement effect:

Restaurants and cafés in Portugal



Notes: These two graphs show prices for two example goods over their respective reform episodes. In each case the first vertical line is the date the reform was announced, and the second is the date it was implemented. The lefthand graph shows a potential anticipation effect, unlike that on the right.

Table 4.B.7: Impact of early announcement on pass-through, for continuous implementation lag

		Dependent variable: change in log prices				
		(1)	(2)	(3)	(4)	(5)
		No FEs	Individual FEs	Interaction FEs	Individual FEs + Controls	Interaction FEs + Controls
Baseline:	Pre-Reform	0.164	0.162*	0.0451	0.161*	0.0476
		(0.189)	(0.0711)	(0.556)	(0.0660)	(0.529)
	Contemporaneous	0.305***	0.257**	0.115	0.263**	0.115
		(0.003)	(0.0131)	(0.336)	(0.0170)	(0.337)
	Post-Reform	0.0838	0.0884	0.007	0.0827	0.00899
		(0.345)	(0.270)	(0.909)	(0.302)	(0.885)
	Total	0.554***	0.507***	0.167	0.507***	0.171
		(0.002)	(0.004)	(0.126)	(0.00442)	(0.122)
Implementation Lag:	Pre-Reform	-0.00248	0.00613	0.0323	0.00838	0.0316
		(0.951)	(0.806)	(0.157)	(0.738)	(0.166)
	Contemporaneous	-0.0263	-0.0114	0.00271	-0.00899	0.0195
		(0.187)	(0.541)	(0.907)	(0.650)	(0.403)
	Post-Reform	0.0304	0.00589	0.00603	0.0107	0.00596
		(0.333)	(0.802)	(0.761)	(0.651)	(0.766)
	Total	0.00165	0.000637	0.0410	0.0101	0.0571*
		(0.976)	(0.987)	(0.155)	(0.801)	(0.053)
	Controls	No	No	No	Yes	Yes
	X_ikt	No	No	No	Yes	Yes
	FEs	None	i,k,t	it,kt,ik	i,k,t	it,kt,ik
	Clustering	None	ik	ik	ik	ik
	N	100,983	100,983	100,983	100,023	100,023

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. 'X_ikt' refers to the inclusion of *Regimpact*, openness to trade and import concentration in the regression. Specifications (4) and (5) also controls for value added, consumption and whether the reform was part of a package. 'Implementation Lag' is measured in months, so a coefficient of 0.01, for example, implies that announcing a VAT reform one additional month in advance is associated with a 1% increase in pass-through.

Table 4.B.8: Impact of early announcement on pass-through, for continuous implementation lag, by durability

		Dependent variable: change in log prices			
		Individual FEs		Interaction FEs	
		Non-Durables	Durables	Non-Durables	Durables
Baseline:	Pre-Reform	0.126	0.156*	-0.0479	0.131
		(0.254)	(0.0705)	(0.392)	(0.346)
	Contemporaneous	0.410***	-0.00241	0.299***	-0.156
		(0.00)	(0.962)	(0.00)	(0.240)
	Post-Reform	0.119	0.0334	0.0473	-0.0509
		(0.314)	(0.446)	(0.586)	(0.238)
	Total	0.655***	0.187	0.298**	-0.0753
		(0.003)	(0.201)	(0.0134)	(0.584)
Imp. Lag:	Pre-Reform	0.00617	0.0183	0.0439*	0.0224
		(0.847)	(0.238)	(0.0505)	(0.408)
	Contemporaneous	-0.0403*	0.0590***	-0.0272	0.0561**
		(0.0748)	(0.001)	(0.213)	(0.0190)
	Post-Reform	0.0126	-0.0209**	0.00150	0.0122
		(0.678)	(0.0241)	(0.947)	(0.493)
	Total	-0.0215	0.0564**	0.0182	0.0906***
		(0.656)	(0.0253)	(0.560)	(0.003)
# of VAT changes:		444	120	444	120
FEs		i,k,t		it,kt,ik	
Clustering		ik		ik	
N		100,983		100,983	

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The 'Individual FEs' and 'Interaction FEs' specifications correspond to models (2) and (3) in Table 4.B.7, but with coefficients estimated independently for Non-Durables and Durables. 'Implementation Lag' is measured in months, so a coefficient of 0.01, for example, implies that announcing a VAT reform one additional month in advance is associated with a 1% increase in pass-through.

Table 4.B.9: Regulation, quality and announcement effects

		Dependent variable: change in log prices			
		Full sample, no quality		Sample incl. quality	
Implementation lag (days):		>32=Early	<32	>32=Early	<32
Baseline β_1:	Pre-Reform	0.054	0.0165	0.766	0.059
		(0.708)	(0.765)	(0.147)	(0.647)
	Contemporaneous	0.26***	0.282***	-0.0356	0.0591
		(0.008)	(0.008)	(0.928)	(0.642)
	Post-Reform	0.101	-0.0349	-0.517	0.147**
		(0.440)	(0.663)	(0.245)	(0.021)
	Total	0.415***	0.263**	0.214	0.265
		(0.009)	(0.032)	(0.781)	(0.212)
Openness:	Total	-0.0145	-0.0123	4.195***	-1.474**
		(0.982)	(0.978)	(0.005)	(0.043)
Concentration:	Total	-0.0197	-0.0198	-0.286	-0.233
		(0.898)	(0.889)	(0.174)	(0.283)
Regimpact:	Pre-Reform	0.364	0.0531	1.387***	0.0397
		(0.118)	(0.382)	(0.000)	(0.749)
	Contemporaneous	0.0801	-0.254***	0.309	-0.523***
		(0.541)	(0.003)	(0.359)	(0.000)
	Post-Reform	-0.0033	0.0176	0.321	-0.136***
		(0.990)	(0.701)	(0.585)	(0.006)
	Total	0.441	-0.183*	2.017***	-0.62***
		(0.274)	(0.068)	(0.010)	(0.000)
Quality range:	Pre-Reform			-0.186	-0.0587
				(0.168)	(0.705)
	Contemporaneous			0.0127	0.418***
				(0.906)	(0.000)
	Post-Reform			0.398**	0.0616
				(0.012)	(0.527)
	Total			0.224*	0.421*
				(0.089)	(0.086)
# of VAT changes:		344	502	185	264
# of which:	Standard	308	414	178	234
	Reduced	33	83	7	29
	Reclassification	3	5	0	1
Average size of VAT change (pp):		1.6	0.6	1.6	0.7
FEs		it,kt,ik		it,k,t,ik	
Clustering		ik		ik	
N		100,983		49,598	

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 4.B.10: Estimates using discrete PMR variable

		Dependent variable: change in log prices		
		No FEs	Individual FEs	Interaction FEs
Baseline:	Pre-Reform	0.210	0.190*	0.0341
		(0.135)	(0.059)	(0.555)
	Contemporaneous	0.323***	0.317***	0.243***
		(0.000)	(0.000)	(0.001)
	Post-Reform	0.159	0.112	0.0373
		(0.139)	(0.248)	(0.609)
	Total	0.692***	0.619***	0.314***
		(0.000)	(0.001)	(0.002)
Openness:	Total	0.691	0.589	-0.0212
		(0.134)	(0.306)	(0.954)
Concentration:	Total	-0.0406	-0.0246	-0.0378
		(0.807)	(0.874)	(0.747)
$RegimpactHML$:	Pre-Reform	-0.137	-0.0596	0.0631
		(0.333)	(0.550)	(0.533)
	Contemporaneous	-0.199*	-0.252**	-0.351**
		(0.058)	(0.011)	(0.011)
	Post-Reform	-0.0664	-0.0177	-0.0606
		(0.666)	(0.865)	(0.490)
	Total	-0.402*	-0.330*	-0.348**
		(0.083)	(0.091)	(0.043)
FEs		None	i,k,t	it,kt,ik
Clustering		None	ik	ik
N		100,983	100,983	100,983

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption. $RegimpactHML$ is a discrete variable taking value 1 if the observation is in the top quartile of the *Regimpact* distribution, value -1 if in the bottom quartile, and zero otherwise. Openness and market concentration are standardised so the coefficients can be interpreted as the impact on pass-through of a one-standard-deviation rise in the regressor. Pre-Reform, Contemporaneous and Post-Reform effects are also estimated for Openness and Concentration, but are not significant so omitted for conciseness.

Table 4.B.11: Estimates by direction of VAT change

		Dependent variable: change in log prices		
		Increases	Decreases	Coeff.s Equal
Baseline:	Pre-Reform	0.0435	-0.0511	0.26
		(0.734)	(0.293)	
	Contemporaneous	0.0000215	0.296***	0.00
		(0.459)	(0.001)	
	Post-Reform	0.00122	0.0483	0.71
		(0.990)	(0.543)	
	Total	0.0447	0.293**	0.25
		(0.784)	(0.027)	
Openness:	Total	0.370	-1.123*	0.07
		(0.481)	(0.0826)	
Concentration:	Total	0.126	0.00695	0.58
		(0.470)	(0.957)	
Regimpact:	Pre-Reform	0.0112	-0.0385	0.54
		(0.879)	(0.324)	
	Contemporaneous	-0.172**	-0.126	0.75
		(0.0294)	(0.242)	
	Post-Reform	-0.00767	0.0439	0.62
		(0.894)	(0.612)	
	Total	-0.169	-0.121	0.83
		(0.200)	(0.498)	
# of VAT changes:		707	151	
FEs		it,kt,ik		
Clustering		ik		
N		105,616		

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption. *Regimpact*, openness and market concentration are standardised so the coefficients can be interpreted as the impact on pass-through of a one-standard-deviation rise in the regressor. The final column presents p-values from a Wald test of equality between the Increase and Decrease coefficients.

Table 4.B.12: Estimates by direction of VAT change, including quality range

		Dependent variable: change in log prices		
		Increases	Decreases	Coeff.s Equal
Baseline:	Pre-Reform	0.12	0.162	0.90
		(0.697)	(0.256)	
	Contemporaneous	0.00	0.539***	0.00
		(0.553)	(0.003)	
	Post-Reform	-0.282	0.0747	0.11
		(0.116)	(0.552)	
	Total	-0.163	0.775***	0.02
		(0.609)	(0.000)	
Openness:	Total	-0.322	0.0651	0.78
		(0.729)	(0.942)	
Concentration:	Total	0.0342	-1.16***	0.00
		(0.872)	(0.001)	
Regimpact:	Pre-Reform	0.0928	0.264	0.55
		(0.641)	(0.234)	
	Contemporaneous	-0.421**	-0.0214	0.26
		(0.017)	(0.945)	
	Post-Reform	-0.00824	-0.357	0.15
		(0.927)	(0.113)	
	Total	-0.336	-0.114	0.63
		(0.171)	(0.758)	
Quality range:	Pre-Reform	-0.0621	0.0701	0.50
		(0.635)	(0.694)	
	Contemporaneous	0.187*	0.17	0.95
		(0.083)	(0.443)	
	Post-Reform	0.345***	-0.352*	0.01
		(0.002)	(0.072)	
	Total	0.471**	-0.111	0.16
		(0.030)	(0.691)	
# of VAT changes:		373	80	
FEs		it,k,t,ik		
Clustering		ik		
N		49,598		

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption. *Regimpact*, openness, market concentration and quality range are standardised so the coefficients can be interpreted as the impact on pass-through of a one-standard-deviation rise in the regressor. The final column presents p-values from a Wald test of equality between the Increase and Decrease coefficients.

Table 4.B.13: Estimates across the business cycle

		Dependent variable: change in log prices		
		Expansions	Contractions	Coeff.s Equal FEs
Baseline β_1:	Pre-Reform	-0.0227	0.0602	0.53
		(0.757)	(0.589)	
	Contemporaneous	0.286***	0.13	0.38
		(0.000)	(0.413)	
	Post-Reform	0.142	-0.035	0.20
		(0.181)	(0.689)	
	Total	0.405***	0.155	0.31
		(0.001)	(0.455)	
Openness:	Total	-0.107	0.0354	0.86
		(0.826)	(0.950)	
Concentration:	Total	-0.255	0.118	0.13
		(0.198)	(0.394)	
Regimpact:	Pre-Reform	0.0707	0.0957	0.82
		(0.318)	(0.268)	
	Contemporaneous	-0.219***	-0.187	0.86
		(0.000)	(0.266)	
	Post-Reform	-0.0804	0.114	0.05
		(0.175)	(0.145)	
	Total	-0.228***	0.0226	0.35
		(0.000)	(0.932)	
# of VAT changes:		300	558	
Average size of VAT change (pp):		0.54	1.2	
FEs		it,kt,ik		
Clustering		ik		
N		100,983		

Notes: p-values in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Estimates are the sum of the price elasticity coefficients with respect to tax changes over each period. Prices are de-trended and de-seasonalised, and observations are weighted by their share of national consumption. Openness and market concentration are standardised so the coefficients can be interpreted as the impact on pass-through of a one-standard-deviation rise in the regressor. Pre-Reform, Contemporaneous and Post-Reform effects are also estimated for Openness and Concentration, but are not significant so omitted for conciseness.

Conclusion

This thesis has presented four related essays in applied microeconomics. The first exploited China's accession to the WTO to investigate the impact on Indian manufacturing firms of improved access to intermediate inputs, and found a persistent quality-upgrading effect which spreads across the production network. The second examined the impact of increased adoption of machine learning in Indian white-collar services firms, and found evidence of a direct negative impact on hiring and wage growth in incumbent firms. The third chapter detailed the complex relationship between robot adoption internationally and welfare in developing countries, and highlighted areas where policy could play a beneficial role. The fourth chapter assessed the roles of market structure and timing in determining VAT pass-through, and found a particularly important role for product market regulation.

These results leave many questions unanswered, and highlight new avenues for future research. Similar upgrading effects to those in Chapter 1 may have occurred in other developing countries with manufacturing sectors akin to India's. An analogous but inverse approach could also be used to understand the widespread economic disruption during the early phase of the Covid-19 pandemic, when global production networks amplified a negative Chinese input supply shock. The empirical methodology could be extended, for instance by using planned tariff rates from the accession agreement as instruments for annual realised tariffs (as in Brandt et al. 2017), or by moving beyond industry-wise input-output tables to firm-level supplier-customer relationships (as in Bernard et al. 2019, Carvalho et al. 2020). The model and estimation could be extended into a general equilibrium context, and hence used to derive explicit welfare effects.

Chapter 2 raises many further questions about the impact of AI on employment in India. AI has supported many new jobs and business models, from TikTok stars to data-tagging. Given that we find evidence of negative direct effects on employment growth in incumbent firms, the next step is to size the offsetting positive effects. We also need to understand the indirect effects of AI adoption – for instance, whether reduced hiring by incumbents allows an offsetting expansion by other firms in the industry. Finally, there is important work to be done on the relationship between AI, trade and developing countries. While we focus on domestic AI adoption in India, AI adoption overseas could have major consequences (Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021). Extending our analysis to the international dimension is a key next step for this line of empirical research.

Chapter 3, similarly, is within the early stage of an important literature. The core framework focuses on static gains from specialisation in a world with symmetric sectors and constant returns to scale. Over time, these gains may be outweighed by higher long-run growth rates in some sectors than others. Developing countries may be locked out of manufacturing – and the important positive externalities it generates – by developed countries with mutually reinforcing agglomerations of infrastructure and technology (Rodrik 2016). If the future of manufacturing turns out to be highly automated and close to the consumer, developing countries may need to look elsewhere for jobs (Baldwin & Forslid 2020) – which links back to the previous chapter, on threats to employment in services in developing countries. Disentangling these various mechanisms, and comparing them with the latest data, is a critical ongoing project.

Finally, Chapter 4 could be extended in several ways. With additional data, we could move beyond sector-level regulation measures to direct observation of firm-level markups and marginal costs. Once again, we could extend the theory to a general equilibrium setting, and allow for more interlinkages between upstream and downstream sectors. Conversely, detailed case studies of particular reforms – providing direct evidence on the precise mechanisms through which market structure influences pass-through – would also be a helpful complement to this research agenda.

All four papers contribute to informing policy. Chapter 1 challenges various economic rationales for India rejecting the Regional Comprehensive Economic Partnership, and so links closely to current debates on trade and industrial policy. Chapters 2 and 3 contribute directly to literatures aiming to understand the potential impacts of new technologies on firms and workers, debates which underpin potential policies ranging from grand national strategy (e.g. subsidising services exports or AI innovation) to protection of the most vulnerable (e.g. trade adjustment assistance for laid-off workers, or indeed automation adjustment assistance). Lastly, Chapter 4 speaks directly to an ongoing debate within fiscal authorities and other policy institutions. Of course, all of these questions require further exploration, and I leave precise policy prescriptions for future work.

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