Three Essays in Applied Econometrics

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A thesis submitted for the degree of Doctor of Philosophy in Economics

Hillary Term 2016

Abstract

This thesis presents three essays in the field of applied econometrics. In the first essay, we use the establishment-level Annual Respondents Database (ARD) data and the sector-level Confederation of British Industry (CBI) Industrial Trends Survey data to identify the key determinants of U.K. manufacturing investment. We first examine the trends in the ARD microdata aggregates, the relative price of investment goods data, and the CBI survey data. Subsequently, we estimate a baseline dynamic error correction investment model which separates out short-run and long-run investment dynamics. When we introduce additional variables derived from the CBI survey data to the baseline model, the estimation results show that survey variables pertaining to financing constraints and demand uncertainty have negative effects on investment, while the survey variable related to the volume of total new orders has a positive effect on investment.

In the second essay, we develop forecasting models for aggregate U.K. manufacturing investment. After assessing the CBI's forecasting record over the recent financial crisis, we conclude that CBI forecasters were slow in realizing the severe negative effect of the credit crisis on manufacturing investment. Subsequently, we develop our own baseline error-correction forecasting model, which conditions only on lagged explanatory variables, and apply the general-to-specific modeling approach to simplify the model. However, the selected baseline specification has poor out-of-sample forecast properties over the crisis period. When we include additional CBI survey variables in the baseline model, there is an improvement in the out-of-sample forecast performance in most cases. Survey measures of business optimism and expected future demand are found to be particularly useful in this context.

Finally, in the third essay, we employ a Threshold Vector Autoregression (TVAR) model to examine the potentially nonlinear impact of fiscal stimulus on output under tight and loose credit supply conditions in the U.S.. In our main specification, we choose the excess bond premium as the threshold variable to identify periods of tight credit and loose credit. The empirical results suggest that government spending increases are more effective at stimulating output than tax cuts, especially when credit conditions are loose.

Acknowledgements

First and foremost, I would like to express my deepest gratitude to my supervisors, Prof. Stephen Bond and Prof. Christopher Bowdler, for their invaluable guidance, thoughtful comments, and continued encouragement throughout my doctoral journey. I am also very grateful to Prof. Alessandra Guariglia and Prof. Guido Ascari for being my examiners and their insightful comments on this thesis. I would like to extend my gratitude to the Secure Lab at the U.K. Data Service for making available the Annual Respondents Database. I would further like to thank the Confederation of British Industry for giving me convenient access to its Industrial Trends Survey data. My sincere thanks also go to Prof. Nathan Balke for sharing his RATS codes, which I modified for the empirical analysis in Chapter 4, and for his helpful discussion.

Contents

Chapter 1
Introduction

This thesis consists of three essays in the field of applied econometrics. In Chapter 2, we use the establishment-level Annual Respondents Database (ARD) data and the sector-level Confederation of British Industry (CBI) Industrial Trends Survey data to investigate the factors influencing U.K. manufacturing investment over the period 1997-2012. The manufacturing industry is important for the U.K. economy as it makes a disproportionately large contribution to research and development and exports (see Rhodes, 2014). However, in comparison with manufacturing industries in other developed economies, U.K. manufacturing has seen a faster decline as a proportion of both total output and total employment since the 1970s (see Kitson and Michie, 1997; Kitson and Michie, 2014; Nickell et al., 2008). One possible explanation for this rapid deindustrialization in the U.K. is that persistently low manufacturing investment has caused the manufacturing industry's capital stock to fall substantially below its optimal level (Kitson and Michie, 1996). Therefore, an in-depth analysis of the drivers of U.K. manufacturing investment can help the government adopt more effective industrial policies to promote growth in manufacturing.

Following Bean (1981) and Bond et al. (2003), we first construct a baseline dynamic investment model containing an error correction term related to the long-term path of the capital stock to output ratio. The estimates of the baseline model suggest that the investment rate is linked with short-run fluctuations in past investment, current and past output growth, current and past changes in the relative price of investment goods, the deviation of the capital stock from its long-run steady state relationship with output, and the long-run effect of the relative price of investment goods on the capital stock. When we introduce additional explanatory variables derived from the CBI survey data, we find that survey variables pertaining to financing constraints and demand uncertainty have negative effects on manufacturing investment, while the survey variable related to the volume of new orders has a positive effect on manufacturing investment.

In Chapter 3, we develop forecasting models of aggregate U.K. manufacturing investment. Accurate manufacturing investment forecasts in times of crisis could be important for economic recovery because they can help the government to assess the outlook for the economy and to implement timely policies to revive the manufacturing industry. We first assess the CBI's forecasting record over the recent financial crisis and conclude that CBI forecasters were slow in realizing the severe negative effect of the credit crisis on manufacturing investment. Subsequently, we follow Bean (1981) and develop a baseline error correction forecasting model for aggregate manufacturing investment which conditions only on lagged explanatory variables. We apply the general-to-specific methodology and employ the computer program Autometrics (see Doornik, 2009) to simplify the baseline forecasting specification. The reduced baseline model retains both the previous period's investment growth term and the error-correction term related to the long-run desired investment path. However, it does not perform well in the out-of-sample forecasts over the period 2007-2012. When we introduce additional CBI survey variables to our baseline specification, there is an improvement in the post-sample forecast properties in most cases. Our preferred forecasting specification contains survey variables related to business optimism and expected future orders, and outperforms the published CBI forecasts in forecasting manufacturing investment over the financial crisis.

In Chapter 4, we analyze the impacts of fiscal policy on output under different credit conditions over the period 1973Q1-2012Q4. Unlike the previous two chapters, we focus on the U.S. rather than the U.K. in this chapter because there is no reliable measure of credit supply conditions for the U.K. available for our sample period. Fernandez-Corugedo and Muellbauer (2006) derive a credit conditions index for the U.K., but this index only covers the period 1975-2001 and does not include the more recent years. The excess bond premium, the credit supply measure constructed in Gilchrist and Zakrajsek (2012) and used in this chapter, is only available for the U.S. but not for the U.K.

In a credit crisis, the Federal Reserve can normally provide liquidity to the economy by lowering its policy interest rate. However, at the height of the Great Recession, interest rate policy appeared to be insufficient to alleviate credit constraints because it has been constrained by the zero lower bound since December 2008. As credit market conditions continued to deteriorate, the U.S. government implemented various fiscal stimulus measures to stabilize the economy, the largest being the $787 billion spending provided by the American Recovery and Reinvestment Act (ARRA) of 2009. The main question that we address in this chapter is whether the output effects of fiscal expansions in periods of tight credit differ from those in periods of loose credit. To answer this question, we employ a Threshold Vector Autoregression (TVAR) model to examine the nonlinear output effects of fiscal policy. In the main specification, we choose the excess bond premium, a measure of credit supply conditions developed in Gilchrist and Zakrajsek (2012), as the threshold variable. If the excess bond premium is higher than the estimated threshold value, the economy is in a tight credit regime. Conversely, if the excess bond premium is lower than the estimated threshold value, the economy is in a loose credit regime. The estimation results reveal that, compared with spending increases, tax cuts either have less certain output effects under tight credit conditions or generate lower output growth under loose credit conditions. Therefore, spending increases seem to be more effective at stimulating output, especially when credit conditions are loose.

References

Bean, C. R. (1981). "An Econometric Model of Manufacturing Investment in the UK," Economic Journal 91:106–121.

Bond, S. R., J. Elston, J. Mairesse, and B. Mulkay (2003). "Financial Factors and Investment in Belgium, France, Germany and the UK: A Comparison Using Company Panel Data," Review of Economics and Statistics 85 (1): 153–165.

Doornik, J. A. (2009). "Autometrics," in: Castle, J. L. and N. Shephard (2009), The Methodology and Practice of Econometrics, Oxford University Press.

Fernandez-Corugedo, E. and J. Muellbauer (2006). "Consumer Credit Conditions in the U.K.," Bank of England Working Paper 314.

Gilchrist, S. and E. Zakrajsek (2012). "Credit Spreads and Business Cycle Fluctuations," American Economic Review, 102 (4): 1692-1720.

Kitson, M. and J. Michie (1996). "Britain's Industrial Performance Since 1960: Underinvestment and Relative Decline," Economic Journal, 106 (434): 196-212.

Kitson, M. and J. Michie (1997). "Does Manufacturing Matter?" International Journal of the Economics of Business, 4(1): 71-95.

Kitson, M. and J. Michie (2014). "The Deindustrial Revolution: The Rise and Fall of Manufacturing, 1870-2010," Working Paper No. 459, Center for Business Research, University of Cambridge.

Nickell, S., S. Redding, and J. Swaffield (2008). "The Uneven Pace of Deindustrialisation in the OECD," The World Economy 31(9): 1154-1184.

Rhodes, C. (2014). "Manufacturing: Statistics and Policy," available at: http://www.parliament.uk/briefing-papers/SN01942.pdf.

Chapter 2

Investment Dynamics in U.K. Manufacturing: Evidence from ARD Microdata[1]

2.1. Introduction

Compared with manufacturing industries in other developed countries, U.K. manufacturing has experienced a faster decline as a percentage of both Gross Domestic Product (GDP) and total employment since the 1970s (see Kitson and Michie, 1997; Kitson and Michie, 2014; Nickell et al., 2008). One important cause for this continuing contraction of U.K. manufacturing could be that chronic underinvestment in manufacturing has resulted in an insufficient level of manufacturing capital stock (Kitson and Michie, 1996). The financial crisis that began in 2007 has led to a further slowdown in U.K. manufacturing investment. Thus, a better understanding of the fluctuations in manufacturing investment can help policymakers formulate more appropriate responses for stimulating manufacturing investment and reviving the manufacturing industry. The objective of this chapter is to identify the key determinants of manufacturing investment in the U.K. using both the establishment-level Annual Respondents Database (ARD) data and the sector-level Confederation of British Industry (CBI) Industrial Trends Survey data.

The establishment-level ARD dataset is compiled by the Office for National Statistics (ONS) from the production survey data that is used to construct the

[1] Disclaimer: This work contains statistical data from the Office for National Statistics (ONS), which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The data have been made available through the U.K. Data Service. The use of the statistical data in this work does not imply the endorsement of the ONS or the U.K. Data Service in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

macroeconomic aggregates in the National Accounts. This dataset has two advantages over the more commonly used firm-level datasets in the empirical investment literature. First, since each manufacturing firm consists of one or several establishments, the establishment-level ARD data are more disaggregated and therefore contain more heterogeneity than the firm-level data. Second, because the ARD is a sample of small establishments and a census of large establishments in the U.K., it has a wider coverage of the manufacturing industry than most of the available U.K. firm-level datasets. To the best of our knowledge, our study is the first attempt in the literature to model U.K. manufacturing investment using the establishment-level ARD dataset.

Although the ARD contains measures of investment and output, it does not include financial information such as profits, interest, and tax payments that can be useful for studying manufacturing investment. In order to provide a richer investment analysis, we use business survey data to provide additional information about corporate investment. Earlier studies have used survey data to identify firms' financial and legal obstacles to growth (Beck at al., 2005) and financing sources (Ayyagari et al., 2010), as well as to measure the uncertainty level (Guiso and Parigi, 1999). In this chapter, we use the sector-level CBI survey data to supplement the establishment-level ARD data and obtain valuable information related to corporate investment such as financing constraints and demand uncertainty.

We first compare our ARD sample data with the published aggregate manufacturing data from the Office for National Statistics (ONS). In terms of the investment to output ratio, the capital stock to output ratio, and the investment to capital stock ratio, our microdata aggregates and the published ONS macro-data aggregates show trends of similar direction but different magnitude. This could be because our sample mainly consists of large enterprises that are sampled continuously but may not be representative of the whole U.K. manufacturing industry. Furthermore, we examine the sector-level CBI Industrial Trends Survey data. The survey data are a useful guide for understanding manufacturing investment patterns because they provide information that is otherwise not available from the official macroeconomic data.

Subsequently, we build on the preceding qualitative discussion and estimate econometric models for investment by manufacturing establishments. Following Bean (1981) and Bond et al. (2003), we estimate a dynamic investment model containing an error correction term related to the long-term movements in the capital stock to output ratio. When we incorporate additional variables derived from the CBI survey responses in the investment model, we find that survey measures related to financing constraints and uncertainty have significant negative effects on investment while the survey measure related to past orders has a significant positive effect on investment.

The rest of the chapter is structured as follows. Section 2.2 reviews the relevant literature on the effects of uncertainty and financing constraints on investment spending. Section 2.3 examines the data used in our analysis. Section 2.4 derives the dynamic error correction investment model. Section 2.5 presents the estimation results. Section 2.6 concludes.

2.2. Literature Review

In this section, we first review two important strands of investment literature. The first strand studies whether investment is constrained by the availability of finance, and the second strand investigates the effect of uncertainty on investment. Furthermore, we also review earlier studies which use survey data to study firm behavior.

2.2.1. Financing Constraints

Under the assumption of a perfect and complete capital market, the capital structure irrelevance theorem introduced in Modigliani and Miller (1958) implies that a firm's investment policy is unrelated to its financial structure because external finance and internal finance are perfect substitutes. However, many theoretical studies contend that financial constraints may affect investment because of capital market imperfections. According to the pecking order theory proposed in Myers (1984) and Myers and Majluf (1984), due to information asymmetry between corporate management and investors, firms tend to have the following order of preference over the sources of funds to finance investment: first internal finance (retained earnings), then external debt, and lastly external equity. The pecking order theory predicts that if external sources of finance are more costly than internal sources, then investment spending may depend on the availability of low cost internal funds.

Numerous empirical studies have tried to address the question of whether corporate investment is subject to financing constraints. The pioneering work of Fazzari et al. (1988) employs the investment-cash flow sensitivity to measure financial constraints and classifies a sample of 422 U.S. manufacturing firms *a priori* as constrained or unconstrained based on the dividend-income ratio. Fazzari et al. (1988) draw on the q-theory of investment, and include a measure of q to control for investment opportunities. By regressing investment on cash flow and q, they find that corporate investment of constrained firms is more sensitive to cash flow than that of unconstrained firms.

Kaplan and Zingales (1997) disagree with the methodological approach of Fazzari et al. (1988) and point out that the investment-cash flow sensitivity may not be a reliable indicator of the severity of financial constraints because the relationship between the investment-cash flow sensitivity and the cost premium for external funds may be non-monotonic. In addition, they also question the validity of Fazzari et al. (1988)'s classification criteria of financially constrained firms. In their empirical analysis, they focus on a group of 49 low dividend firms in the sample studied by Fazzari et al. (1988) and apply an alternative classification scheme based on both qualitative and quantitative information that companies provided to the Securities and Exchange Commission. Their results indicate that more financially constrained firms in this group have lower investment-cash flow sensitivities. Cleary (1999) constructs a financial constraints index using variables which are correlated with the availability of internal funds and the cost of external funds for a sample of 1317 U.S. firms. His results show that firms with high creditworthiness exhibit higher investment-cash flow sensitivities, which corroborates the findings in Kaplan and Zingales (1997).

For a large panel of 24184 mostly unlisted U.K. firms, Guariglia (2008) first uses the cash flow to capital ratio and the interest coverage ratio to proxy for the level of internal funds and finds a U-shaped relationship between the investment-cash flow sensitivity and internal funds. Next, she employs firm size and firm age to measure the availability of external funds and finds a positive and monotonic relationship between the investment-cash flow sensitivity and the extent of external financial constraints. As a result, she argues that Fazzari et al. (1988) and Kaplan and Zingales (1997) have conflicting findings because they apply different criteria to identify financially constrained firms.

Following Fazzari et al. (1988), a large body of literature has used the investment-cash flow sensitivity to study the impact of financing constraints on investment decisions. We focus here on some of the main studies which have used data for U.K. firms. Using data for 626 publicly traded U.K. manufacturing firms, Bond and Meghir (1994) rely on an Euler equation model to test the pecking order theory. Their estimation results suggest that a shortage of internal funds is likely to influence the level of company investment, which is consistent with the pecking order theory. Bond et al. (2003) develop a reduced form error correction investment model and find that cash flow has a larger effect on firm investment in the U.K. than in Belgium, France, or Germany. They point out that the market-based financial system in the U.K. could be less effective in financing profitable corporate investment projects compared with the bank-based financial system in continental Europe. Bond et al. (2005) analyze data for manufacturing firms in the U.K. and Germany also within the error correction model framework. Their findings indicate that cash flow has a significant effect on corporate investment in the U.K, but not in Germany. Their results also show that the investment-cash flow sensitivity is lower for U.K. firms with research and development (R&D) activity compared with U.K. firms with no R&D activity. For a panel of 693 listed U.K. firms, Carpenter and Guariglia (2008) use data on contracted investment spending as a proxy for investment opportunities not captured by Tobin's q. When they add the contracted investment spending variable to the investment equation containing q, the investment-cash flow sensitivity decreases for large firms but remains the same for small firms. They conclude that, at least for small firms, this provides evidence that cash flow is correlated with investment not because of mismeasurement of q but because of capital market imperfections.

2.2.2. Uncertainty

The role of uncertainty in investment decision-making has long been a topic of intense academic research. Theoretical studies have produced contrasting results on the relationship between uncertainty and investment. Hartman (1972) and Abel (1983) argue that an increase in output price uncertainty has a positive effect on the investment spending of risk-neutral and perfectly competitive firms as the marginal revenue product of capital is strictly convex in output price. Caballero (1991) contends that imperfect competition and decreasing returns to scale tend to weaken the positive Harman-Abel effect. Furthermore, he demonstrates that the investment-uncertainty relationship may become negative if the firm has high market power. Dixit and Pindyck (1994) use the real options model to study the effect of uncertainty on investment. Under their real options framework, if investment decisions are at least partially irreversible, the option of postponing investment projects is more valuable for firms facing a higher level of uncertainty. Therefore, the real options model predicts that firms will be less likely to invest when facing a high level of uncertainty. However, Abel and Eberly (1999) find that the negative real options effect highlighted by Dixit and Pindyck (1994) is more relevant for short-run investment dynamics. In the short run, when uncertainty increases, they note that the user cost of capital will rise under irreversibility and firms will therefore invest less. In the long run, they suggest that firms also face a so-called "hangover" effect: firms facing a low marginal revenue product of capital will not be able to sell their capital because of irreversibility and will therefore be stuck with more capital than is desired. Because the user cost and hangover effects work in opposite directions, they contend that the overall impact of increased uncertainty on the long-run investment level depends on which effect dominates and is therefore ambiguous.

While most of the theoretical literature uses comparative static analysis comparing differences in investment behavior when faced with permanent (time-invariant) differences in the level of uncertainty, the works of Bloom et al. (2007) and Bloom (2009) consider time-varying changes in the level of uncertainty. Bloom et al. (2007) construct and numerically solve an investment model which allows for the uncertainty level to evolve over time. Based on simulation results, they show the relationship between uncertainty and the short-term response of capital expenditure to demand shocks is negative. Bloom (2009) relies on stock-market volatility as a measure for uncertainty, and estimates a firm-level structural model to study the impact of a sudden increase in macroeconomic uncertainty. In the short run, he shows that higher uncertainty increases the value of the option to delay investment, which leads to a reduction in investment. In the medium term, when uncertainty reverts to its normal level, his model shows that investment quickly rebounds and overshoots.

The majority of the empirical results are broadly consistent with the prediction of the real options theory, suggesting that an increase in uncertainty reduces investment at least in the short run. Leahy and Whited (1996) study a panel of 600 publicly traded U.S. manufacturing firms and develop firm-level measures of uncertainty based on share price volatility. They find that a higher level of uncertainty is associated with a lower rate of investment. However, once they control for marginal q, the negative impact of uncertainty on investment becomes insignificant. Therefore, they conclude that uncertainty reduces investment mainly through marginal q. Guiso and Parigi (1999) use survey results to directly measure demand uncertainty for a panel of 549 Italian manufacturing firms. The Survey on Investment in Manufacturing conducted by the Bank of Italy asked firms about their subjective probability distribution of the expected growth in demand. Using the variance of the expected demand growth as a measure of uncertainty, they find that greater uncertainty reduces the positive effect of expected demand on investment spending. For a panel of publicly traded U.S. companies, Bond and Cummins (2004) use the dispersion across different securities analysts in their profits forecasts for the same company as a proxy for uncertainty. They find that higher uncertainty significantly reduces investment in the long run. Bloom et al. (2007) use a proxy for uncertainty based on stock-market return volatility for a panel of 672 U.K. manufacturing firms. They document an inverse relationship between uncertainty and the short-run response of investment to demand growth, which is the main implication of the real options model. However, they do not find a significant effect of uncertainty on the long-run level of investment or the capital stock.

2.2.3. Using Survey Data to Study Firm Behavior

There have been a number of existing studies which utilize survey data to analyze firm behavior. For example, Beck et al. (2005) use survey data of over 4000 firms in 54 countries to investigate how financial, legal, and corruption problems affect firms' growth rates. Their results indicate that all three obstacles constrain firms' growth and the smallest firms in their sample are consistently the most negatively affected by all obstacles. Ayyagari et al. (2010) use the firm-level survey data of over 2400 Chinese firms to study the relationship between the source of financing and firm growth. Their findings show that firms which rely on bank financing grow faster than firms which rely on alternative financing.

2.3. Data

2.3.1. Reporting Unit-level ARD Data

2.3.1.1. ARD Dataset

The ARD is a micro-level dataset constructed from the ONS business surveys. Prior to 1997, the ARD data were drawn from the Annual Census of Production and the Annual Census of Construction. Between 1997 and 2008, it was created from the Annual Business Inquiry that covered most sectors of the economy. Starting from 2009, the ARD uses data from the Annual Business Survey, which replaced the Annual Business Inquiry.

The most disaggregated unit in the ARD is a local unit (LU), which is defined as an individual factory in a single location. Often a LU is too small to report the full range of data for the survey. Hence, companies are required to provide their survey data only at the reporting unit (RU) level. An RU is the smallest group of local units on which the full survey data can be collected, and it can consist of several LUs or just one LU. Large companies in the ARD often have several RUs. The microdata used in this chapter are at the RU level.

In terms of the sampling frame, the ARD is a census only of large RUs but not the small and medium ones. For RUs with employment below a certain threshold, only a sample is randomly selected every year. The stratified sampling framework has changed over the years. From 1998 onwards, the employment threshold is set to 250.[2]

[2] For more detailed background information about the ARD, please refer to ONS (2012).

The main variables we use from the ARD are gross value added at market price and net investment. The ONS derives these two variables using the relevant survey data. Gross value added at market price is calculated as the total sales of finished goods and services minus the total costs of inputs used in production. Net investment is constructed as acquisitions less disposals of capital assets. More information on the construction of these two variables is provided in Appendix 2.1. We deflate nominal gross value added at market price in the ARD using the sector-level manufacturing output price deflator from the ONS to obtain real gross value added at market price, i.e. real output (Y). Furthermore, we deflate nominal net investment in the ARD using the sector-level manufacturing investment deflator from the ONS to obtain real investment (I). The base year of both deflators is 2005.

2.3.1.2. Estimating the Capital Stock

The ARD does not contain the RU-level capital stock data. We follow the methodology of Gilhooly (2008) and Gilhooly (2009) to construct the RU-level capital stock using the available information in the ARD. As in Gilhooly (2009), we use the standard Perpetual Inventory Model (PIM) for $t \geq 1$:

$$K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t} \qquad (2.1)$$

where $K_{i,t}$ is the capital stock of RU i in period t, δ is the geometric depreciation rate, and $I_{i,t}$ is investment in period t. As suggested in Gilhooly (2008), we set the depreciation rate δ to be 9.3%, which is used by the ONS in its capital stock estimation.

In order to apply the PIM, we need to estimate a starting capital stock value in the first observation period $K_{i,0}$. Following Gihooly (2009), we use a mix of each RU's total purchases of goods and services and employment number as the basis for allocating a share of the aggregate capital stock published by the ONS to individual RUs. Detailed information on the estimation of $K_{i,0}$ is provided in Appendix 2.2.

2.3.1.3. Summary Statistics

We consider six sectors within the manufacturing industry: engineering and vehicles (**engineering**); manufacture of food, drink and tobacco (**food**); manufacture of textiles and leather (**textiles**); chemicals and pharmaceutical products (**chemicals**); manufacture of metal products (**metal products**); and metal manufacture (**metal manufacture**).[3] The sample period is 1997-2012. The initial sample has 100702 observations on 39248 RUs. We clean the data in four steps. In the first step, we drop the RU-year observations with non-positive or missing output, non-positive or missing capital stock, or missing investment. In the second step, to control for potential outliers, separately for each sector, we pool the observations across years and exclude the observations if the investment rate (i.e. the ratio of current year investment to previous year capital stock), the growth rate of the capital stock, the growth rate of output, or the natural logarithm of the capital stock to output ratio fall in the top and bottom one percentiles of their respective empirical distributions within the sector.[4] In the third step, we discard the RUs with less than five consecutive years of observations. This step is important for estimating

[3] The two manufacturing sectors excluded from our sample are: manufacture of coke and refined petroleum products (petroleum) and other manufacturing (others). For the petroleum sector, the CBI survey results are not available continuously over the sample period.
[4] We use the first difference of the natural logarithm to approximate the growth rate.

dynamic models to explain investment[5], but skews the sample heavily towards the RUs that are large enough to be sampled in each year. In the fourth step, we drop the RUs that had changed sectors during our sample period because we want to focus on the RUs that remained in the same sector over the sample period. The number of observations lost in each of the data cleaning steps is shown in Appendix 2.4.

The resulting sample includes 22967 annual observations on 3307 RUs. The distribution of observations by year for the full sample and each of the six sectors is summarized in Table A2.1 of Appendix 2.5. In Table A2.2 of Appendix 2.5, we report the distribution of observations by the number of consecutive years. In Table A2.3 of Appendix 2.5, we provide the summary statistics of the key variables. Tables A2.4, A2.5, and A2.6 of Appendix 2.5 present each sector's share of total investment, output, and capital stock, respectively, in the full sample.

2.3.1.4. Comparison with Aggregate Trends

The ARD is a census only of large enterprises. For the RUs with employment below a certain threshold, only a sample is randomly drawn each year. Therefore, it is unlikely for a small or medium-sized RU to be surveyed for five consecutive years or more. Because we exclude the RUs with less than five consecutive years of observations, our sample is overrepresented by relatively large RUs. As the investment behavior of large businesses may be considerably different from that of small and medium enterprises, our sample may not be representative of the whole manufacturing industry in the U.K. In this

[5] In later analysis, we will use the Generalized Method of Moments (GMM) method to estimate the dynamic investment model (2.11) in first-differences (please refer to section 2.5.3 for a detailed discussion of the GMM estimation methodology) and employ the second order serial correlation test (please refer to section 2.5.4) to check that the model is correctly specified. According to Arellano and Bond (1991), at least five years of consecutive observations are needed to compute asymptotically efficient second order serial correlation tests.

section, we compare our ARD microdata sample with the published ONS aggregate data for the six manufacturing sectors included in our study. In Table A2.7 of Appendix 2.5, we summarize the share of aggregate manufacturing investment, output and capital stock of the six sectors accounted for by the RUs in the estimation sample.

Figure 2.1 looks at the investment to output ratio (I_t/Y_t), which is a measure of investment rate. The ratio for the ARD microdata sample is computed by dividing the total investment of all the RUs in the sample in year t by the total output of all the RUs in year t. For the aggregate data, the ratio is constructed simply by dividing the aggregate investment of the six sectors in year t by the aggregate output of the six sectors in year t. The investment to output ratio for the aggregate data was generally higher than that for the microdata during most of the sample period. However, both ratios were gently trending downwards over the sample period. There are several possible causes for this decline in manufacturing investment. First, the U.K. manufacturers have faced increased competition from low-wage emerging markets which have a comparative advantage in manufacturing in recent years, especially after China joined the WTO in 2001(Kitson and Michie, 2014). Second, as the U.K. becomes more developed, there has been a structural shift in domestic consumption away from manufactured goods towards services (Kitson and Michie, 2014). Third, the strong pound over the period 1997-2007 made U.K. manufacturing exports less competitive and contributed to the decline in UK manufacturing (Cobham, 2013). During the recent financial crisis, the investment to output ratios for the aggregate data and the microdata experienced falls in 2009 and in 2010, respectively. The fall in the investment to output ratio for our microdata was later than that for aggregate data in the Great Recession. This could be because our microdata sample consists of relatively large RUs, which may have slower capital adjustment speeds than smaller RUs.

As our microdata sample consists of relatively large RUs that are likely to invest more, we would expect the microdata sample as a whole to have a higher investment rate than the ONS aggregate data. However, in Figure 2.1, we find that the investment to output ratio for the microdata sample is lower than the aggregate data. There are three possible reasons for this unexpected observation. First, the data cleaning process described in 2.3.1.3 may distort the investment to output ratio for the resulting microdata sample. To investigate this possibility, we plot the investment to output ratio for the initial sample before data cleaning and the intermediate samples after every data cleaning step in Figures A2.1-A2.4 in Appendix 2.6. As one can see from Figure A2.1, the investment to output ratio for the initial sample is already below that for the aggregate data before we undertake data cleaning. After each sample selection step, the ratio of the microdata sample stays below that of the aggregate data as shown in Figures A2.2-A2.4. Therefore, we do not find evidence that the investment to output ratio for the microdata sample being lower than that for the aggregate data is a result of the sample selection procedures.

Second, the ARD investment data and the ONS aggregate investment data are sourced from two different surveys, which makes them less comparable. The ONS estimates the aggregate investment primarily using the data collected from its Quarterly Survey of Capital Expenditure (QSCE), while the ARD investment data are obtained from the Annual Business Survey. According to Jones et al. (2014), the Annual Business Survey provides more reliable investment data than the QSCE because it has a larger sample and the sampled firms in the Annual Business Survey are more likely to provide investment data from the audited accounts. As a result, Jones et al. (2014) point out that, beginning in 2011, the ONS has started to benchmark the quarterly aggregate investment data collected from the QCSE to the annual aggregate investment data collected from the Annual Business Survey so that annual totals calculated from these two different surveys are consistent. This is likely the reason why the investment to output ratio constructed from the microdata is much closer to that suggested by the aggregate data in the final two years of our sample, as can be seen in Figure 2.1. Indeed the ratio for the microdata has started to lie above that for the aggregate data since 2011, which is consistent with the prediction that the ARD microdata sample as a whole would have a higher investment rate than the ONS aggregate data.

Third, according to the ONS, the ARD dataset may not exactly reproduce National Statistics aggregates. After collecting the microdata, the ONS undertakes complicated data adjustments and benchmarking to produce the aggregate investment and output data. As mentioned earlier, the ONS benchmarks the quarterly investment data collected from the QCSE, which are used to construct its published aggregate investment data, to the annual investment data from the Annual Business Survey so that annual totals calculated from these two surveys are consistent (Jones et al., 2014). In addition, the ONS uses secondary economic evidence such as "labor market and price statistics produced by the ONS, analyses from other government departments, data gathered by trade associations and observations by industry experts" to adjust the investment and output data for each of the112 industries in order to obtain consistent measures of GDP using the production, income and expenditure approaches and present a credible economic picture (ONS, 2016). In Figure 2.1, we simply sum up the investment and output of all the RUs in the microdata sample to produce our aggregates without any adjustment and benchmarking.

Figure 2.2 compares the capital stock to output ratio (K_t/Y_t). The ratio for the microdata sample is estimated by dividing the total capital stock of all the RUs in our sample in year t by the total output of all the RUs in year t. For the aggregate data, the ratio is computed by dividing the aggregate capital stock of the six sectors in year t by the aggregate output of the six sectors in year t. The aggregate capital stock data for the six sectors are only available until 2009. The capital stock to output ratio for the aggregate data was higher than that of the microdata over 1997-2009. Both ratios had relatively flat trends. For the microdata, the ratio remained in the range of 0.9-1.4. For the aggregate data, the ratio stayed at a level of around 2.

Figure 2.3 illustrates the investment to capital stock ratio (I_t/K_{t-1}). For the microdata sample, the ratio is calculated by dividing the sum of investment for all the RUs in our estimation sample in year t by the sum of capital stock for all the RUs in year $t-1$. For the aggregate data, the ratio is computed by dividing the aggregate investment of the six sectors in year t by the aggregate capital stock of the six sectors in year $t-1$. In Figure 2.3, the investment to capital stock ratio for the microdata and that for the ONS aggregate data exhibited similar trends. From 1998 to 2003, both had downward trends. Between 2004-2010, the ratios for both the microdata and the aggregate data remained more or less constant. Contrary to the observation for the investment to output ratio series in Figure 2.1, the investment to capital stock ratio for the microdata was consistently higher than that for the ONS aggregate data over the sample period. However, it should be noted that the investment to capital stock ratio for the microdata and that for the aggregate data are not directly comparable because there is no measure of the capital stock in the ARD and the RU-level capital stock data are imputed using the Perpetual Inventory Model as described in section 2.3.1.2.

2.3.2. Sector-level Relative Price of Investment Goods Data

The relative price of manufacturing investment goods is calculated as the ratio of the price of manufacturing investment goods (manufacturing investment implicit price deflator) to the price of manufacturing output goods (manufacturing output implicit price deflator). A fall in the relative price of investment goods is likely to raise the desired capital stock.[6] Figure 2.4A depicts the relative price of investment goods for the six manufacturing sectors. Assuming that the RUs in the same sector face the same relative price of investment goods, we match the sector-level relative price of investment goods data from the ONS with the RU-level data from the ARD.

The base year for both the investment and output deflators is 2005. Therefore, the relative price is one in 2005 for all sectors by construction. For all sectors except the food sector, the relative price series was relatively flat at around 1.00 over the sample period. For the food sector, the relatively price rose from 1.00 in 2005 to a peak of 1.71 in 2010, an increase of about 70%. This increase in the relative price was mainly due to an increase in the price of investment goods in the food sector between 2005-2010 as depicted in Figure 2.4B.

2.3.3. Sector-level CBI Industrial Trends Survey Data

[6] According to equation (2.2) in section 2.4, the desired ratio of capital stock to output is negatively related to the real user cost of capital. Based on equation (2.4) in the same section, the relative price of investment goods is a component of the real user cost of capital.

Business surveys ask firms to assess the current business situation and forecast the short-term trends. They can generate valuable information that is otherwise not available from the ONS, and thereby help us understand the trends in manufacturing investment. Started in 1958, the CBI Industrial Trends Survey is the longest running private sector business survey in the U.K. The survey regularly asks a sample of about 400 manufacturing companies in the U.K., and the response of each company is weighted based on its sector/employment size group's share in total U.K. manufacturing output. The CBI disaggregates the Industrial Trends Survey results by sectors within the manufacturing industry and publishes the results every January (Q1), April (Q2), July (Q3), and October (Q4).[7] We focus on six survey questions directly related to important factors affecting corporate investment decisions. Most of the survey results are presented in the form of a balance statistic, which is the difference between the percentage responding in the positive (e.g., "up" or "more") and the percentage reporting in the negative (e.g., "down" or "less"). The precise wording of each question and further information on the construction of the data series are presented in Appendix 2.7.

Question 1 asks firms whether they are more or less optimistic about the business prospects in their industry than three months ago (***BUSOPT***) (Figure 2.5). This is one of the most widely publicized survey questions in the media. For the chemicals, engineering, and metal products sectors, the balance statistic was at the series low in late 2008 or early 2009 after the collapse of Lehman Brothers. For the textiles sector, the business optimism series was at a local low of -69% in 2009Q1, but this was still higher

[7] The survey results are directly available for five sectors: food, textiles, chemicals, metal products, and metal manufacture. The CBI does not directly report the results for the engineering sector and the survey results for the engineering and allied industries sector are the weighted average of the results from the engineering sector and the metal products sector. Using the weights provided by the CBI, we are able to derive the results for the engineering sector.

than its series low of -75% in 1998Q4. For the food sector, there was relatively little movement in the balance statistic over the sample period.

Question 3 concerns firms' investment intentions for the next year relative to the past year. In Figure 2.6, the capital expenditure intentions for buildings (***CAPEX_B***) series experienced a large fall for all sectors except for the engineering sector in 2008 and 2009 during the recent financial crisis. In particular, for the chemicals, metal products and textiles sectors, the balance statistic reached the series low in early 2009. For the engineering sector, we observe relatively little variation in the balance statistic over the sample period.

Figure 2.7 shows the capital expenditure intentions for plant and machinery balance statistic series (***CAPEX_PM***). For all sectors, the balance statistic fell to the series low in 2008 and 2009 during the credit crunch. For the chemicals, metal manufacture, metal products, and textiles sectors, the balance statistic experienced a much sharper fall in the recent crisis period than in the previous downturns.

Question 4 asks firms whether their present output is lower than what they can produce at full capacity (***LOWCAP***) (Figure 2.8). Low capacity utilization is likely to be associated with low investment spending because firms producing below their existing capacity tend to have less incentive to expand than those suffering capacity constraints. For all sectors, the proportion of firms reporting working below capacity rose to a high level in 2009. The increase was especially pronounced for the engineering and textiles sectors. For the engineering sector, the proportion arrived at a peak of 91% in 2009Q4, the highest since 1997Q1. For the textiles sector, the proportion reached the series peak of 86% in 2009Q1. After 2009, the percentage of firms working below capacity gradually decreased for all sectors except for the metal manufacture sector. For the metal manufacturing sector, the proportion reached 100% in 2009Q2, and stayed at a high level of around 80%-90% after 2009 with the brief exception of two quarters in 2011Q1 and 2011Q2.

Question 7 studies the short-term trends in the volume total new orders. Figure 2.9 presents the balance statistic series for the trend in the volume of total new orders over the previous three months balance series (***ORDER_P***). For the chemicals, metal manufacture, metal products, and textiles sectors, the past orders series arrived at the series low in 2009 after the bankruptcy of Lehman Brothers. For the metal manufacture sector, there was a large decline in the balance statistic in 2008 and 2009. The series arrived a local trough of -79% in 2009Q3, which was only slightly higher than the series low of -80% in 1998Q3. For the food sector, there was little variation in the balance statistic over the sample period.

Figure 2.10 presents the balance statistic series for the expected trend in the volume of total new orders over the next three months (***ORDER_N***). For all sectors except the chemicals and metal manufacture sectors, the balance statistic fell to the series low in 2009. For the chemicals sector, there was a fall in the balance statistic from 23% in 2008Q3 to -29% in 2009Q2. However, this fall was much less dramatic than the fall in 2011 when the euro zone sovereign debt crisis intensified. The series arrived at its lowest point of -67% in 2011Q4. For the metal manufacture sector, the balance was at a local low of -70% in 2009Q1, which was still higher than the trough in 1998Q3 (-80%).

Question 8 is related to the short-term trends in the volume of output. Figure 2.11 illustrates the balance statistic for the trend in output over the past three months (***OUTPUT_P***). For all sectors, the past output series experienced a large decline during the peak of the recent financial crisis. For the metal products sector, the series reached a local trough of -60% in 2009Q3, which was still higher than the series low of -68% in 1999Q1. For all the other five sectors, the series reached its low point around early 2009.

The balance statistic series for the expected trend over the next three months for the volume of output (***OUTPUT_N***) is shown in Figure 2.12. For all sectors except the chemicals sectors, the balance statistic reached the series low in 2009. For the chemicals sector, the balance declined from 20% in 2007Q2 to -31% in 2009Q2. This was much smaller than the fall in 2011 during the euro zone debt crisis. The series fell from 35% in 2011Q2 to -68% in 2011Q4.

Question 16C tries to identify factors limiting corporate investment over the next twelve months.[8] First, we illustrate the trends in the proportion of firms reporting "shortage of internal finance" (***INTFIN***) as a limiting factor for investment (Figure 2.13). For the engineering, metal products, and textiles sectors, there was relatively little variation in the percentage over the sample period. For the chemicals sector, the series peak of 61% was reached in 2007Q1, at a very early stage of the crisis. For the food sector, the proportion rose from 2% in 2006Q4 to a local peak of 41% in 2007Q4. In 2008Q4, after the bankruptcy of Lehman Brothers, the proportion was at 38%. The series peak of 52% was reached in 2010Q3. For the metal manufacture sector, the proportion

[8] Firms can cite more than one limiting factor.

was at a record low of 0% in 2007Q4. It rose rapidly for six consecutive quarters, arriving at the series peak of 72% in 2009Q2.

Next, we investigate the trends in the percentage of firms citing “inability to raise external finance” (***EXTFIN***) as a limiting factor for investment (Figure 2.14). For the metal products and textiles sectors, we observe both low levels and relatively little variation in the percentage over the sample period. For the food sector, the percentage reached a local peak of 25% in 2009Q2. However, this was still 11% lower than the series peak of 36% in 2005Q1. For the chemicals, engineering, and metal manufacture sectors, the percentage rose to the series peak in 2008-2009.

Finally, we analyze the trends in the proportion of firms citing “uncertainty about demand” (***UNCERT***) as a factor constraining investment plans (Figure 2.15). For the chemicals sector, the proportion increased quickly from 13% in 2008Q1 to the series peak of 86% in 2009Q1. For the other five sectors, the proportion did not rise to a significantly higher level during the crisis period compared with the pre-crisis period.

As one can observe, the trends in the balance statistic, which is defined as the percentage of firms answering in the positive (e.g., “up” or “more”) minus the percentage of firms answering in the negative (e.g., “down” or “less”), in Figures 2.5-2.7 and 2.9-2.12 and the trends in the percentage of firms reporting a certain answer in Figures 2.8 and 2.13-2.15 in the crisis period rarely stand out as being very different from the rest of the sample period for these manufacturing sectors. This is broadly in line with the relatively flat trend for the aggregate manufacturing investment series over the crisis period in Figures 2.1 and 2.3. We assume that the proportion of firms in a sector that report being more optimistic about the business situation, intending to authorize more investment on buildings or plant and machinery, working below capacity, an upward trend for past orders or expected future orders, an upward trend for past output or expected future output, or investment being limiting by financial constraints or demand uncertainty is positively related with the probability that an individual RU in the sector will be experiencing these conditions, and match the sector-level CBI survey data with the RU-level ARD data.

2.4. Methodology

In the empirical investment literature, the error correction specification was first used in Bean (1981) to model aggregate manufacturing investment. Subsequently, Bond et al. (2003), Bloom et al. (2007), Guariglia (2008) and many others employ the error correction model to study firm-level investment data. In this section, we follow the methodology of Bean (1981) and Bond et al. (2003) to derive an error correction model for the rate of investment, which can be estimated using the microdata obtained from the ARD.

Based on the neoclassical investment model proposed in Jorgenson (1963), in the absence of any adjustment costs or frictions, the desired capital stock of a profit-maximizing RU i with a constant returns to scale, constant elasticity of substitution production function at time t can be expressed as:

$$k_{i,t} = y_{i,t} - \sigma r_{i,t} + \lambda_i \quad (2.2)$$

where $k_{i,t}$ is the natural logarithm of the desired capital stock, $y_{i,t}$ is the natural logarithm of output, $r_{i,t}$ is the logarithm of the real user cost of capital, σ is the elasticity of substitution between labour and capital in the production function, and λ_i is some RU-specific constant.

As Bond et al. (2003) point out, in the presence of adjustment costs or frictions, RU i will not immediately adjust to its target level of capital stock, which is assumed to be proportional to the frictionless optimum given in (2.2). To account for this dynamic process of capital stock adjustment, we follow Bond et al. (2003) and adopt an autoregressive-distributed lag (ADL) specification with first order lag:

$$k_{i,t} = \rho_0 + \rho_1 k_{i,t-1} + \rho_2 y_{i,t} + \rho_3 y_{i,t-1} + \rho_4 r_{i,t} + \rho_5 r_{i,t-1} + \epsilon_{i,t} \quad (2.3)$$

where $\epsilon_{i,t}$ is an error term.

In their seminal work, Hall and Jorgenson (1967) show that the real user cost of capital $R_{i,t}$ is related to the real interest rate $c_{i,t}$, the depreciation rate δ_i, the relative price of investment goods $P_{i,t}$, the corporate income tax rate $T_{i,t}$, the present value of current and expected future tax savings due to investment allowances $Z_{i,t}$, and the expected rate of change in the relative price of investment goods $\pi_{i,t}$. The full Hall-Jorgenson equation is:

$$R_{i,t} = P_{i,t}(c_{i,t} + \delta_i - \pi_{i,t})\frac{1 - Z_{i,t}}{1 - T_{i,t}} \quad (2.4)$$

It is however challenging to measure most components of this expression for the real user cost of capital. For simplicity, we assume that the natural logarithms of $(c_{i,t} + \delta_i - \pi_{i,t})$ and $(1 - Z_{i,t})/(1 - T_{i,t})$ are absorbed into the sector-specific effects (sector dummies) s_j, the time-specific effects (year dummies) h_t, and the RU-specific effects η_i. Hence, we use only the sector-level relative price of investment goods $P_{j,t}$ and rewrite (2.3) as:

$$k_{i,t} = \alpha_0 + \alpha_1 k_{i,t-1} + \alpha_2 y_{i,t} + \alpha_3 y_{i,t-1} + \alpha_4 p_{j,t} + \alpha_5 p_{j,t-1} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.5)$$

where $p_{j,t}$ is the natural logarithm of the relative price of investment goods. By re-parameterizing (2.5), we obtain:

$$\Delta k_{i,t} = \alpha_0 + \alpha_2 \Delta y_{i,t} + \alpha_4 \Delta p_{j,t} + (\alpha_1 - 1) k_{i,t-1} + (\alpha_2 + \alpha_3) y_{i,t-1} + (\alpha_4 + \alpha_5) p_{j,t-1} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.6)$$

Equation (2.2) implies that the long-run elasticity of the capital stock with respect to output is one. Following Bond et al. (2003) and Guariglia (2008), we impose the restriction that $(\alpha_2 + \alpha_3)/(1 - \alpha_1) = 1$ and nest the steady state relationship (2.2) within equation (2.6) to derive a first order dynamic error correction model:

$$\Delta k_{i,t} = \alpha_0 + \alpha_2 \Delta y_{i,t} + \alpha_4 \Delta p_{j,t} + (\alpha_1 - 1)(k_{i,t-1} - y_{i,t-1}) + (\alpha_4 + \alpha_5) p_{j,t-1} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.7)$$

The error correction specification has the advantage of capturing both short-run (first-differenced terms) and long-run (level terms) investment dynamics. The error correction term $(k_{i,t-1} - y_{i,t-1})$ reflects the deviation of the capital stock from its long-term desired path. If $(k_{i,t-1} - y_{i,t-1})$ is positive (negative), the capital stock was above (below) its equilibrium in the previous year and, all else equal, is expected to adjust downwards (upwards) in the current year. Hence, the coefficient on the error correction term represents the adjustment speed of the capital stock towards its long-run equilibrium and is expected to have a negative sign.

Finally, as in Bond et al. (2003), we use the approximation $\Delta k_{i,t} \approx I_{i,t}/K_{i,t-1} - \delta_i$, where δ_i denotes the RU-specific rate of depreciation, and derive a first order dynamic specification for the investment rate $I_{i,t}/K_{i,t-1}$ from (2.7):

$$I_{i,t}/K_{i,t-1} = \gamma_0 + \gamma_1 \Delta y_{i,t} + \gamma_2 \Delta p_{j,t} + \gamma_3 (k_{i,t-1} - y_{i,t-1}) + \gamma_4 p_{j,t-1} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.8)$$

The depreciation rate δ_i is subsumed in the time-invariant unobserved RU-specific effect η_i.

By increasing the autoregressive-distributed lag length in equation (2.3) to two, we obtain an investment model with richer dynamics:

$$k_{i,t} = \pi_0 + \pi_1 k_{i,t-1} + \pi_2 k_{i,t-2} + \pi_3 y_{i,t} + \pi_4 y_{i,t-1} + \pi_5 y_{i,t-2} + \pi_6 p_{j,t} + \pi_7 p_{j,t-1} + \pi_8 p_{j,t-1} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.9)$$

Re-parameterizing (2.9) and imposing the restriction that the long-run elasticity of the capital stock with respect to output is one (i.e., $(\pi_3 + \pi_4 + \pi_5)/(1 - \pi_1 - \pi_2) = 1)$), we obtain:

$$\Delta k_{i,t} = \pi_0 + (\pi_1 - 1)\Delta k_{i,t-1} + \pi_3 \Delta y_{i,t} + (\pi_3 + \pi_4)\Delta y_{i,t-1} + \pi_6 \Delta p_{j,t} + (\pi_6 + \pi_7)\Delta p_{j,t-1} + (\pi_1 + \pi_2 - 1)\left(k_{i,t-2} - y_{i,t-2}\right) + (\pi_6 + \pi_7 + \pi_8)\, p_{j,t-2} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.10)$$

We can then approximate the growth rate of the capital stock using the investment data and derive the following second order dynamic investment model from equation (2.10):

$$I_{i,t}/K_{i,t-1} = \phi_0 + \phi_1 I_{i,t-1}/K_{i,t-2} + \phi_2 \Delta y_{i,t} + \phi_3 \Delta y_{i,t-1} + \phi_4 \Delta p_{j,t} + \phi_5 \Delta p_{j,t-1} + \phi_6 \left(k_{i,t-2} - y_{i,t-2}\right) + \phi_7 p_{j,t-2} + s_j + h_t + \eta_i + \epsilon_{i,t} \quad (2.11)$$

2.5. Results

2.5.1. Time Series Properties

Following Bond et al. (2003), we first examine the time series properties of the variables used in our investment models. If $k_{i,t}$ and $y_{i,t,}$ are both nonstationary $I(1)$ variables and $p_{i,t}$ and all other level-based long-run components are stationary $I(0)$ variables, our specification implies that $k_{i,t}$ and $y_{i,t}$ are cointegrated and the error correction term $(k_{i,t} - y_{i,t})$ is stationary. We test the unit root properties of $k_{i,t}$, $y_{i,t}$, and $(k_{i,t} - y_{i,t})$ through the ordinary least squares (OLS) estimation of the first-order autoregressive (AR(1)) models of these variables. The results are presented in Table 2.1A. For reference, the fixed-effects (FE) estimates are also reported. Although the unit root hypothesis is formally rejected for both $k_{i,t}$ and $y_{i,t}$, the OLS coefficient estimates of $k_{i,t-1}$ and $y_{i,t-1}$ are close to one. Therefore, it is appropriate to treat $k_{i,t}$ and $y_{i,t}$ as near unit root variables. The unit root hypothesis is rejected more strongly for $(k_{i,t} - y_{i,t})$ and the estimated coefficient on the lagged value is well below one, which provides evidence supporting the stationarity of the error correction term. In addition, we conduct the unit root test on the remaining variables $\Delta k_{i,t}$, $\Delta y_{i,t}$, and $I_{i,t}/K_{i,t-1}$. The results are also reported in Table 2.1A. The unit root hypothesis is rejected for all three variables. Hence, we regard $\Delta k_{i,t}$, $\Delta y_{i,t}$, and $I_{i,t}/K_{i,t-1}$ as stationary $I(0)$ series.

In equations (2.7), (2.8), (2.10), and (2.11), we restrict the long-run elasticity of the capital stock with respect to output to be one. To investigate whether this is a reasonable assumption, we estimate the static OLS regression of $k_{i,t}$ on $y_{i,t}$. The results are shown in Table 2.1B, and the FE estimates are also presented for comparison. The OLS point estimate of the coefficient on $y_{i,t}$ is 0.933 with a small standard error. As a robustness check on our main results, we estimate models that impose 0.933 as the long-run elasticity of the capital stock with respect to output in section 2.5.8.

2.5.2. OLS and FE Estimates of Baseline Models

In this section, we proceed to estimate our baseline specifications using OLS and FE. We first estimate the investment equations with $I_{i,t}/K_{i,t-1}$ as the dependent variable. Table 2.2 presents both the OLS (column 1) and FE (column 2) estimates of the first order dynamic equation (2.8). For the OLS estimation in column 1, all the variables are significant at the 5% level and have the expected signs. The coefficient on the output growth term $\Delta y_{i,t}$ is positive, suggesting that the current investment rate is positively associated with current output growth. The relative price growth term $\Delta p_{i,t}$ has the expected negative sign, indicating that an increase in the relative price of investment goods affects the investment rate negatively. The coefficient on the error correction term is -0.040, which implies that 4.0% of the long-term disequilibrium in the capital stock is corrected each year. The relative price level term $p_{j,t-1}$ has a negative coefficient, indicating a negative long-run effect of the relative price of investment goods on the capital stock to output ratio.

Because the unobserved time-invariant RU-specific effect η_i is potentially correlated with the observed explanatory variables in our investment equation, the OLS estimator may suffer from omitted variable bias and therefore be biased and inconsistent. The FE estimation performs a within transformation by demeaning each variable in the investment equation. The transformation removes the RU-specific effect η_i and thus controls for the omitted variable problem. In column 2, the FE coefficient estimates of all the variables remain significant at the 5% level. The coefficient on the error correction term in column 2 is -0.079, higher in magnitude than that in column 1. Therefore, the FE estimation suggests a faster adjustment speed of the capital stock to its long-run steady state than the OLS estimation.

Table 2.2 also reports the OLS (column 3) and FE (column 4) estimates of the second order dynamic equation (2.11). In both columns 3 and 4, the first lag of the dependent variable $I_{i,t-1}/K_{i,t-2}$, the longer lag of the output growth $\Delta y_{i,t-1}$, and the longer lag of the relative price growth $\Delta p_{j,t-1}$ are all statistically significant at 1%. In both columns, the coefficient on the error correction term $(k_{i,t-2} - y_{i,t-2})$ is significant and negative.

In addition, we estimate the investment equations with $\Delta k_{i,t}$ as the dependent variable. In Table 2.3, we report the OLS and the FE estimates of equation (2.7) (columns 1 and 2) and equation (2.10) (columns 3 and 4). By comparing the results in Table 2.2 and Table 2.3, one can observe that the coefficient estimates of equation (2.7) are similar to those of equation (2.8), and the point estimates of equation (2.10) are close to those of equation (2.11). Because the second order dynamic model (2.11) includes the investment variable $I_{i,t}$ which is directly measured in this data, and provides richer information than the first order dynamic model, we focus on this specification for later analysis.

2.5.3. GMM Estimators

2.5.3.1. OLS and FE Estimation Biases

For the dynamic investment models (2.7), (2.8), (2.10), and (2.11) with unobserved individual effects, the OLS and the FE estimates of the coefficient on the lagged dependent variable are expected to be biased. To illustrate the potential biases in the OLS and the FE estimators, consider the following dynamic model:

$$z_{i,t} = \phi + \rho z_{i,t-1} + \psi' X_{i,t} + r_i + v_{i,t} \quad for\ i = 1, \dots, N, and\ t = 2, \dots, T \quad (2.12)$$

where $|\rho| < 1$, ϕ is a constant, $X_{i,t}$ is a vector of explanatory variables, r_i is an unobserved individual-specific effect that is fixed over time, and $v_{i,t}$ is an idiosyncratic shock that varies across time and individuals. The two error components r_i and $v_{i,t}$ satisfy:

$$E(r_i) = E(v_{i,t}) = E(r_i v_{i,t}) = 0 \quad for\ i = 1, \dots, N, and\ t = 2, \dots, T \quad (2.13)$$

Because the lagged dependent variable $z_{i,t-1}$ is positively correlated with r_i by construction, it can be shown that the OLS estimate of ρ in equation (2.12) is inconsistent and biased upwards (see Hsiao 1986).

The FE estimator does not solve this bias problem in panels with a small number of time periods (T). The FE estimation eliminates both the constant term and the time-invariant fixed effects r_i by demeaning the variables and transforming (2.12) into:

$$\tilde{z}_{i,t} = \rho\tilde{z}_{i,t-1} + \psi'\tilde{X}_{i,t} + \tilde{v}_{i,t} \quad for\ i = 1, \dots, N, and\ t = 2, \dots, T \quad (2.14)$$

where $\tilde{z}_{i,t} = z_{i,t} - \frac{1}{T-1}(z_{i,2} + \ \dots\ z_{i,T})$, $\tilde{z}_{i,t-1} = z_{i,t-1} - \frac{1}{T-1}(z_{i,1} + \ \dots\ z_{i,T-1})$, $\tilde{X}_{i,t} = X_{i,t} - \frac{1}{T-1}(X_{i,2} + \ \dots\ X_{i,T})$, and $\tilde{v}_{i,t} = v_{i,t} - \frac{1}{T-1}(v_{i,2} + \ \dots\ v_{i,T})$. Since $z_{i,t-1}$ is negatively correlated with $-\frac{1}{T-1}v_{i,t-1}$ and $v_{i,t}$ is negatively correlated with $-\frac{1}{T-1}z_{i,t}$, we can infer that $E(\tilde{z}_{i,t-1}\tilde{v}_{i,t}) < 0$ and is of order $\frac{1}{T-1}$. Consequently, the FE estimator gives a downward biased and inconsistent estimate of ρ unless T is large. Nickell (1981) formally derives the expression for the asymptotic bias and demonstrates that the bias tends to zero as T approaches infinity.

Both the coefficient on $\Delta k_{i,t-1}$, $(\pi_1 - 1)$, in equation (2.10) and the coefficient on $I_{i,t-1}/K_{i,t-2}$, ϕ_1, in equation (2.11) depend on the coefficient on the lagged dependent variable $k_{i,t-1}$, π_1, in the underlying ADL specification (2.9). As the OLS estimate of π_1 is likely to have an upward bias while the FE estimate of π_1 is likely to have a downward bias, we would expect that the OLS estimates of $(\pi_1 - 1)$ and ϕ_1 to be biased upwards and the FE estimates of $(\pi_1 - 1)$ and ϕ_1 to be biased downwards. Consistent with this expectation, in Table 2.2, we obtain a positive coefficient on $I_{i,t-1}/K_{i,t-2}$ using the OLS estimator in column 3, which is higher than the negative coefficient on $I_{i,t-1}/K_{i,t-2}$ obtained using the FE estimator in column 4. Similarly, in Table 2.3, the positive OLS coefficient estimate of $\Delta k_{i,t-1}$ in column 3 is higher than the negative FE coefficient estimate of $\Delta k_{i,t-1}$ in column 4.

In addition, both the coefficient on the error correction term in equation (2.7), $(\alpha_1 - 1)$, and the coefficient on the error correction term in equation (2.8), γ_3, depend on coefficient on the lagged dependent variable in the underlying ADL specification (2.5), α_1. Because the OLS estimate of α_1 is likely to have an upward bias while the FE estimate of α_1 is likely to have a downward bias, we would expect the OLS estimate of $(\alpha_1 - 1)$ to lie above the FE estimate of $(\alpha_1 - 1)$ and the OLS estimate of γ_3 to lie above the FE estimate of γ_3. Similarly, both the coefficient on the error correction term in equation (2.10), $(\pi_1 + \pi_2 - 1)$, and the coefficient on the error correction term in equation (2.11), ϕ_6, depend on the sum of the coefficients on the lagged dependent variables in the underlying ADL specification (2.9), $(\pi_1 + \pi_2)$. Therefore, the OLS estimates of $(\pi_1 + \pi_2 - 1)$ and ϕ_6 are expected to be biased upwards while the FE estimates of $(\pi_1 + \pi_2 - 1)$ and ϕ_6 are expected to be biased downwards. In Tables 2.2 and 2.3, one can observe that the OLS estimate of the error correction coefficient is higher (i.e. lower in absolute value) than the corresponding FE estimate in each specification.

2.5.3.2. First-Differenced GMM Estimator

To avoid these biases associated with the OLS and the FE estimators, Arellano and Bond (1991) propose the first-differenced generalized method of moments (GMM) estimator for dynamic models in panels with a small number of time period observations. We will review their estimation technique below.

First, they remove the constant and the individual-specific heterogeneity r_i by first-differencing equation (2.12):

$$\Delta z_{i,t} = \rho \Delta z_{i,t-1} + \psi' \Delta X_{i,t} + \Delta v_{i,t} \quad (2.15)$$

In addition to (2.13), they also assume that the idiosyncratic errors are not serially correlated:

$$E(v_{i,s} v_{i,t}) = 0 \; for \; s \neq t \quad (2.16)$$

and the initial conditions are predetermined with respect to the idiosyncratic shocks:

$$E(z_{i,1} v_{i,t}) = 0 \; for \; t = 2, \dots, T \quad (2.17)$$

As a result, they obtain $0.5(T-1)(T-2)$ linear moment conditions for the equations in first-differences (2.15):

$$E(z_{i,t-s} \Delta v_{i,t}) = 0 \; for \; t = 3, \dots, T \; and \; s \geq 2 \quad (2.18)$$

By exploiting these orthogonality conditions, Arellano and Bond (1991) develop the first-differenced GMM estimator which uses the lagged observations on $z_{i,t}$ dated $t-2$ and earlier as instruments for the first-differenced equations. The first-differenced GMM estimation is designed for dynamic panel data models when T is small and N is large.

2.5.3.3. System GMM Estimator

Blundell and Bond (1998) argue that the first-differenced GMM estimator may suffer from large finite sample biases if these instruments are weak. Based on simulation results, they report that the first-differenced GMM estimate of the coefficient on the lagged dependent variable may have a large downward bias in these cases. To address this problem, Blundell and Bond (1998) incorporate additional moment conditions and construct the system GMM estimator. We will briefly explain their methodology as follows.

Besides (2.13), (2.16), and (2.17), they further assume that:

$$E\left(\Delta z_{i,2} r_i\right) = 0 \; for \; i = 1, \dots N \quad (2.19)$$

which imposes a mean stationary restriction on the initial observations $z_{i,1}$, and that the first-differences of the explanatory variables $\Delta X_{i,t}$ are also uncorrelated with r_i. As a result, they obtain $(T-2)$ linear moment conditions for the equations in levels (2.12):

$$E\left(\Delta z_{i,t-1}(r_i + v_{i,t})\right) = 0 \; for \; i = 1, \dots, N \; and \; t = 3, \dots, T \quad (2.20)$$

The system GMM estimator proposed by Blundell and Bond (1998) combines both sets of moment conditions (2.18) and (2.20). It augments the first-differenced GMM estimator by including the equations in levels (2.12) with $\Delta z_{i,t-1}$ as instruments, in addition to the equations in first-differences (2.15) with lagged $z_{i,t}$ dated $t-2$ and earlier as instruments.

2.5.3.4. Explanatory Variables

If an explanatory variable $x_{i,t}$ in $X_{i,t}$ is strictly exogenous, i.e., uncorrelated with both the individual effects and the idiosyncratic shocks from all time periods:

$$E(x_{i,t}r_i) = 0 \; and \; E(x_{i,t}v_{i,s}) = 0 \; for \; all \; s,t \quad (2.21)$$

then $x_{i,t}$ can be instrumented by itself, both in the equations in levels and in the equations in first-differences.

If the explanatory variable $x_{i,t}$ is endogenous, different sets of orthogonality conditions can be used, depending on the form of the correlation between $x_{i,t}$ and the error components r_i and $v_{i,s}$. Suppose that $x_{i,t}$ is correlated with the individual effects and correlated with current but not with future values of the idiosyncratic shocks:

$$E(x_{i,t}r_i) \neq 0 \; and \; E(x_{i,t}v_{i,s}) = 0 \; for \; t < s \quad (2.22)$$

These assumptions imply the following linear moment conditions for the first-differenced equations (2.15) in addition to the moment conditions (2.18):

$$E(x_{i,t-s}\Delta v_{i,t}) = 0 \; for \; t = 3, \dots, T \; and \; s \geq 2 \quad (2.23)$$

In addition, if $\Delta x_{i,t}$ is also uncorrelated with the time-invariant individual characteristics r_i:

$$E(\Delta x_{i,t} r_i) = 0 \; for \; i = 1, \dots, N, and \; t = 2, \dots, T \quad (2.24)$$

then the following moment conditions can be derived for the levels equations (2.12) in addition to the moment conditions (2.20):

$$E(\Delta x_{i,t-1}(r_i + v_{i,t})) = 0 \; for \; i = 1, \dots, N, and \; t = 2, \dots, T \quad (2.25)$$

2.5.4. GMM Estimates of the Baseline Model

In Table 2.4, we proceed to apply these GMM methods to estimate the baseline investment equation (2.11) and compare the results with the OLS and the FE estimates in Table 2.2. As we have discussed in section 2.5.3.1, the OLS estimate of the coefficient on the error correction term ϕ_6 is likely to have an upward bias while the FE estimate of ϕ_6 is likely to have a downward bias, a consistent GMM estimate of ϕ_6 is expected to lie in the range between these two estimates.

We rely on three specification tests to assess the validity of the GMM instruments. First, we use the Hansen (1982) test of over-identifying restrictions. The test statistic has an asymptotic Chi-squared distribution under the null hypothesis that the instruments are jointly valid. Anderson and Sorenson (1996), Bowsher (2002), and Roodman (2009a) point out that having too many instruments weakens the power of the Hansen test and may lead to high p-values close to one. Second, we employ the difference-in-Hansen test of the exogeneity of the instruments used in the levels equations in the system GMM estimation. The test static is asymptotically Chi-squared distributed under the null hypothesis that the additional moment conditions used in the levels equations are valid. Last, we employ the Arellano and Bond (1991) tests of first order serial correlation ($m1$ test) and second order serial correlation ($m2$ test) in the first-differenced residuals $\Delta\epsilon_{i,t}$. Both test statistics are asymptotically distributed as $N(0,1)$ under the null hypothesis of no such serial correlation in $\Delta\epsilon_{i,t}$. The validity of the GMM instruments requires no first order serial correlation in the idiosyncratic errors $\epsilon_{i,t}$, which implies that $\Delta\epsilon_{i,t}$ and $\Delta\epsilon_{i,t-1}$ are expected to be negatively correlated ($m1$ test rejected) while $\Delta\epsilon_{i,t}$ and $\Delta\epsilon_{i,t-2}$ are expected to be uncorrelated ($m2$ test not rejected).

In column 1 of Table 2.4, we estimate the investment equation (2.11) using the first-differenced GMM estimator.[9] We treat the capital stock and output as endogenous and use the lagged values of $k_{i,t}$ and $y_{i,t}$ dated $t-2$, $t-3$, and $t-4$ as instruments for the equations in first-differences. We regard the relative price of investment goods as strictly exogenous because it is unlikely that the sector-level relative price of investment goods is correlated with the RU-level idiosyncratic shocks. Therefore, the first-differences $\Delta p_{j,t}$, $\Delta p_{j,t-1}$, and the lagged level $p_{j,t-2}$ are instrumented by themselves in the first-differenced equations. The exogeneity of the instruments is not rejected by the Hansen test. The $m1$ test rejects the null hypothesis of no first-order serial correlation in the first-differenced residuals and the $m2$ test does not reject the null hypothesis of no second-order serial correlation in the first-differenced errors. The autocorrelation test results are consistent with the absence of serial correlation in the idiosyncratic errors $\epsilon_{i,t}$. However,

[9] GMM estimation in this chapter is done using the xtabond2 command in Stata (see Roodman 2009b). Two-step GMM estimates are reported, together with standard errors that are asymptotically robust to heteroscedasticity and autocorrelation, and finite-sample corrected using the method proposed by Windmeijer (2005).

the estimated coefficient on the error correction term is -0.084, close to the likely downward biased FE estimate of -0.092 in column 4 of Table 2.2. Blundell and Bond (1998) use simulations to show that the first-differenced GMM estimates of autoregressive parameters will be biased in the direction of the fixed effects estimates if the lagged levels are weak instruments for the variables in first-differences. To avoid the potential weak instruments problem, we apply the system GMM in subsequent estimation.

In column 2, we report the system GMM estimates. The instrument set for the equations in first-differences remains the same as that in column 1. We further assume that both $\Delta k_{i,t-1}$ and $\Delta y_{i,t-1}$ are uncorrelated with the error terms in the levels equations $(\eta_i + v_{i,t})$, and use the lagged values of $\Delta k_{i,t}$ and $\Delta y_{i,t}$ dated $t-1$ as instruments for the levels equations. $\Delta p_{j,t}$, $\Delta p_{j,t-1}$, and $p_{j,t-2}$ are treated as strictly exogenous and uncorrelated with η_i, and are instrumented by themselves in the levels equations. The estimated coefficient of the error correction term is -0.068, which lies in the middle of the FE and the OLS estimates. However, the overall validity of the instruments is rejected by the Hansen test. In addition, the validity of the instruments used in the levels equations is strongly rejected by the difference-in-Hansen test.

In column 3, we modify the instrument set used for the levels equations in column 2. $\Delta p_{j,t}$, $\Delta p_{j,t-1}$, and $p_{j,t-2}$ continue to be instrumented by themselves in the levels equations. However, we only assume that $\Delta y_{i,t-1}$ are uncorrelated with the error terms in the levels equations $(\eta_i + v_{i,t})$, and therefore use $\Delta y_{i,t-1}$ but not $\Delta k_{i,t-1}$ as instruments for the levels equations. This version of the system GMM estimator produces a coefficient on the error correction term (-0.054) that lies comfortably between the OLS and the FE estimates. The Hansen test signals that the instruments are uncorrelated with the error term, and the difference-in-Hansen test confirms that the additional instruments used in the levels equations are exogenous. In addition, the $m1$ and $m2$ test results indicate that there is no serial correlation in the error process.

As the Hansen test in column 1 of Table 2.4 does not reject the joint validity of the instruments which include the lagged values of $k_{i,t}$ dated $t-2$, $t-3$, and $t-4$ for the equations in first-differences, these lagged values of $k_{i,t}$ are likely to be uncorrelated with the error terms in the first-differenced equations, $\Delta v_{i,t}$. On the other hand, because the difference-in-Hansen test in column 2 rejects the hypothesis that $\Delta y_{i,t-1}$ and $\Delta k_{i,t-1}$ are jointly exogenous instruments for the levels equations while the difference-in-Hansen test in column 3 does not reject the hypothesis that $\Delta y_{i,t-1}$ are exogenous instruments for the levels equations, $\Delta k_{i,t-1}$ appear to be endogenous and correlated with the error terms in the levels equations, $(\eta_i + v_{i,t})$. This could be because $\Delta k_{i,t-1}$ are correlated with the RU-specific effects η_i. Consequently, we will use the instrument set in column 3 of Table 2.4, which includes the lagged values of $k_{i,t}$ dated $t-2$, $t-3$, and $t-4$ as instruments for the first-differenced equations and does not include $\Delta k_{i,t-1}$ as instruments for the levels equations, in our subsequent system GMM estimations.

2.5.5. Incorporating the CBI Survey Information

In section 2.3.3, we discussed the usefulness of the following CBI survey questions in studying corporate investment: *BUSOPT* (business optimism), *CAPEX_PM* (expected capital expenditure on plant and machinery), *CAPEX_B* (expected capital expenditure on buildings), *ORDER_P* (past orders), *ORDER_N* (expected orders), *OUTPUT_P* (past output), *OUTPUT_N* (expected output), *LOWCAP* (low capacity utilization), *UNCERT* (demand uncertainty), *INTFIN* (internal financial constraints), and *EXTFIN* (external financial constraints). The precise wording of these questions is presented in Appendix 2.7. In this section, we will consider adding variables derived from the CBI survey results to the baseline specification. The CBI publishes its survey results each calendar quarter. However, the RUs in the ARD report their information based on their respective fiscal years, which are usually different from calendar years. Therefore, we first match the fiscal quarters of a RU with the calendar quarters. Appendix 2.8 shows the rules we use for matching based on the start month of a RU's fiscal year.

Next, we annualize the CBI survey results by constructing a four-quarter moving average. The four-quarter moving average for a particular quarter is defined as the arithmetic mean of the CBI balance statistic for that quarter and the previous three quarters. For example, the four-quarter moving average for quarter 3 of fiscal year t is calculated by dividing the sum of the CBI survey balance statistic for quarters 1, 2, and 3 in fiscal year t and quarter 4 in fiscal year $t-1$ by four. *A priori* it is not clear whether averaging over the four quarters of fiscal year t is the most appropriate way to annualize our CBI survey variables to explain investment during fiscal year t. For example, Question 16CE asks whether uncertainty about demand is likely to limit investment during the next year. Given the forward-looking nature of the question, it is likely that the average balance statistic over the four quarters in fiscal year $t-1$ has the highest explanatory power for investment spending in fiscal year t. In order not to impose a strong assumption on the most informative timing, we explore five different four-quarter moving averages for each survey question *CBI* as follows:

1. $CBI\_MA4_{j,t}$: four-quarter moving average for the period ending in quarter 4 of fiscal year t;

2. $CBI\_MA3_{j,t}$: four-quarter moving average for the period ending in quarter 3 of fiscal year t;

3. $CBI\_MA2_{j,t}$: four-quarter moving average for the period ending in quarter 2 of fiscal year t;

4. $CBI\_MA1_{j,t}$: four-quarter moving average for the period ending in quarter 1 of fiscal year t;

5. $CBI\_MA4_{j,t-1}$: four-quarter moving average for the period ending in quarter 4 of fiscal year $t - 1$.

For each CBI question, we add each of the aforementioned five moving averages individually to equation (2.11). Because the CBI survey variables measured at the sector level are unlikely to be correlated with the idiosyncratic shocks at the RU level, they are always treated as strictly exogenous and are instrumented by themselves in both the first-differenced and the levels equations. Among the five moving averages, we choose the moving average whose coefficient has the lowest *p*-value and is significant at 10% as the most informative timing.

Following this procedure, we find that all five moving averages of *CAPEX_PM*, *ORDER_N*, *OUTPUT_N*, and *LOWCAP* are insignificant at 10% and are therefore not informative for explaining investment. The most significant moving averages for *BUSOPT*, *CAPEX_B*, *ORDER_P*, *OUTPUT_P*, *EXTFIN*, *INFIN*, and *UNCERT* are $BUSOPT\_MA4_{j,t}$, $CAPEX\_B\_MA4_{j,t-1}$, $ORDER\_P\_MA4_{j,t-1}$, $OUTPUT\_P\_MA4_{j,t-1}$, $EXTFIN\_MA4_{j,t-1}$, $INTFIN\_MA1_{j,t}$, and $UNCERT\_MA4_{j,t}$, respectively. In column 1 of Table 2.5, we add these CBI survey variables to equation (2.11). In this specification, $BUSOPT\_MA4_{j,t}$, $CAPEX\_B\_MA4_{j,t-1}$, and $OUTPUT\_P\_MA4_{j,t-1}$ are individually and jointly insignificant at conventional levels.[10] In column 2 of Table 2.5, we first drop these three insignificant variables and derive a more parsimonious model. The coefficients on $UNCERT\_MA4_{j,t}$ and $ORDER\_P\_MA4_{j,t\text{-}1}$ are both significant at conventional levels. $UNCERT\_MA4_{i,t}$ has a negatively signed coefficient, implying that a lower RU-level investment rate in the current year is correlated with a higher proportion of firms in the manufacturing sector that the RU belongs to citing demand uncertainty as a factor discouraging investment over the four quarters of the current year. This finding is consistent with the results of many theoretical studies, such as the real options model, which predict that investment is lower in periods of higher uncertainty. It is also in line with the empirical findings of Guiso and Parigi (1999), which also uses survey data to construct an indicator of demand uncertainty, and finds that uncertainty adversely affects investment. The coefficient on $ORDER\_P\_MA4_{j,t\text{-}1}$ has the expected positive sign, indicating that a higher RU-level investment rate in the current year is correlated with a higher proportion of firms in the relevant sector reporting an upward trend in the volume of total new orders over the four quarters of the previous year. Our finding is consistent with the assumption of dynamic investment models that, because of adjustment costs, investment responds to changes in demand with a time lag. Although the coefficients on $EXTFIN\_MA4_{j,t\text{-}1}$ and $INTFIN\_MA1_{j,t}$ are individually insignificant, they are jointly significant at the 10% level.[11]

In column 3, we exclude $INTFIN\_MA1_{j,t}$ from the specification in column 2 to check whether the coefficient on $EXTFIN\_MA4_{j,t\text{-}1}$ is significant in the absence of $INTFIN\_MA1_{j,t}$. Both the coefficients on $ORDER\_P\_MA4_{j,t\text{-}1}$ and $UNCERT\_MA4_{j,t}$

[10] The Wald test statistic of the joint significance of $BUSOPT\_MA4_{j,t}$, $CAPEX\_B\_MA4_{j,t\text{-}1}$, and $OUTPUT\_P\_MA4_{j,t\text{-}1}$ is $\chi^2(3)$=4.87 with a p-value of 0.182.
[11] The Wald test statistic of the joint significance of $EXTFIN\_MA4_{j,t\text{-}1}$ and $INTFIN\_MA1_{j,t}$ is $\chi^2(2)$= 5.59 with a p-value of 0.061.

remain significant at the 5% level with the expected signs. More importantly, the coefficient on $EXTFIN\_MA4_{j,t-1}$ becomes significant at the 5% level. The negative coefficient on $EXTFIN\_MA4_{j,t-1}$ suggests that the investment rate of a RU in the current year is negatively correlated with the proportion of firms in the relevant sector citing inability to raise external finance as a limiting factor for investment over the four quarters of the previous year. This finding provides support for theories, such as the pecking order theory of capital structure, which predict that investment is sensitive to the availability of external funds. It is also consistent with the empirical results of Fazzari et al. (1988) and Guariglia (2008), according to which external financing constraints have a negative impact on corporate investment.

In column 4, we drop $EXTFIN\_MA4_{j,t-1}$ from the specification in column 2 to investigate whether the statistical significance of the coefficient on $INTFIN\_MA1_{j,t}$ is sensitive to the presence of $EXTFIN\_MA4_{j,t-1}$. In this model, the coefficient on $INTFIN\_MA1_{j,t}$ is negative and close to being statistically significant at the 10% level, with a p-value of 0.104. This provides weak evidence that the current year RU-level investment rate is negatively linked with the percentage of firms in its sector citing shortage of internal finance as a limiting factor for investment over quarter 1 of the current year and quarters 2, 3, and 4 of the previous year. Because $INTFIN\_MA1_{j,t}$ is measured at the sectoral level while $I_{i,t}/K_{i,t-1}$ is measured at the RU-level, a possible explanation for the weak correlation between these two variables might be that the RU-level effects of internal financial constraints on investment cancel out with each other at the sector level. Our finding provides some support for theories, such as the pecking order theory of capital structure, which claim that internal financing constraints lead to under-investing. It is also in line with the empirical results of Bond and Meghir (1994) and Bond et al. (2003), which show that corporate investment is constrained by a shortage of internal finance. In column 5, we exclude $ORDER\_P\_MA4_{j,t\text{-}1}$ from the specification in column 4 and in this case the negative coefficient on $INTFIN\_MA1_{j,t}$ becomes significant at the 5% level. By comparing the results in columns 4 and 5, we can infer that the inclusion of $ORDER\_P\_MA4_{j,t\text{-}1}$ in our investment model significantly weakens the estimated effect of $INTFIN\_MA1_{j,t}$ on investment.[12]

The coefficients on the CBI survey variables represent the short-term responses of the RU-level investment rate ($I_{i,t}/K_{i,t-1}$) to one unit rises in the sector-level balance statistics of the survey questions. Based on the estimation results in column 3 of Table 2.5, one unit increases in $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t\text{-}1}$, and $EXTFIN\_MA4_{j,t\text{-}1}$ lead to changes in the investment rate of -0.000272, 0.000179, and -0.000304, respectively. The standard deviations of $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t\text{-}1}$, and $EXTFIN\_MA4_{j,t\text{-}1}$ in our sample are 12.314, 16.734, and 7.130, respectively. Hence, one standard deviation increases in $UNCERT\_MA4_{i,t}$, $ORDER\_P\_MA4_{j,t\text{-}1}$, and $EXTFIN\_MA4_{j,t\text{-}1}$ change the investment rate by -0.00335, 0.00300, and -0.00216, respectively. As the sample mean of $I_{i,t}/K_{i,t-1}$ is 0.074, one standard deviation increases in $UNCERT\_MA4_{i,t}$, $ORDER\_P\_MA4_{j,t\text{-}1}$, and $EXTFIN\_MA4_{j,t\text{-}1}$ result in changes in the investment rate by -4.45%, 4.05%, and -2.92%, respectively. Therefore, a one standard deviation increase $UNCERT\_MA4_{i,t}$ has the largest absolute effect on the investment rate among these three CBI survey variables, while a one standard increase in $EXTFIN\_MA4_{j,t\text{-}1}$ has the lowest. Although statistically significant, the effects of changes in these sector-level annualized survey measures on the RU-level investment rates are

[12] To check whether this finding could be due to a high correlation between $ORDER\_P\_MA4_{j,t\text{-}1}$ and $INTFIN\_MA1_{j,t}$, in Appendix 2.9 we present a correlation table of the CBI survey variables used in columns 4 and 5 of Table 2.5. As the correlation coefficient between $ORDER\_P\_MA4_{j,t\text{-}1}$ and $INTFIN\_MA1_{j,t}$ is only 0.006, these two survey variable do not appear to be highly correlated.

quantitatively small. One reason may be that not all of the RUs in a given sector will be experiencing higher orders, higher demand uncertainty, or financing difficulties at the same time.

2.5.6. Effects of the Great Recession

The bursting of the U.S. housing bubble in 2007 marked the beginning of the Great Recession. The crisis quickly spread from the U.S. to other countries, leading to a meltdown of the global financial market. Although the Great Recession peaked in September 2008 when Lehman Brothers filed for bankruptcy, many countries including the U.K. have still not recovered from the repercussions of the credit crunch. Given the unprecedented magnitude and the devastating economic impact of the Great Recession, it is reasonable to suspect that this financial crisis may have resulted in a structural break in the parameters of our investment equations. In this section, we analyze whether the effects of the CBI survey variables on investment during the post-crisis period differ from the pre-crisis period.

In column 1 of Table 2.6, we first present a model in which all the original explanatory variables in the specification in column 3 of Table 2.5 are interacted with the crisis dummy (*CRISIS*), which equals one after the onset of the Great Recession in 2007, i.e. years 2007-2012, and equals zero otherwise. The coefficients on $(CRISIS)*EXTFIN\_MA4_{j,t-1}$ and $(CRISIS)*ORDER\_P\_MA4_{j,t-1}$ are not significant at conventional levels while the coefficient on $(CRISIS)*UNCERT\_MA4_{j,t}$ attains statistical significance at the 5% level. In column 2, we derive a more parsimonious specification by dropping jointly insignificant interactions on the control variables (non-CBI survey variables) from the specification in column 1.[13] The significance of the coefficients on $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ in this specification shows that the relationship between the RU-level investment rate and these survey measures of financial constraints and demand uncertainty can be detected using only the data from the pre-crisis sub-period. The coefficients on $(CRISIS)*EXTFIN\_MA4_{j,t-1}$ and $(CRISIS)*ORDER\_P\_MA4_{j,t-1}$ both remain statistically insignificant at conventional levels. Therefore, there does not appear to be a structural change in the relationship between the investment rate at the RU level and the proportion of firms in the sector citing external financial constraints as a limiting factor for investment or the proportion of firms in the sector reporting higher orders after the financial crisis.

The coefficient on $(CRISIS)*UNCERT\_MA4_{j,t}$ is very close to being significant at the 5% level with a p-value of 0.053. This highlights a possible change in the relationship between the RU-level investment and the sector-level proportion of firms reporting demand uncertainty as a limiting factor for investment. The effect of $UNCERT\_MA4_{j,t}$ on the investment rate in the post-crisis period is equal to sum of the coefficients on $(CRISIS)*UNCERT\_MA4_{j,t}$, and $UNCERT\_MA4_{j,t}$. Hence, the coefficient on $UNCERT\_MA4_{j,t}$ after the financial crisis is 0.000341-0.000366=-0.000025, which is very small and statistically insignificantly different from zero.[14] Therefore, $UNCERT\_MA4_{j,t}$ is not very informative about RU-level investment in the post-crisis period. This could be explained by the so-called hangover effect emphasized in Abel and Eberly (1999): as demand decreases and uncertainty increases after the financial crisis, RUs would like to disinvest some of their installed capital but cannot because of the

[13] The Wald test statistic of the joint significance of the interaction terms dropped between column 1 and 2 in Table 2.6 is $\chi^2(11)$=11.75 with a p-value of 0.383.
[14] The Wald test statistic for the null hypothesis that the sum of the coefficients on $(CRISIS)*UNCERT\_MA4_{j,t}$ and $UNCERT\_MA4_{j,t}$ is zero is $\chi^2(1)$=0.02 with a p-value of 0.875.

irreversibility constraint. Therefore, the hangover effect suggests that increased uncertainty does not have a significant negative effect on investment.

Another possible reason for the insignificant effect of $UNCERT\_MA4_{j,t}$ after the financial crisis could be that there is less sectoral variation in $UNCERT\_MA4_{j,t}$ in the post-crisis period, and the common time variation in $UNCERT\_MA4_{j,t}$ is already captured by the year dummies included in our investment model. To compare the sectoral variation in $UNCERT\_MA4_{j,t}$ over the pre-crisis and post-crisis periods, we regress $UNCERT\_MA4_{j,t}$ on year dummies over these two periods separately and compute the R-squares. A R-square of zero would suggest that there is only sectoral variation but no common time variation in $UNCERT\_MA4_{j,t}$, while a R-square of one would imply that there is only common time variation but no sectoral variation in $UNCERT\_MA4_{j,t}$. Therefore, a higher R-square indicates a lower degree of sectoral variation in $UNCERT\_MA4_{j,t}$. The R-square for the post-crisis period is 0.196, almost twice as high as the R-square of 0.108 for the pre-crisis period. Hence, there is considerably less sectoral variation in the proportion of firms citing demand uncertainty as a limiting factor for investment after the financial crisis.

In addition, the coefficient on the interaction term between the crisis dummy and the chemicals sector dummy (*CRISIS*)**CHEMICALS* is 0.014 and significant at the 5% level. This implies that, all else being equal, the difference in the investment rates between a RU in the chemicals sector and that in the reference sector increases by 0.014 in the post-crisis period. After the financial crisis, because of falling demand, manufacturing firms may have lower levels of desired capital stock and may want to disinvest. However, as the capital-intensive chemicals companies tend to use expensive long-lived heavy machinery in their production process, they are likely to find it hard to sell costly capital equipment on the secondary market during a recession (Gilbert et al., 2013). As a result, chemicals companies may face higher capital adjustment costs and therefore may not be able to decrease their capital stock as fast as companies in other sectors in the post-crisis period.[15]

Although we only find an insignificant negative effect of $INTFIN\_MA1_{j,t}$ on investment in section 2.5.5, we also check whether this effect differs across the pre-crisis and post-crisis sub-periods. In column 3 of Table 2.6, we add $INTFIN\_MA1_{j,t}$ and the interaction term ($CRISIS$)*$INTFIN\_MA1_{j,t}$ to the specification in column 2. The coefficient on ($CRISIS$)*$INTFIN\_MA1_{j,t}$ is insignificant at the 5% level. Therefore, we do not find evidence of a structural change in the effect of $INTFIN\_MA1_{j,t}$ on investment after the financial crisis. For subsequent analysis, we will focus on the specification without the $INTFIN\_MA1_{j,t}$ variable, as presented in column 3 of Table 2.5.

2.5.7. Allowing for Sectoral Heterogeneity

There are six different sectors within the manufacturing industry included in our sample: chemicals, engineering, food, metal manufacture, metal products, and textiles. So far, we have been running pooled regressions which do not allow the slope parameters to differ across sectors. However, the effects of the explanatory variables on investment may be sector-specific. In addition to using the sector-specific intercept dummies, we allow for more sector heterogeneity by including interaction terms between the explanatory variables and the sector dummies in this section. As the engineering sector has the

[15] In section 2.5.7, we will further investigate the sectoral differences in investment behavior by interacting sector dummies with the other explanatory variables. In column 2 of Table 2.7, we find that the interaction term $(CHEMICALS)*(CRISIS)*(k_{i,t-2} - y_{i,t-2})$ is positive and statistically significant, which implies that the chemicals companies have slower capital adjustment speeds than companies in other sectors after the financial crisis.

largest number of observations in the sample, we choose it to be the reference sector. Because the relative price of investment goods and the CBI survey variables are measured at the sector-level, we do not interact them with the sector dummies.

In column 1 of Table 2.7, we report the results for the saturated model in which we interact all the RU-level explanatory variables ($I_{i,t-1}/K_{i,t-2}$, $\Delta y_{i,t}$, $\Delta y_{i,t-1}$, and $(k_{i,t-2} - y_{i,t-2})$) with the sector dummies. Among all the coefficients on the sector interaction terms, only the coefficient on (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) is significant at the 5% level. In column 2, we refine our specification by excluding jointly insignificant sector interactions.[16] The coefficients on $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ remain significantly different from zero. The coefficient on the interaction term (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) remain significant at the 5% level. The coefficient on $I_{i,t-1}/K_{i,t-2}$ is 0.142, and the coefficient on (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) is -0.116. Therefore, the coefficient on $I_{i,t-1}/K_{i,t-2}$ for the textiles sector is 0.142-0.116=0.026, which is more than five times smaller than the $I_{i,t-1}/K_{i,t-2}$ coefficient for the other five sectors (0.142) and also statistically insignificantly different from zero.[17] This indicates that the correlation between the investment rate in the current year and the investment rate in the previous year is significantly positive for all sectors except the textiles sector, which implies that the investment of the textiles sector is less persistent than that of other sectors. A likely explanation could be that because textiles companies have low capital intensity and investment costs and employ mostly low skilled labor, they can change their investment levels relatively fast (Nordas, 2004).

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[16] The Wald test statistic of the joint significance of the terms dropped in moving from column 1 to column 2 in Table 2.7 is $\chi^2(19)$=23.81 with a p-value of 0.204.

[17] The Wald test statistic for the null hypothesis that the sum of the coefficients on $I_{i,t-1}/K_{i,t-2}$ and (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) in column 2 of Table 2.7 is zero is $\chi^2(1)$=0.211 with a p-value of 0.646.

Furthermore, we consider a more general specification and allow the slope parameters to differ both across sectors (for those explanatory variables where this is feasible) and across the pre-crisis and the post-crisis periods. First, we estimate a saturated model by interacting all the explanatory variables in the regression in column 1 of Table 2.7 with the crisis dummy. Therefore, we have two-way interactions of the sector dummies and the RU-level variables ($I_{i,t-1}/K_{i,t-2}$, $\Delta y_{i,t}$, $\Delta y_{i,t-1}$, and $(k_{i,t-2} - y_{i,t-2})$), three-way interactions of the crisis dummy, the sector dummies, and the RU-level variables ($I_{i,t-1}/K_{i,t-2}$, $\Delta y_{i,t}$, $\Delta y_{i,t-1}$, and $(k_{i,t-2} - y_{i,t-2})$), and two-way interactions of the crisis dummy and the sector-level variables ($\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, the CBI survey variables, and the sector dummies) in our equation.[18] Next, we drop the jointly insignificant interaction terms on the control variables and derive the more parsimonious specification reported in Table 2.8.[19] The estimated coefficients on $(CRISIS)*EXTFIN\_MA4_{j,t-1}$ and $(CRISIS)*ORDER\_P\_MA4_{j,t-1}$ are both insignificant at the 5% level. Therefore, we find no evidence of a structural change in the coefficients on these two CBI variables over the pre-crisis and the post-crisis periods, which corroborates the findings in section 2.5.6. On the other hand, the coefficient on $(CRISIS)*UNCERT\_MA4_{j,t}$ is significant at the 5% level. The coefficient on $(CRISIS)*UNCERT\_MA4_{j,t}$ is 0.000299, while the coefficient on $UNCERT\_MA4_{j,t}$ is -0.000342. Therefore, the effect of $UNCERT\_MA4_{j,t}$ on the investment rate after the crisis is -0.000342+0.000299=-0.000043, which is very small and statistically insignificantly different from zero.[20] As a result, we find no significant effect of

[18] The full regression results are available upon request.
[19] The Wald test statistic of the joint significance of the terms dropped is $\chi^2(46)$=33.57 with a *p*-value of 0.914.
[20] The Wald test statistic for the null hypothesis that the sum of the coefficients on $(CRISIS)*$ $UNCERT\_MA4_{j,t}$ and $UNCERT\_MA4_{j,t}$ is zero is $\chi^2(1)$=0.10 with a *p*-value of 0.757.

$UNCERT\_MA4_{j,t}$ on investment after the financial crisis, also consistent with the findings in section 2.5.6.

The coefficients on (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) and (*CRISIS*)*(*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) are both significant at the 10% level. The coefficient on $I_{i,t-1}/K_{i,t-2}$ is 0.183, while the coefficient on (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) is -0.118. Therefore, the coefficient on $I_{i,t-1}/K_{i,t-2}$ for the textiles sector before the financial crisis is 0.183-0.118=0.065, which is about three times lower than the coefficient on $I_{i,t-1}/K_{i,t-2}$ for the other sectors (0.183) and insignificantly different from zero.[21] The coefficient on $I_{i,t-1}/K_{i,t-2}$ for the textiles sector after the financial crisis is equal to the sum of the coefficients on $I_{i,t-1}/K_{i,t-2}$, (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$), and (*CRISIS*)*(*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$), which is 0.183-0.118-0.214=-0.149 but insignificantly different from zero.[22] Therefore, these findings suggest that the investment rate in the current year is significantly positively correlated with the investment rate in the previous year in all sectors except the textiles sector. A possible explanation for the less persistent investment of the textiles sector could be that, because textiles manufacturers have low capital intensity and investment costs and employ mainly low skilled workers, they are able to adjust their investment plans relatively quickly (Nordas, 2004).

The coefficients on the interaction terms (*FOOD*)*$\Delta y_{i,t}$ and (*CRISIS*)*(*FOOD*)*$\Delta y_{i,t}$ are both significant at the 5% level. The coefficient on $\Delta y_{i,t}$ is 0.040, while the

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[21] The Wald test statistic for the null hypothesis that the sum of the coefficients on $I_{i,t-1}/K_{i,t-2}$ and (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) is zero is $\chi^2(1)$=1.18 with a *p*-value of 0.278.

[22] The Wald test statistic for the null hypothesis that the sum of the coefficients on $I_{i,t-1}/K_{i,t-2}$, (*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$), (*CRISIS*)*(*TEXTILES*)*($I_{i,t-1}/K_{i,t-2}$) is zero is $\chi^2(1)$ = 2.07 with a *p*-value of 0.1505.

coefficient on ($FOOD$)*$\Delta y_{i,t}$ is -0.056. Therefore, the coefficient on $\Delta y_{i,t}$ for the food sector in the pre-crisis period is 0.040-0.056=-0.016, which is negative but statistically insignificantly different from zero.[23] This suggests that current investment rate is positively linked with current output growth for all sectors except for the food sector prior to the financial crisis. Therefore, there is a longer time lag in the adjustment of investment to the current change in demand for the food sector. A possible explanation could be that since the food sector has less room for growth than other sectors, due to limited consumption capacity of consumers, food manufacturers may be more cautious about expanding their productive capacity and take a longer time to plan investment projects (DEFRA, 2014). The coefficient on $\Delta y_{i,t}$ for the food sector in the post crisis period is equal to the sum of the coefficients on $\Delta y_{i,t}$, ($FOOD$)*$\Delta y_{i,t}$, and ($CRISIS$)*($FOOD$)*$\Delta y_{i,t}$, which is 0.040-0.056+0.076=0.060 and close in magnitude to the coefficient on $\Delta y_{i,t}$ (0.040) for the other sectors. In addition, the sum of the coefficients on ($FOOD$)*$\Delta y_{i,t}$ and ($CRISIS$)*($FOOD$)*$\Delta y_{i,t}$ is insignificantly different from zero.[24] This implies that the relationship between the current investment rate and current output growth for the food sector is not significantly different from that for the other five sectors after the financial crisis.

Lastly, the coefficients on the interaction terms ($CHEMICALS$)*$\Delta y_{i,t-1}$ and ($CHEMICALS$)*($CRISIS$)*$(k_{i,t-2} - y_{i,t-2})$ are both significant at the 5% level. The coefficient on $\Delta y_{i,t-1}$ is 0.045, while the coefficient on ($CHEMICALS$)*$\Delta y_{i,t-1}$ is -0.011. Therefore, the coefficient on $\Delta y_{i,t-1}$ for the chemicals sector is about 25% lower than

[23] The Wald test statistic for the null hypothesis that the sum of the coefficients on ($FOOD$)*$\Delta y_{i,t}$ and $\Delta y_{i,t}$ is zero is $\chi^2(1) = 0.39$ with a p-value of 0.530.
[24] The Wald test statistic for the null hypothesis that the sum of the coefficients on ($FOOD$)*$\Delta y_{i,t}$ and ($CRISIS$)*($FOOD$)*$\Delta y_{i,t}$ equals zero is $\chi^2(1)=0.83$ with a p-value of 0.364.

the coefficient on $\Delta y_{i,t-1}$ for the other sectors. This suggests that the current investment rate of the chemicals sector is less positively correlated with previous output growth than the investment rate of the other sectors. The fact that past output growth is an important determinant of current investment may be because past demand conditions are an indicator of future profitability. Because chemicals is a high technology sector in which market conditions are fast-changing and new products can replace old ones at a rapid rate, past demand conditions may be less correlated with future profitability (Heaton, 2013). Therefore, the effect of past output growth on current investment is smaller for the chemicals sector. The error correction term $(k_{i,t-2} - y_{i,t-2})$ has a coefficient of -0.042, and the interaction term (*CHEMICALS*)*(*CRISIS*)*$(k_{i,t-2} - y_{i,t-2})$ has a coefficient of 0.014. Therefore, the absolute value of coefficient on $(k_{i,t-2} - y_{i,t-2})$ for the chemicals sector in the post-crisis period is about 30% lower than that for the chemicals sector before the crisis and those for other sectors over the whole sample period. This indicates that the chemicals sector has a slower capital stock adjustment speed towards the long-run equilibrium in the post-crisis period compared with itself in the pre-crisis period and the other sectors over the whole sample period. After the financial crisis, as demand declines sharply (see Figures 2.9-2.12) and capacity usage is low (see Figure 2.18), chemical firms are likely to have lower levels of desired capital stock. However, as most chemicals companies are capital-intensive and utilize expensive long-lived heavy machinery in their production, they may find it difficult to sell their costly capital equipment on the secondary market and reverse their investment decisions during an economic downturn (Gilbert et al., 2013). Consequently, they may face higher capital adjustment costs and thus have a slower capital stock adjustment speed in the post-crisis period.

2.5.8. Alternative Error Correction Term

In the previous analysis, we restricted the long-run elasticity of the capital stock with respect to output to be one. In Table 2.1B, the OLS estimate of the coefficient on $y_{i,t}$ is 0.933 when regressing $k_{i,t}$ on $y_{i,t}$. In this section, we use an alternative long-run capital stock to output elasticity value of 0.933. In Table 2.9, we present the results for the investment model with $(k_{i,t-2} - 0.933y_{i,t-2})$ as the error correction term. The coefficients on $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ are statistically significant with the expected signs. The coefficient on the error correction term is -0.056, very close to its estimated value of -0.055 in column 3 of Table 2.5.

In Table 2.10, we use $(k_{i,t-2} - 0.933y_{i,t-2})$ as the error correction term and re-estimate the investment model with the crisis dummy in column 2 of Table 2.6. Consistent with the results in column 2 of Table 2.6, the coefficients on both $(CRISIS)*EXTFIN\_MA4_{j,t-1}$ and $(CRISIS)*ORDER\_P\_MA4_{j,t-1}$ are insignificant while the coefficient on $(CRISIS)*UNCERT\_MA4_{j,t}$ is significant at the 5% level. Furthermore, the coefficient on $UNCERT\_MA4_{j,t}$ for the post-crisis period is equal to the sum of the coefficients on $(CRISIS)*UNCERT\_MA4_{j,t}$ and $UNCERT\_MA4_{j,t}$, which is 0.000339-0.000382=-0.000043 and insignificantly different from zero.[25] Therefore, we again do not find a significant effect of $UNCERT\_MA4_{j,t}$ on the RU-level investment rate after the financial crisis.

2.5.9. Using Quarterly CBI Survey Variables

In the preceding analysis, we assumed that the survey balance statistic in each of the four quarters in a twelve-month period has an equal impact on the investment rate, and used

[25] The Wald test statistic for the null hypothesis that the sum of $(CRISIS)*UNCERT\_MA4_{j,t}$ and $UNCERT\_MA4_{j,t}$ is zero is $\chi^2(2)$=14.18 with a p-value of 0.290.

the four-quarter moving average CBI survey variables in our regressions. In this section, we explore using quarterly CBI survey variables directly in the investment model. To designate quarterly survey variables, we end the variable name with the quarter number. For example, $EXTFIN\_Q1_{j,t-1}$ is the proportion of firms in quarter 1 of fiscal year $t-1$ citing the inability to raise external finance as a constraint on investment for the next twelve months.

In column 1 of Table 2.11, we modify the specification in column 3 of Table 2.5 by replacing $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ with the 12 corresponding quarterly variables $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $UNCERT\_Q2_{j,t}$, $UNCERT\_Q1_{j,t}$, $ORDER\_P\_Q1_{j,t-1}$, $ORDER\_P\_Q2_{j,t-1}$, $ORDER\_P\_Q3_{j,t-1}$, $ORDER\_P\_Q4_{j,t-1}$, $EXTFIN\_Q1_{j,t-1}$, $EXTFIN\_Q2_{j,t-1}$, $EXTFIN\_Q3_{j,t-1}$, and $EXTFIN\_Q4_{j,t-1}$. The Wald test statistic for the null hypothesis that the coefficients on the four *UNCERT* quarterly variables are equal is χ^2 (3) =1.52 with an associated *p*-value of 0.677. The Wald test statistic for the null hypothesis that the four *ORDER_P* quarterly variables have equal coefficients is χ^2 (3) =2.99 with an associated *p*-value of 0.393. Furthermore, the Wald test statistic for the null hypothesis that the coefficients on the *EXTFIN* quarterly variables are equal is χ^2 (3) =1.15 with an associated *p*-value of 0.765. Therefore, these tests do not reject the use of the annualized averages $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ in our specification in column 3 of Table 2.5. However, as one can observe from column 1 of Table 2.11, among the coefficients on the four *UNCERT* variables, only the coefficients on $UNCERT\_Q4_{j,t}$ and $UNCERT\_Q3_{j,t}$ are significant at the 10% level.[26] Among the coefficients on four *ORDER_P* variables,

[26] The p-values of the coefficients on $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $UNCERT\_Q2_{j,t}$, and $UNCERT\_Q1_{j,t}$ are 0.078, 0.082 ,0.507, and 0.707, respectively.

only that on $ORDER\_P\_Q4_{j,t\text{-}1}$ is significant at the 5% level.[27] In addition, the coefficient on $EXTFIN\_Q1_{j,t\text{-}1}$ has the lowest p-value among the coefficients on the four *EXTFIN* variables.[28] In column 2, we keep $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t\text{-}1}$, and $EXTFIN\_Q1_{j,t\text{-}1}$, and drop the other quarterly CBI survey variables.[29] In this more parsimonious specification, the coefficients on all these four quarterly CBI survey variables are significant and have the expected signs. The results suggest that the proportion of firms at the sector level reporting higher orders in quarter 4 of the previous year, the proportion of firms at the sector level citing external financing constraints as a factor liming investment in quarter 1 of the previous year, and the proportion of firms at the sector level citing demand uncertainty as a factor limiting investment in quarters 3 and 4 of the current year, have the highest information value for explaining the investment rate at the RU level in the current year.

The coefficients on $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t\text{-}1}$, and $EXTFIN\_Q1_{j,t}$ in column 2 are -0.000118, -0.000121, 0.000114, and -0.000199, respectively. The standard deviations of $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t\text{-}1}$, and $EXTFIN\_Q1_{j,t}$ are 15.841, 15.555, 22.045, and 8.67 respectively. Hence, one standard deviation increases in $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t\text{-}1}$, and $EXTFIN\_Q1_{j,t}$ change the investment rate by -0.00187, -0.00188, 0.0025, and -0.00173 respectively. As the sample mean of $I_{i,t}/K_{i,t-1}$ is 0.074, one standard deviation increases in $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t\text{-}1}$, and $EXTFIN\_Q1_{j,t}$ result in -2.53%, -2.54%, 3.38%, and -2.34% changes in the investment

[27] The p-values of the coefficients on $ORDER\_P\_Q1_{j,t\text{-}1}$, $ORDER\_P\_Q2_{j,t\text{-}1}$, $ORDER\_P\_Q3_{j,t\text{-}1}$, and $ORDER\_P\_Q4_{j,t\text{-}1}$ are 0.404, 0.700, 0.437, and 0.008, respectively.
[28] The p-values of the coefficients on $EXTFIN\_Q1_{j,t\text{-}1}$, $EXTFIN\_Q2_{j,t\text{-}1}$, $EXTFIN\_Q3_{j,t\text{-}1}$, and $EXTFIN\_Q4_{j,t\text{-}1}$ are 0.125, 0.830, 0.442, and 0.920, respectively.
[29] The Wald test statistic of the joint significance of the terms dropped in moving from column 1 to column 2 in Table 2.11 is $\chi^2(8)$=4.53 with a p-value of 0.806.

rate, respectively. Therefore, the effects of these sector-level quarterly survey measures on the RU-level investment rate are also quantitatively small. This is likely because these sector-level survey balances measure the conditions facing individual RUs with error.

In column 3 of Table 2.11, we add the three four-quarter moving average CBI survey variables $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ used in the specification reported in column 3 of Table 2.5 to the specification reported in column 2 of Table 2.11. The coefficients on the seven CBI survey variables are jointly significant at the 5% level.[30] However, neither the three annualized survey variables $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ nor the four quarterly survey variables $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t-1}$, and $EXTFIN\_Q1_{j,t-1}$ are jointly significant at conventional levels in this specification.[31] Therefore, there is no strong statistical ground for favoring using the quarterly survey measures over using the annualized survey measures in our investment model.

2.6. Conclusions and Policy Implications

This chapter investigates important factors influencing manufacturing investment in the U.K. using both the RU-level ARD data and the sector-level CBI survey data. We begin our analysis by estimating an error correction investment model for a panel of RUs in the ARD over the sample period 1997-2012. The system GMM estimates of the baseline model indicate that the investment rate is related with short-run fluctuations in past investment, current and past output growth, current and past changes in the relative price

[30] The Wald test statistic for the joint significance of $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, $EXTFIN\_MA4_{j,t-1}$, $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t-1}$, and $EXTFIN\_Q1_{j,t-1}$ is $\chi^2(7)=23.79$ with an associated p-value of 0.001.

[31] The Wald test statistic for the joint significance of the three annualized averages $UNCERT\_MA4_{j,t}$, $ORDER\_P\_MA4_{j,t-1}$, and $EXTFIN\_MA4_{j,t-1}$ is $\chi^2(3)=4.31$ with an associated p-value of 0.233, and the Wald test statistic for the joint significance of $UNCERT\_Q4_{j,t}$, $UNCERT\_Q3_{j,t}$, $ORDER\_P\_Q4_{j,t-1}$, and $EXTFIN\_Q1_{j,t-1}$ is $\chi^2(4)=6.04$ with an associated p-value of 0.196.

of investment goods, the deviation of the capital stock from its long-term equilibrium, and the long-run effect of the relative price of investment goods on the capital stock. We then proceed to include a number of the CBI survey variables in our investment model and find that the investment rate is negatively correlated with the survey variables pertaining to financing constraints and demand uncertainty and positively correlated with the survey variable related to the volume of total new orders.

Our findings have potentially important policy implications. First, as we find that the volume of orders received has a positive impact on manufacturing investment, demand management policies could be effective at stimulating manufacturing investment. For instance, the government could pursue expansionary fiscal policy or loose monetary policy to increase demand for manufacturing products. Second, because we find that manufacturing investment is constrained by the availability of finance, the government could work to improve access to finance for manufacturing firms. For example, it may consider creating a national development bank that lends directly to viable manufacturing businesses. It could also explore providing tax relief to encourage potential investors to invest in the manufacturing industry. Third, because our results indicate that a higher level of uncertainty is associated with lower manufacturing investment, macroeconomic policy that emphasizes stability is likely to facilitate manufacturing investment decisions. For example, the government may want to keep inflation, the exchange rate, and the public debt to GDP ratio at stable and predictable levels to reduce uncertainty facing manufacturers.

Table 2.1A. OLS and FE estimations of AR(1) specifications for variables

Panel A

Dependent Variable: $k_{i,t}$

VARIABLES	(1) OLS	(2) FE
$k_{i,t-1}$	0.997***	0.849***
	(0.001)	(0.006)
Constant	0.014	1.353***
	(0.008)	(0.055)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	19957	19957
R-squared	0.997	0.800

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Panel B

Dependent Variable: $y_{i,t}$

VARIABLES	(1) OLS	(2) FE
$y_{i,t-1}$	0.970***	0.408***
	(0.002)	(0.013)
Constant	0.314***	5.434***
	(0.023)	(0.123)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	19957	19957
R-squared	0.943	0.182

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Panel C

Dependent Variable: $(k-y)_{i,t}$

VARIABLES	(1) OLS	(2) FE
$(k-y)_{i,t-1}$	0.873***	0.397***
	(0.004)	(0.012)
Constant	-0.050***	-0.070***
	(0.016)	(0.018)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	19957	19957
R-squared	0.787	0.242

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Panel D

Dependent Variable: $\Delta k_{i,t}$

VARIABLES	(1) OLS	(2) FE
$\Delta k_{i,t-1}$	0.386***	0.041***
	(0.011)	(0.013)
Constant	-0.008**	-0.024***
	(0.004)	(0.004)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	17046	17046
R-squared	0.183	0.018

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Panel E

Dependent Variable: $\Delta y_{i,t}$

VARIABLES	(1) OLS	(2) FE
$\Delta y_{i,t-1}$	-0.238***	-0.339***
	(0.010)	(0.010)
Constant	-0.020	-0.063***
	(0.015)	(0.017)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	17046	17046
R-squared	0.072	0.128

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Panel F

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) OLS	(2) FE
$I_{i,t-1}/K_{i,t-2}$	0.364***	0.034**
	(0.011)	(0.014)
Constant	0.055***	0.070***
	(0.004)	(0.005)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	17046	17046
R-squared	0.166	0.016

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2.1B. OLS and FE regressions of $k_{i,t}$ on $y_{i,t}$.

Dependent Variable: $k_{i,t}$

VARIABLES	(1) OLS	(2) FE
$y_{i,t}$	0.933***	0.111***
	(0.010)	(0.007)
Constant	0.685***	8.328***
	(0.090)	(0.070)
Sector dummies	Yes	No
Year dummies	Yes	Yes
Observations	22964	22964
R-squared	0.786	0.161

Notes:
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1.

Table 2.2. OLS and FE estimates of baseline models with $I_{i,t}/K_{i,t-1}$ as the dependent variable

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE
$I_{i,t-1}/K_{i,t-2}$			0.295***	-0.050***
			(0.012)	(0.014)
$\Delta y_{i,t}$	0.037***	0.048***	0.033***	0.046***
	(0.002)	(0.002)	(0.002)	(0.003)
$\Delta y_{i,t-1}$			0.036***	0.071***
			(0.002)	(0.004)
$\Delta p_{j,t}$	-0.064***	-0.065***	-0.057***	-0.067***
	(0.012)	(0.012)	(0.011)	(0.012)
$\Delta p_{j,t-1}$			-0.060***	-0.096***
			(0.012)	(0.015)
$(k-y)_{i,t-2}$			-0.028***	-0.092***
			(0.001)	(0.004)
$p_{j,t-2}$			-0.077***	-0.134***
			(0.010)	(0.015)
$(k-y)_{i,t-1}$	-0.040***	-0.079***		
	(0.002)	(0.003)		
$p_{j,t-1}$	-0.090***	-0.105***		
	(0.010)	(0.011)		
Constant	Yes	Yes	Yes	Yes
Sector dummies	Yes	No	Yes	No
Year dummies	Yes	Yes	Yes	Yes
Observations	19957	19957	16950	16950
R-squared	0.119	0.092	0.213	0.091

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2.3. OLS and FE estimates of baseline models with $\Delta k_{i,t}$ as the dependent variable

Dependent Variable: $\Delta k_{i,t}$

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE
$\Delta k_{i,t-1}$			0.314***	-0.047***
			(0.012)	(0.013)
$\Delta y_{i,t}$	0.036***	0.045***	0.031***	0.043***
	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta y_{i,t-1}$			0.033***	0.066***
			(0.002)	(0.003)
$\Delta p_{j,t}$	-0.062***	-0.062***	-0.055***	-0.063***
	(0.011)	(0.011)	(0.010)	(0.011)
$\Delta p_{j,t-1}$			-0.056***	-0.089***
			(0.011)	(0.013)
$(k-y)_{i,t-2}$			-0.026***	-0.086***
			(0.001)	(0.004)
$p_{j,t-2}$			-0.073***	-0.126***
			(0.009)	(0.013)
$(k-y)_{i,t-1}$	-0.038***	-0.073***		
	(0.001)	(0.003)		
$p_{j,t-1}$	-0.086***	-0.099***		
	(0.010)	(0.010)		
Constant	Yes	Yes	Yes	Yes
Sector dummies	Yes	No	Yes	No
Year dummies	Yes	Yes	Yes	Yes
Observations	19957	19957	16950	16950
R-squared	0.128	0.097	0.230	0.096

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2.4. GMM estimates of the baseline model

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) DIFF GMM	(2) SYS GMM	(3) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.104***	0.196***	0.144***
	(0.026)	(0.024)	(0.022)
$\Delta y_{i,t}$	0.080***	0.090***	0.067***
	(0.021)	(0.017)	(0.016)
$\Delta y_{i,t-1}$	0.082***	0.069***	0.057***
	(0.014)	(0.008)	(0.007)
$\Delta p_{j,t}$	-0.088***	-0.078***	-0.074***
	(0.019)	(0.015)	(0.014)
$\Delta p_{j,t-1}$	-0.095***	-0.066***	-0.068***
	(0.020)	(0.014)	(0.014)
$(k-y)_{i,t-2}$	-0.084***	-0.068***	-0.054***
	(0.014)	(0.008)	(0.007)
$p_{j,t-2}$	-0.118***	-0.092***	-0.094***
	(0.020)	(0.013)	(0.011)
Constant	No	Yes	Yes
Sector dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes
m1	-16.11	-17.62	-16.33
	[0.000]	[0.000]	[0.000]
m2	-1.07	0.50	-0.89
	[0.282]	[0.617]	[0.376]
Hansen	0.486	0.020	0.515
Dif Hansen		0.000	0.827
Observations	13943	16950	16950

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
DIFF GMM is the first-differenced GMM estimation.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

In all columns, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$. In column 2, the instruments used in the levels equations are: $\Delta k_{i,t-1}$ and $\Delta y_{i,t-1}$. In column 3, the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In all columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, and $p_{i,t-2}$ are treated as strictly exogenous.

Table 2.5. Investment models incorporating the CBI survey variables

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM	(2) SYS GMM	(3) SYS GMM	(4) SYS GMM	(5) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.142***	0.142***	0.141***	0.142***	0.143***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
$\Delta y_{i,t}$	0.068***	0.068***	0.069***	0.068***	0.068***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
$\Delta y_{i,t-1}$	0.057***	0.057***	0.058***	0.057***	0.057***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\Delta p_{j,t}$	-0.077***	-0.079***	-0.080***	-0.078***	-0.075***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$\Delta p_{j,t-1}$	-0.055***	-0.058***	-0.059***	-0.060***	-0.054***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$(k-y)_{i,t-2}$	-0.054***	-0.054***	-0.055***	-0.054***	-0.054***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$p_{j,t-2}$	-0.095***	-0.092***	-0.093***	-0.091***	-0.085***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
EXTFIN_MA4$_{j,t-1}$	-0.000257	-0.000274	-0.000304**		
	(0.000168)	(0.000168)	(0.000132)		
INTFIN_MA1$_{j,t}$	-0.000039	-0.000041		-0.000157	-0.000213**
	(0.000122)	(0.000122)		(0.000096)	(0.000094)
UNCERT_MA4 $_{j,t}$	-0.000308***	-0.000267***	-0.000272***	-0.000232**	-0.000231**
	(0.000099)	(0.000095)	(0.000095)	(0.000092)	(0.000092)
CAPEX_B_ MA4 $_{j,t-1}$	0.000109				
	(0.000077)				
ORDER_P_ MA4 $_{j,t-1}$	0.000182	0.000172**	0.000179***	0.000152**	
	(0.000127)	(0.000067)	(0.000064)	(0.000066)	
BUSOPT_ MA4$_{j,t}$	-0.000087				
	(0.000063)				
OUTPUT_P_ MA4$_{j,t-1}$	-0.000108				
	(0.000120)				
Constant	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
m1	-16.34	-16.34	-16.35	-16.33	-16.34
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
m2	-0.86	-0.89	-0.90	-0.88	-0.90
	[0.389]	[0.376]	[0.370]	[0.379]	[0.369]
Hansen	0.428	0.452	0.468	0.437	0.480
Dif Hansen	0.893	0.901	0.896	0.899	0.881
Observations	16950	16950	16950	16950	16950

Notes: See next page.

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

In all columns, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In both columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Table 2.6. Investment models with crisis interactions

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM	(2) SYS GMM	(3) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.141***	0.145***	0.145***
	(0.023)	(0.022)	(0.022)
(CRISIS)*($I_{i,t-1}/K_{i,t-2}$)	0.050		
	(0.046)		
$\Delta y_{i,t}$	0.065***	0.064***	0.064***
	(0.022)	(0.017)	(0.017)
(CRISIS)*$\Delta y_{i,t}$	-0.023		
	(0.027)		
$\Delta y_{i,t-1}$	0.057***	0.055***	0.055***
	(0.008)	(0.007)	(0.007)
(CRISIS)*$\Delta y_{i,t-1}$	-0.016*		
	(0.009)		
$\Delta p_{j,t}$	-0.065	-0.063***	-0.065***
	(0.041)	(0.018)	(0.018)
(CRISIS)*$\Delta p_{j,t}$	0.005		
	(0.044)		
$\Delta p_{j,t-1}$	-0.047	-0.048***	-0.048***
	(0.046)	(0.016)	(0.016)
(CRISIS)*$\Delta p_{j,t-1}$	0.001		
	(0.048)		
$(k-y)_{i,t-2}$	-0.050***	-0.052***	-0.052***
	(0.008)	(0.007)	(0.007)
(CRISIS)*$(k-y)_{i,t-2}$	0.008		
	(0.005)		
$p_{j,t-2}$	-0.055	-0.079***	-0.081***
	(0.044)	(0.014)	(0.014)
(CRISIS)*$p_{j,t-2}$	-0.045		
	(0.046)		
ORDER_P_ $MA4_{j,t-1}$	0.000196**	0.000192**	0.000207***
	(0.000083)	(0.000077)	(0.000080)
(CRISIS)*ORDER_P_ $MA4_{j,t-1}$	-0.000111	-0.000036	-0.000068
	(0.000171)	(0.000146)	(0.000145)
EXTFIN_$MA4_{j,t-1}$	-0.000414***	-0.000393***	-0.000491**
	(0.000160)	(0.000140)	(0.000198)
(CRISIS)*EXTFIN_$MA4_{j,t-1}$	0.000040	0.000397	0.000511
	(0.000455)	(0.000406)	(0.000422)
UNCERT_$MA4_{j,t}$	-0.000424***	-0.000366***	-0.000373***
	(0.000118)	(0.000107)	(0.000108)
(CRISIS)*UNCERT_$MA4_{j,t}$	0.000548**	0.000341*	0.000334*
	(0.000231)	(0.000176)	(0.000183)

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Table 2.6 continued

$INTFIN\_MA1_{j,t}$			0.000108
			(0.000143)
$CRISIS*INTFIN\_MA1_{j,t}$			-0.000260
			(0.000230)
CHEMICALS	0.018***	0.020***	0.020***
	(0.005)	(0.005)	(0.005)
FOOD	0.026***	0.029***	0.029***
	(0.004)	(0.004)	(0.004)
METAL MANUFACTURE	0.015**	0.011**	0.011**
	(0.006)	(0.005)	(0.005)
METAL PRODUCTS	-0.000	0.002	0.002
	(0.004)	(0.004)	(0.004)
TEXTILES	-0.006	-0.006	-0.006
	(0.004)	(0.004)	(0.004)
(CRISIS)*(CHEMICALS)	0.010	0.014**	0.014**
	(0.008)	(0.007)	(0.007)
(CRISIS)*(FOOD)	0.006		
	(0.008)		
CRISIS*(METAL MANUFACTURE)	-0.013		
	(0.008)		
(CRISIS)*(METAL PRODUCTS)	-0.003		
	(0.008)		
(CRISIS)*(TEXTILES)	-0.009		
	(0.008)		
Constant	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
m1	-16.11	-16.31	-16.31
	[0.000]	[0.000]	[0.000]
m2	-0.76	-0.85	-0.84
	[0.447]	[0.395]	[0.402]
Hansen	0.442	0.464	0.468
Dif Hansen	0.821	0.916	0.922
Observations	16950	16950	16950

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

In both columns, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In all columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, the CBI survey variables, and their interactions with the crisis dummy are treated as strictly exogenous.

Table 2.7. Investment models with sector interactions

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM	(2) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.143***	0.142***
	(0.028)	(0.022)
(CHEMICALS)*($I_{i,t-1}/K_{i,t-2}$)	0.101	
	(0.076)	
(FOOD)*($I_{i,t-1}/K_{i,t-2}$)	0.013	
	(0.047)	
(METAL MANUFACTURE)*($I_{i,t-1}/K_{i,t-2}$)	-0.006	
	(0.071)	
(METAL PRODUCTS)*($I_{i,t-1}/K_{i,t-2}$)	-0.089	
	(0.070)	
(TEXTILES)*($I_{i,t-1}/K_{i,t-2}$)	-0.103*	-0.116**
	(0.060)	(0.058)
$\Delta y_{i,t}$	0.041***	0.068***
	(0.012)	(0.014)
(CHEMICALS)*$\Delta y_{i,t}$	-0.008	
	(0.024)	
(FOOD)*$\Delta y_{i,t}$	0.004	
	(0.025)	
(METAL MANUFACTURE)*$\Delta y_{i,t}$	-0.004	
	(0.017)	
(METAL PRODUCTS)*$\Delta y_{i,t}$	-0.013	
	(0.016)	
(TEXTILES)*$\Delta y_{i,t}$	-0.008	
	(0.021)	
$\Delta y_{i,t-1}$	0.045***	0.058***
	(0.007)	(0.006)
(CHEMICALS)*$\Delta y_{i,t-1}$	-0.013	
	(0.014)	
(FOOD)*$\Delta y_{i,t-1}$	0.011	
	(0.012)	
(METAL MANUFACTURE)*$\Delta y_{i,t-1}$	0.016	
	(0.013)	
(METAL PRODUCTS)*$\Delta y_{i,t-1}$	-0.006	
	(0.011)	
(TEXTILES)*$\Delta y_{i,t-1}$	-0.012	
	(0.011)	
$\Delta p_{j,t}$	-0.058***	-0.073***
	(0.012)	(0.014)
$\Delta p_{j,t-1}$	-0.056***	-0.055***
	(0.014)	(0.014)
$(k-y)_{i,t-2}$	-0.048***	-0.056***
	(0.008)	(0.007)
(CHEMICALS)*$(k-y)_{i,t-2}$	0.010	
	(0.015)	
(FOOD)*$(k-y)_{i,t-2}$	-0.008	
	(0.012)	

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Table 2.7 continued

(METAL MANUFACTURE)*$(k\text{-}y)_{i,t-2}$	-0.016	
	(0.014)	
(METAL PRODUCTS)*$(k\text{-}y)_{i,t-2}$	0.017	
	(0.013)	
(TEXTILES)*$(k\text{-}y)_{i,t-2}$	0.018	
	(0.014)	
$p_{i,t-2}$	-0.083***	-0.089***
	(0.013)	(0.012)
ORDER_P_ $MA4_{j,t-1}$	0.000104*	0.000161**
	(0.000057)	(0.000064)
EXTFIN_$MA4_{j,t-1}$	-0.000364***	-0.000302**
	(0.000110)	(0.000132)
UNCERT_$MA4_{j,t}$	-0.000387***	-0.000273***
	(0.000080)	(0.000095)
Constant	Yes	Yes
Sector dummies	Yes	Yes
Year dummies	Yes	Yes
m1	-15.01	-16.02
	[0.000]	[0.000]
m2	-0.67	-0.98
	[0.500]	[0.328]
Hansen	0.374	0.176
Dif Hansen	0.860	0.918
Observations	16950	16950

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

In column 1, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, $y_{i,t-4}$, and their interactions with the sector dummies, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$ and their interactions with the sector dummies. In column 2, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $(TEXTILES) * k_{i,t-2}$, $(TEXTILES) * k_{i,t-3}$, $(TEXTILES) * k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In both columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Table 2.8. Investment models with both sector interactions and crisis interactions

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.183***
	(0.023)
(TEXTILES)*$I_{i,t-1}/K_{i,t-2}$	-0.118*
	(0.062)
(TEXTILES)*(CRISIS)*$I_{i,t-1}/K_{i,t-2}$	-0.214*
	(0.114)
$\Delta y_{i,t}$	0.040***
	(0.010)
(FOOD)*$\Delta y_{i,t}$	-0.056**
	(0.023)
(CRISIS)*(FOOD)*$\Delta y_{i,t}$	0.076**
	(0.030)
$\Delta y_{i,t-1}$	0.045***
	(0.005)
(CHEMICALS)*$\Delta y_{i,t-1}$	-0.011*
	(0.006)
$\Delta p_{j,t}$	-0.054***
	(0.014)
$\Delta p_{j,t-1}$	-0.048***
	(0.015)
$(k-y)_{i,t-2}$	-0.042***
	(0.005)
(CHEMICALS)*(CRISIS)*$(k-y)_{i,t-2}$	0.014*
	(0.007)
$p_{j,t-2}$	-0.072***
	(0.013)
UNCERT_MA4$_{j,t}$	-0.000342***
	(0.000096)
(CRISIS)*UNCERT_MA4$_{j,t}$	0.000299**
	(0.000152)
EXTFIN_MA4$_{j,t-1}$	-0.000392***
	(0.000127)
(CRISIS)*EXTFIN_MA4$_{j,t-1}$	0.000027
	(0.000402)
ORDER_P_ MA4$_{j,t-1}$	0.000131*
	(0.000073)
(CRISIS)*ORDER_P_ MA4$_{j,t-1}$	-0.000074
	(0.000136)
Constant	Yes
Sector dummies	Yes
Year dummies	Yes
m1	-15.13
	[0.000]
m2	-0.33
	[0.739]
Hansen	0.048
Dif Hansen	0.275
Observations	16950

Notes: See next page.

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

The instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, and their interactions with the chemicals and textiles sector dummies, as well as $y_{i,t-2}$, $y_{i,t-3}$, $y_{i,t-4}$, and their interactions with the food and chemicals sector dummies. The instruments used in the levels equations are: $\Delta y_{i,t-1}$, and its interactions with the food and chemicals sector dummies. $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Table 2.9. Investment model with $(\boldsymbol{k_{i,t-2} - 0.933y_{i,t-2}})$ as the error correction term

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.139***
	(0.023)
$\Delta y_{i,t}$	0.069***
	(0.017)
$\Delta y_{i,t-1}$	0.056***
	(0.008)
$\Delta p_{j,t}$	-0.079***
	(0.014)
$\Delta p_{j,t-1}$	-0.057***
	(0.014)
$(k-0.933y)_{i,t-2}$	-0.056***
	(0.008)
$p_{j,t-2}$	-0.091***
	(0.012)
$ORDER\_P\_MA4_{j,t-1}$	0.000184***
	(0.000065)
$EXTFIN\_MA4_{j,t-1}$	-0.000303**
	(0.000133)
$UNCERT\_MA4_{j,t}$	-0.000290***
	(0.000096)
Constant	Yes
Sector dummies	Yes
Year dummies	Yes
m1	-16.31
	[0.000]
m2	-0.92
	[0.360]
Hansen	0.335
Dif Hansen	0.802
Observations	16950

Notes: See next page.

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

The instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Table 2.10. Investment models with crisis interactions (error correction term: $k_{i,t-2} - 0.933y_{i,t-2}$)

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.143***
	(0.023)
$\Delta y_{i,t}$	0.063***
	(0.017)
$\Delta y_{i,t-1}$	0.054***
	(0.008)
$\Delta p_{j,t}$	-0.063***
	(0.018)
$\Delta p_{j,t-1}$	-0.047***
	(0.016)
$(k-0.933y)_{i,t-2}$	-0.054***
	(0.008)
$p_{j,t-2}$	-0.078***
	(0.014)
$UNCERT\_MA4_{j,t}$	-0.000382***
	(0.000107)
(CRISIS)*$UNCERT\_MA4_{j,t}$	0.000339*
	(0.000177)
$EXTFIN\_MA4_{j,t-1}$	-0.000392***
	(0.000140)
(CRISIS)*$EXTFIN\_MA4_{j,t-1}$	0.000413
	(0.000410)
$ORDER\_P\_ MA4_{j,t-1}$	0.000194**
	(0.000077)
(CRISIS)*$ORDER\_P\_ MA4_{j,t-1}$	-0.000024
	(0.000148)
CHEMICALS	0.021***
	(0.006)
FOOD	0.030***
	(0.004)
METAL MANUFACTURE	0.009*
	(0.005)
METAL PRODUCTS	-0.000
	(0.004)
TEXTILES	-0.009**
	(0.004)
(CRISIS)*(CHEMICALS)	0.013**
	(0.007)
Constant	Yes
Year dummies	Yes
m1	-16.26
	[0.000]
m2	-0.86
	[0.388]
Hansen	0.317
Dif Hansen	0.807
Observations	16950

Notes: See next page.

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

In both columns, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In both columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Table 2.11. Investment models with quarterly CBI survey variables

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) SYS GMM	(2) SYS GMM	(3) SYS GMM
$I_{i,t-1}/K_{i,t-2}$	0.141***	0.142***	0.141***
	(0.022)	(0.022)	(0.022)
$\Delta y_{i,t}$	0.069***	0.069***	0.069***
	(0.017)	(0.016)	(0.016)
$\Delta y_{i,t-1}$	0.057***	0.058***	0.057***
	(0.007)	(0.007)	(0.007)
$\Delta p_{j,t}$	-0.080***	-0.079***	-0.080***
	(0.014)	(0.014)	(0.015)
$\Delta p_{j,t-1}$	-0.057***	-0.059***	-0.057***
	(0.014)	(0.014)	(0.014)
$(k-y)_{i,t-2}$	-0.054***	-0.054***	-0.054***
	(0.007)	(0.007)	(0.007)
$p_{j,t-2}$	-0.092***	-0.091***	-0.093***
	(0.012)	(0.012)	(0.012)
$UNCERT\_Q4_{j,t}$	-0.000119*	-0.000118*	-0.000081
	(0.000068)	(0.000063)	(0.000082)
$UNCERT\_Q3_{j,t}$	-0.000108*	-0.000121**	-0.000072
	(0.000062)	(0.000059)	(0.000080)
$UNCERT\_Q2_{j,t}$	-0.000046		
	(0.000069)		
$UNCERT\_Q1_{j,t}$	-0.000024		
	(0.000065)		
$ORDER\_P\_Q4_{j,t-1}$	0.000037		
	(0.000044)		
$ORDER\_P\_Q3_{j,t-1}$	0.000017		
	(0.000045)		
$ORDER\_P\_Q2_{j,t-1}$	0.000033		
	(0.000043)		
$ORDER\_P\_Q1_{j,t-1}$	0.000115***	0.000114***	0.000085*
	(0.000044)	(0.000042)	(0.000050)
$EXTFIN\_Q4_{j,t-1}$	-0.000012		
	(0.000121)		
$EXTFIN\_Q3_{j,t-1}$	-0.000106		
	(0.000138)		
$EXTFIN\_Q2_{j,t-1}$	-0.000027		
	(0.000125)		
$EXTFIN\_Q1_{j,t-1}$	-0.000177	-0.000199**	-0.000137
	(0.000115)	(0.000099)	(0.000139)
$EXTFIN\_MA4_{j,t-1}$			-0.000185
			(0.000182)
$UNCERT\_MA4_{j,t}$			-0.000142
			(0.000158)

Continued on next page

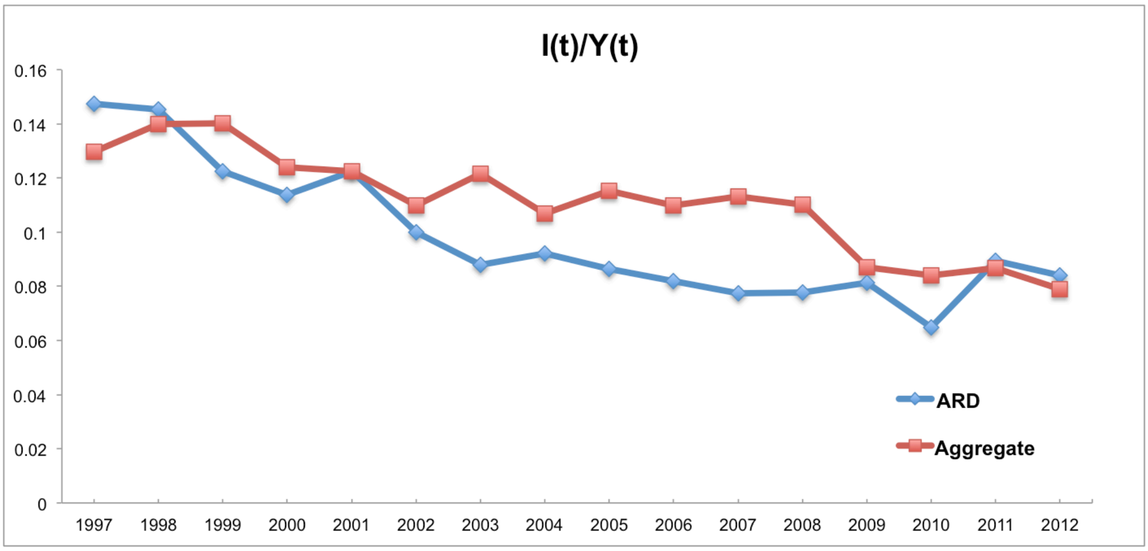
Table 2.11 continued

$ORDER\_P\_MA4_{j,t-1}$			0.000115
			(0.000077)
Constant	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
m1	-16.34	-16.36	-16.36
	[0.000]	[0.000]	[0.000]
m2	-0.90	-0.91	-0.90
	[0.367]	[0.363]	[0.367]
Hansen	0.452	0.495	0.459
Dif Hansen	0.904	0.894	0.909
Observations	16950	16950	16950

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

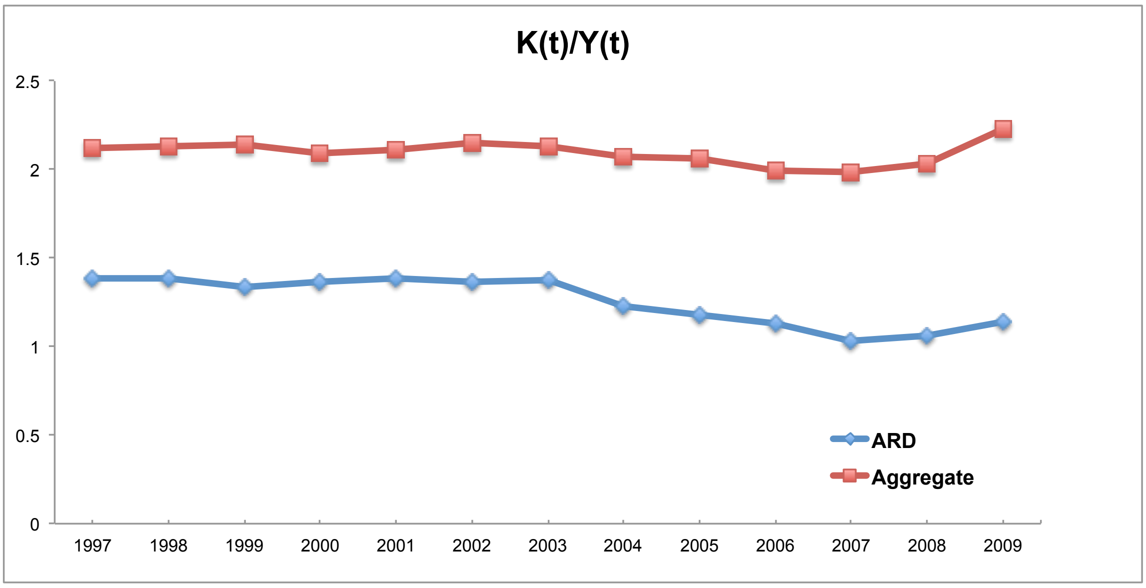
In all columns, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In all columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Figure 2.1. Investment to output ratio



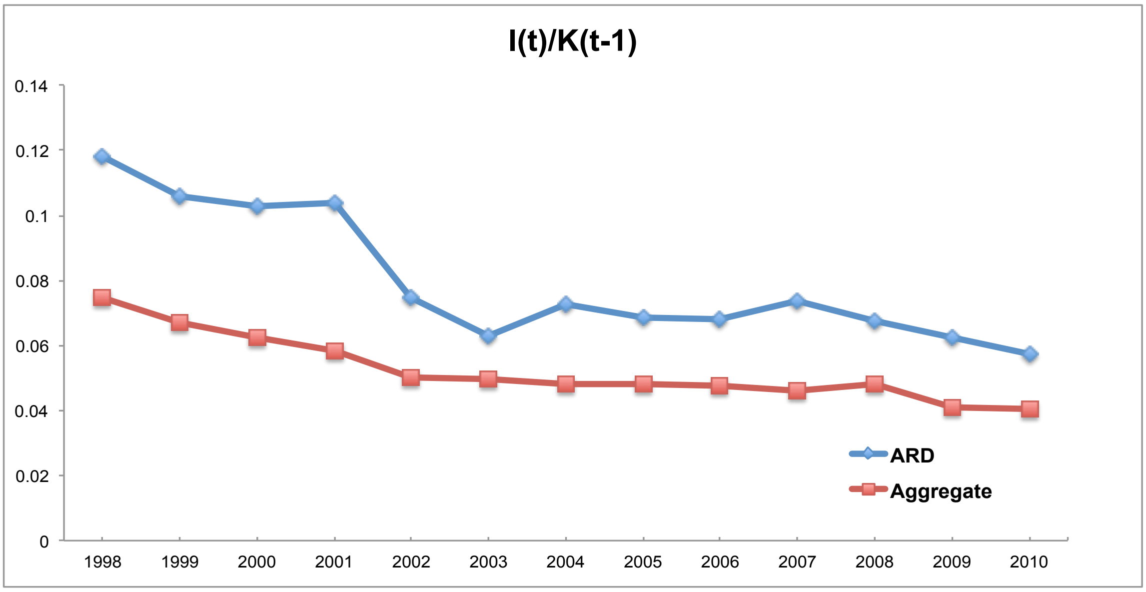
Source: Author's calculations.

Figure 2.2. Capital stock to output ratio



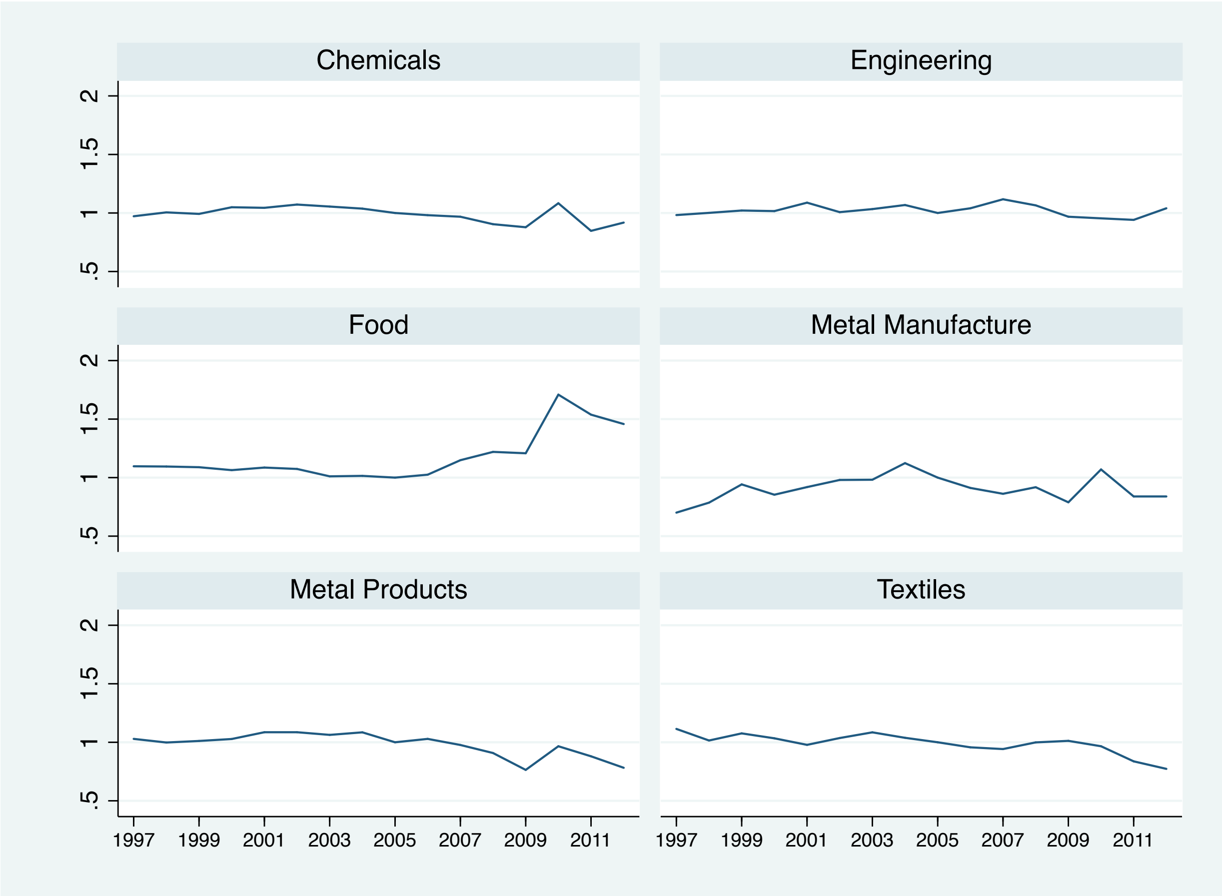
Source: Author's calculations.

Figure 2.3. Investment to capital stock ratio



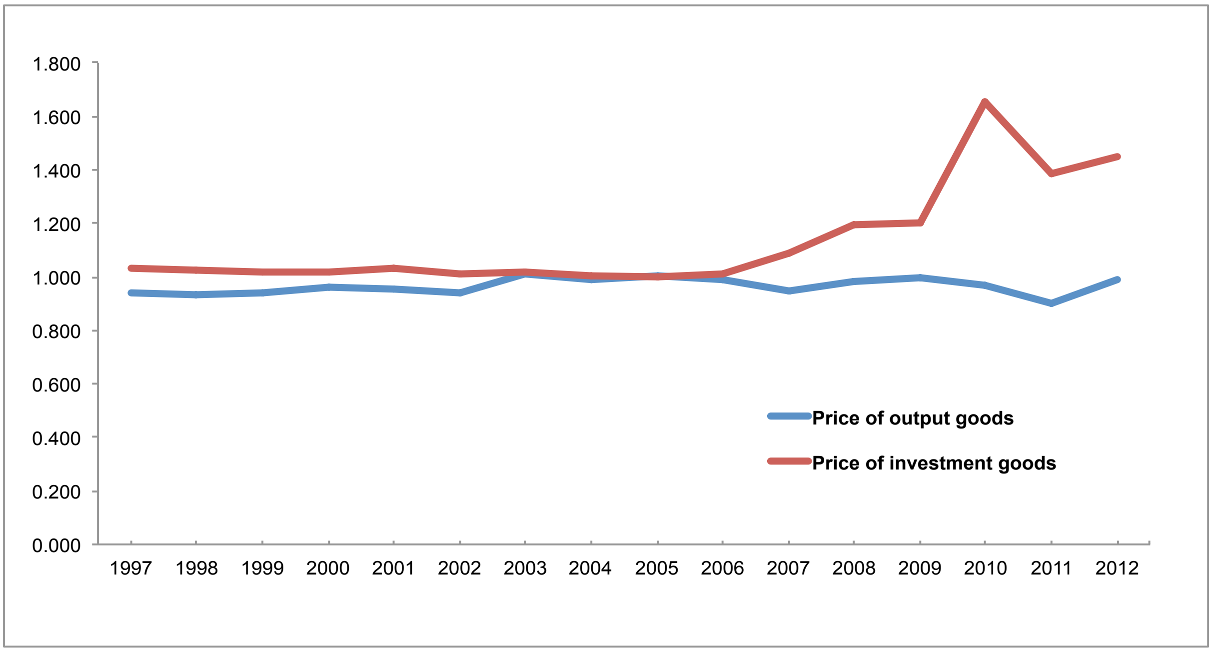
Source: Author's calculations.

Figure 2.4A. Relative price of investment goods by sector



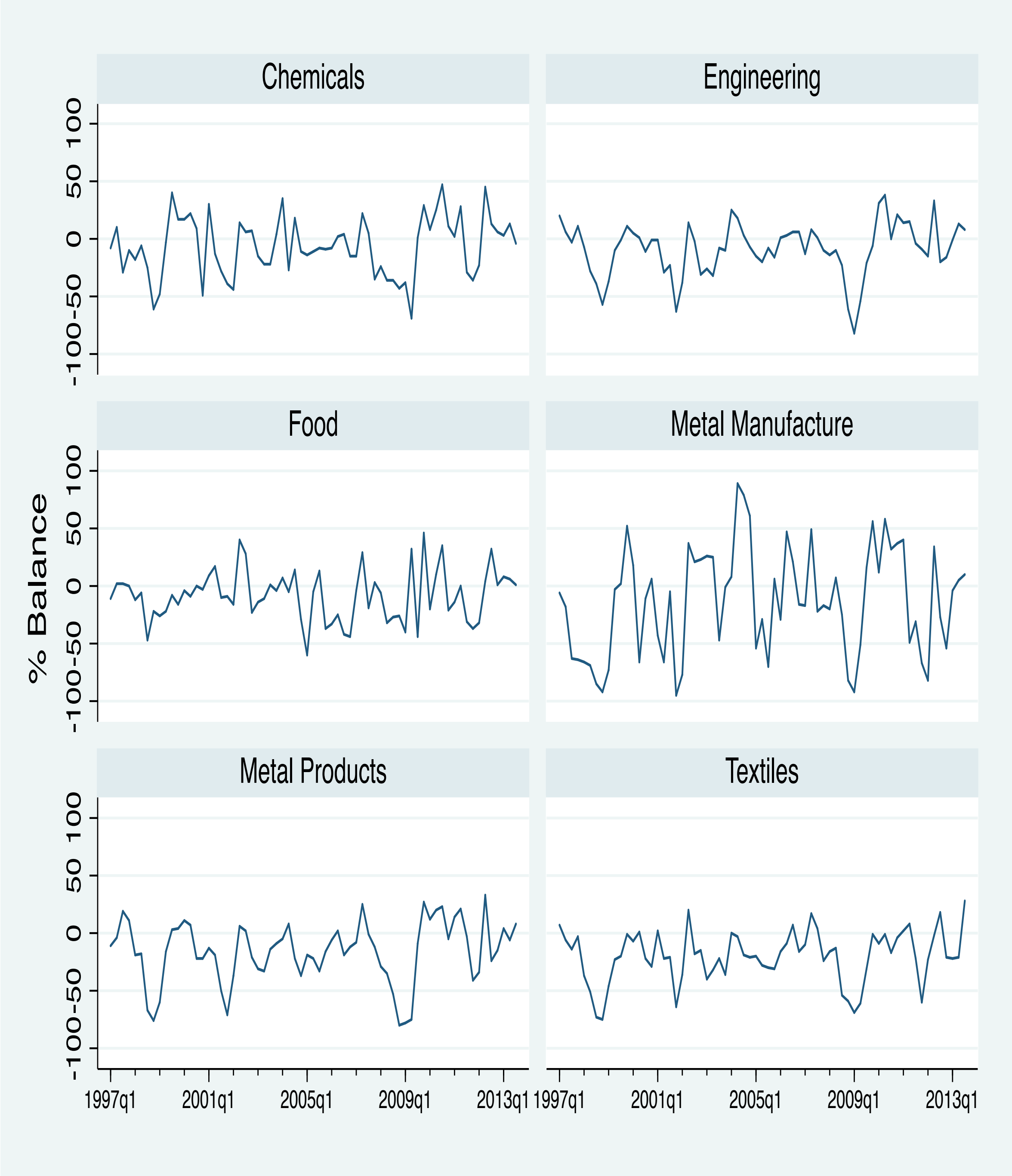
Source: Author's calculations.

Figure 2.4B. Food sector prices of investment goods and output goods



Source: Author's calculations.

Figure 2.5. Business optimism (more/less than three months ago)



Source: CBI Industrial Trends Survey.

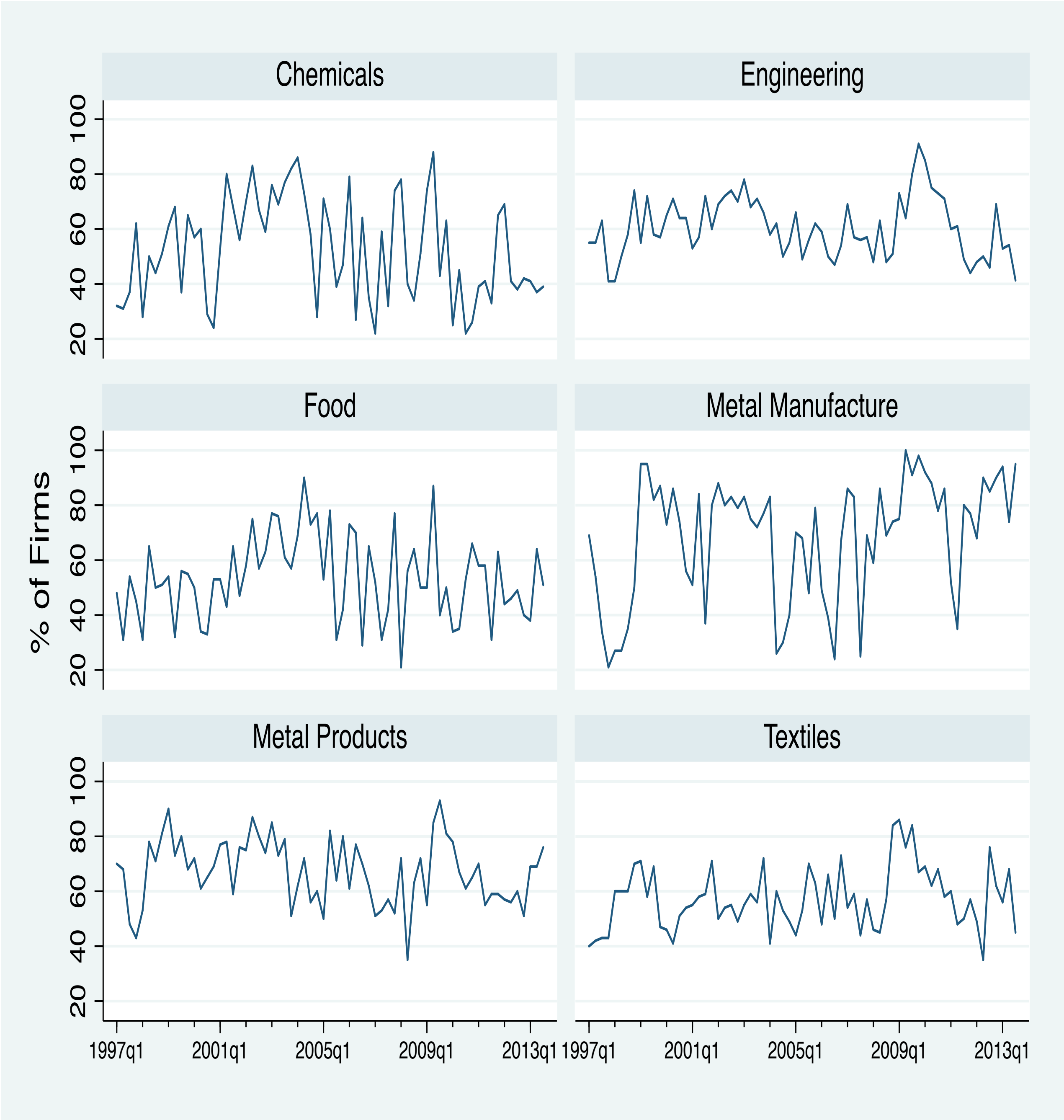
Figure 2.6. Investment on buildings over the next twelve months compared with the past twelve months (more/less)

Source: CBI Industrial Trends Survey.

Figure 2.7. Investment on plant and machinery over the next twelve months compared with the past twelve months (more/less)

Source: CBI Industrial Trends Survey.

Figure 2.8. Level of present output below capacity

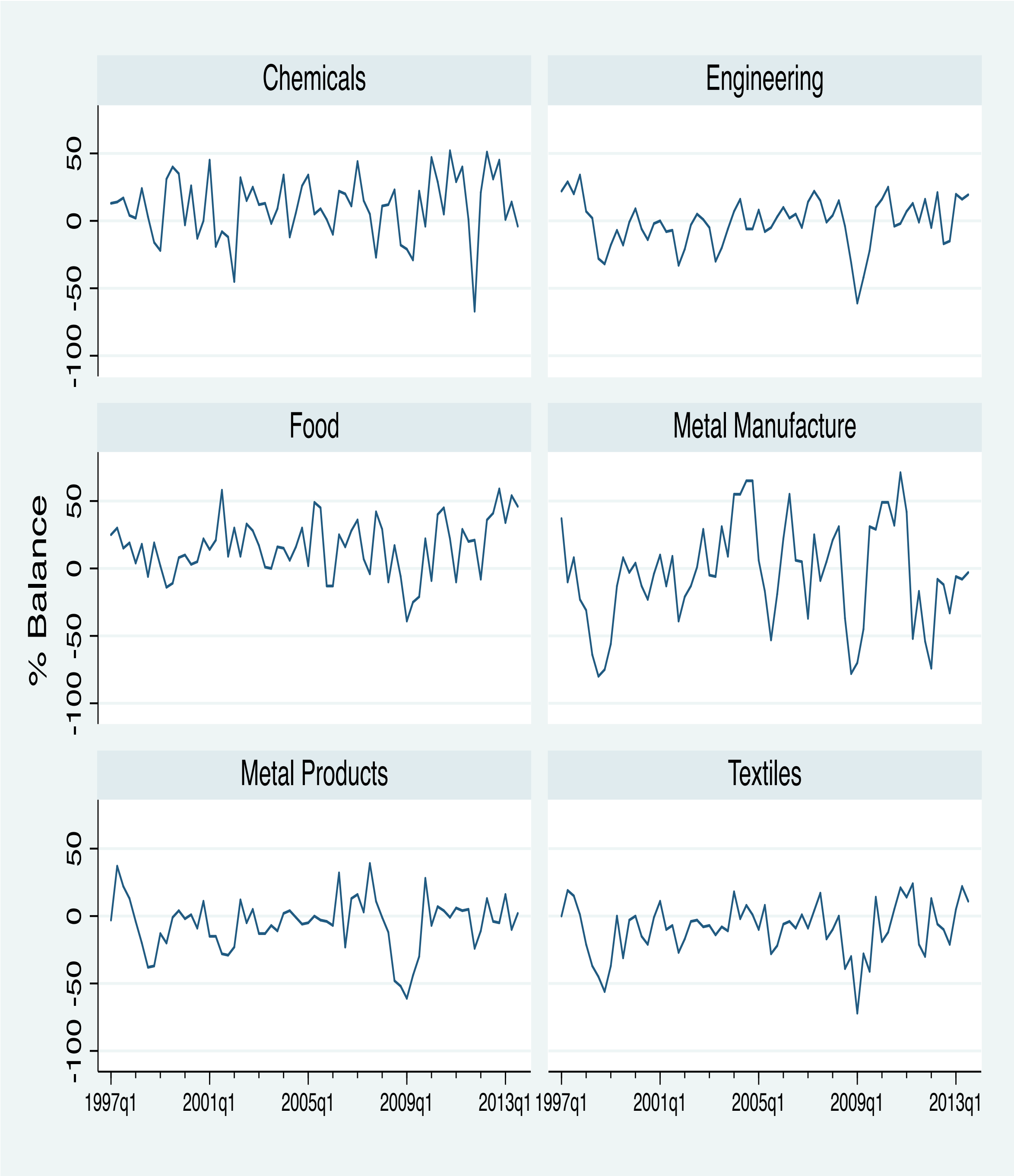


Source: CBI Industrial Trends Survey.

Figure 2.9. Volume of total new orders over the past three months (up/down)

Source: CBI Industrial Trends Survey.

Figure 2.10. Volume of total new orders over the next three months (up/down)

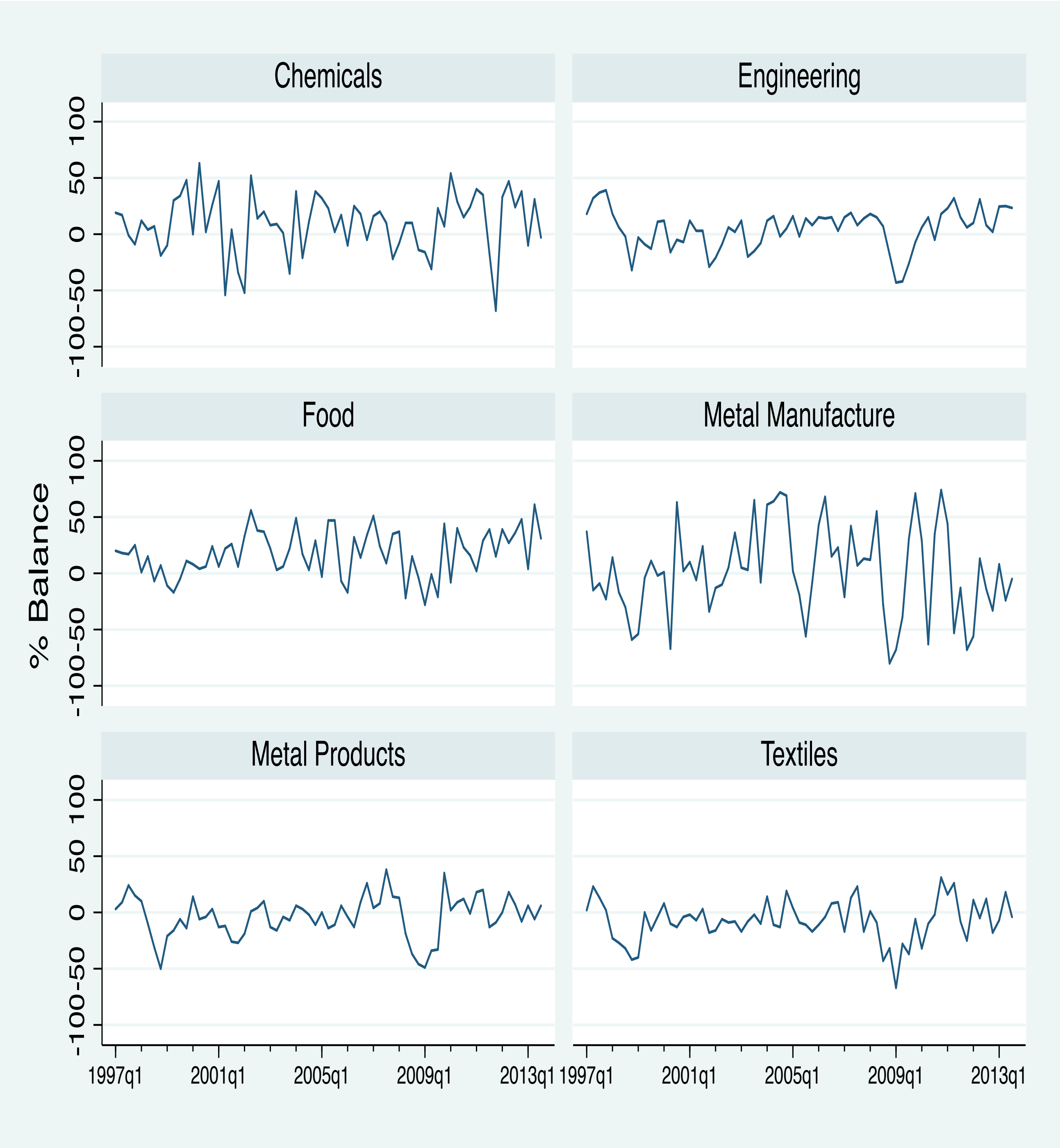


Source: CBI Industrial Trends Survey.

Figure 2.11. Volume of output over the past three months (up/down)

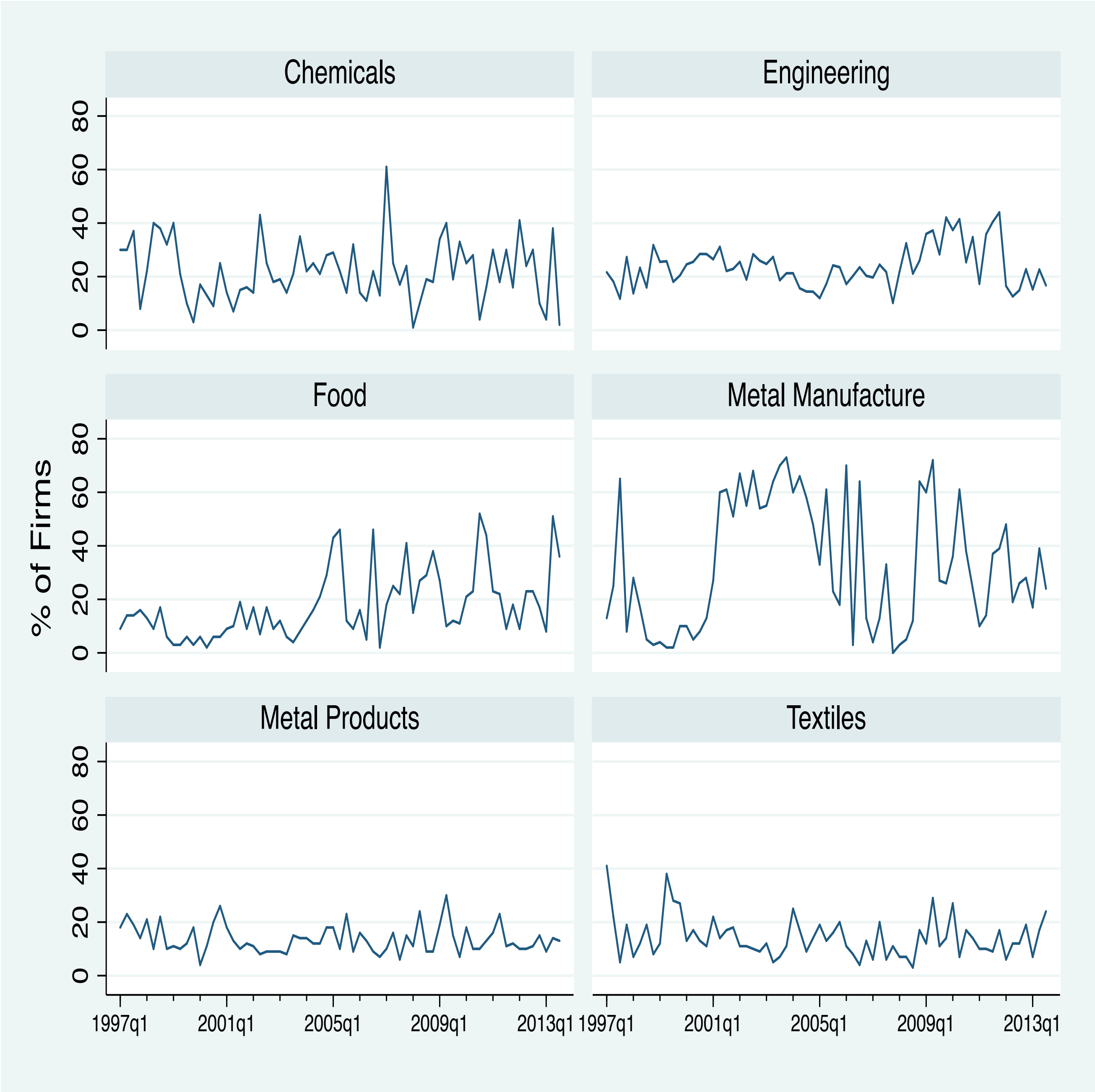
Source: CBI Industrial Trends Survey.

Figure 2.12. Volume of output over the next three months (up/down)



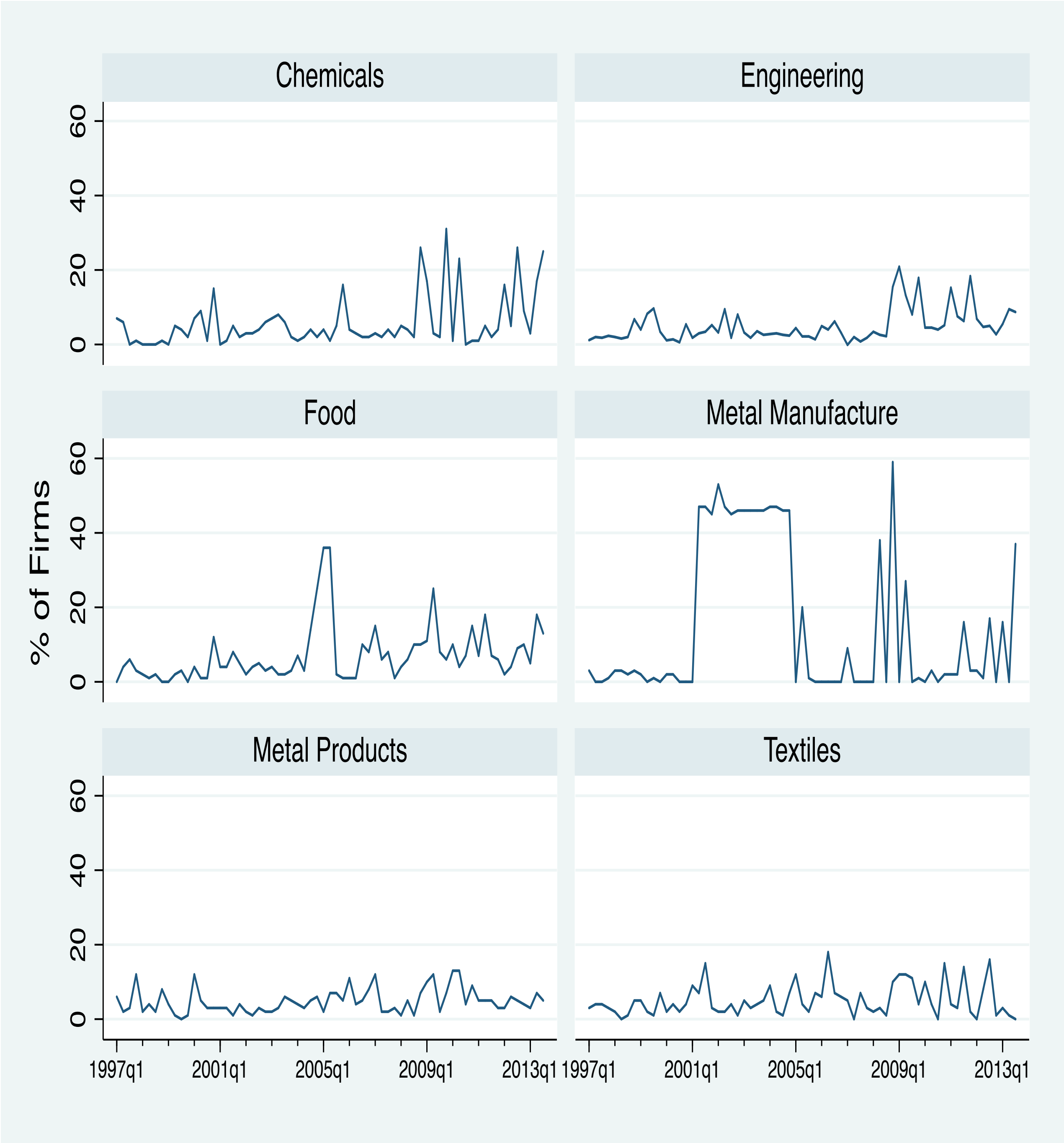
Source: CBI Industrial Trends Survey.

Figure 2.13. Factors limiting firm investment: shortage of internal finance



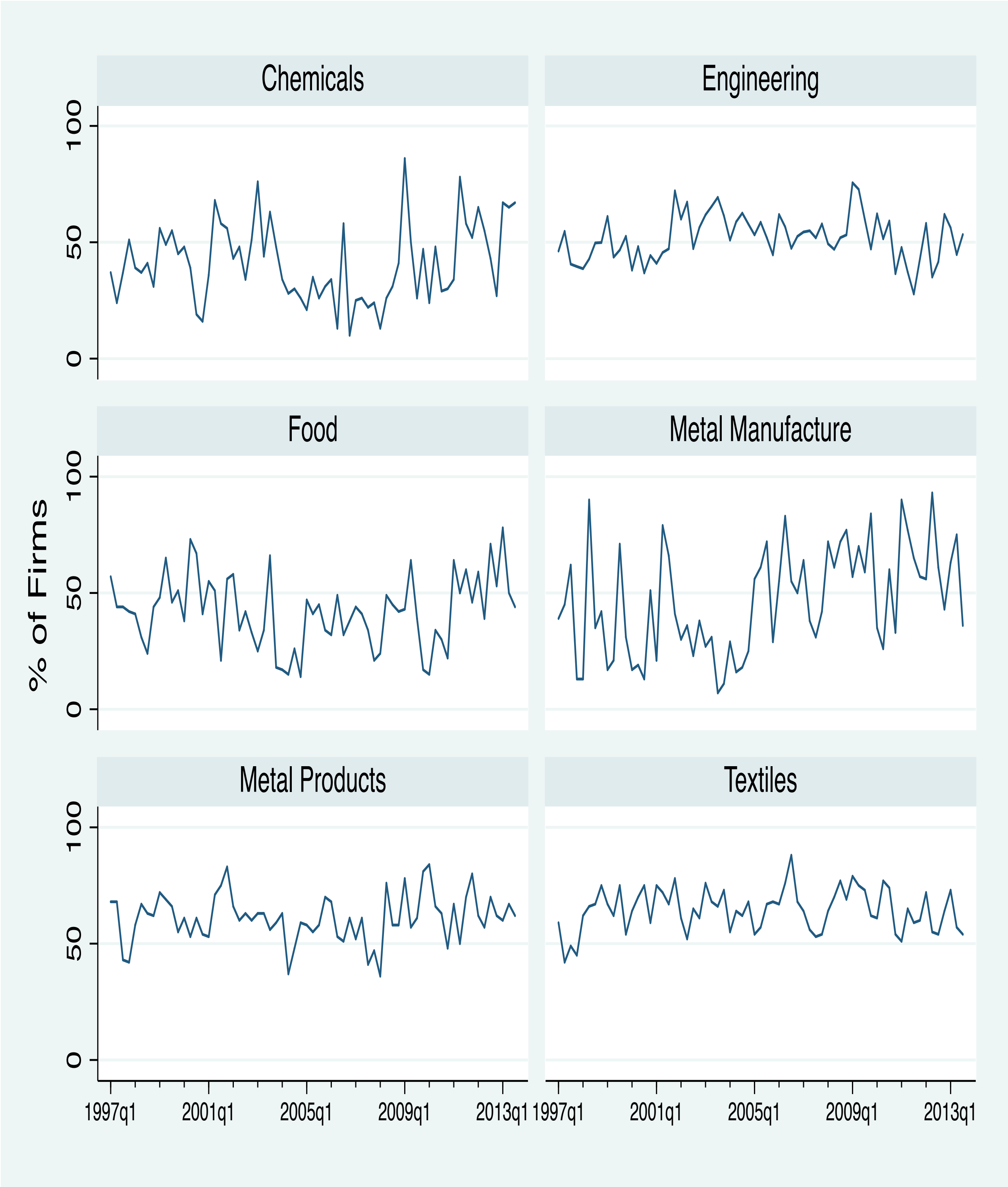
Source: CBI Industrial Trends Survey.

Figure 2.14. Factors limiting firm investment: inability to raise external finance



Source: CBI Industrial Trends Survey.

Figure 2.15. Factors limiting firm investment: uncertainty about demand



Source: CBI Industrial Trends Survey.

Appendix

Appendix 2.1. Construction of gross value added (GVA) and investment variables

GVA at market price = total turnover (wq399) + total amount received from sale of goods and services (wq346) - amount of value added tax included in wq346 (wq321) + total value of all stocks at the end of the year (wq599) - total value of all stocks at the beginning of the year (wq500) + value charged to capital account for work carried out by own staff (wq602) + value of insurance claims received (wq317) - total purchases of goods and services (wq499)

Net investment = total net capital expenditure (excluding units not yet in production) (wq522) + capital expenditure on units not yet in production (wq521)

Notes: ARD variable numbers are in parenthesis

Appendix 2.2. Initial capital stock estimation

Following Gilhooly (2008) and Gilhooly (2009), we construct the starting capital stock $K_{i,0}$ in three steps:

1. Because the ONS uses stratified sampling to select the RUs included in the ARD, we first need to estimate the share of the aggregate capital stock to be allocated to the RUs in the ARD sample each year.[32] For a Standard Industrial Classification (SIC) 1992 2-letter division (e.g., DA= Food, beverage, and tobacco, DB=Textile and leather products) in a given year, we assume that the ratio of the sum of the capital stock of all the RUs in the division surveyed by the ONS to total capital stock of the division is equal to the ratio of the sum of investment of all these RUs in the division to total investment of the division. Detailed information on how SIC 1992 2-letter divisions are classified based on the SIC 1992 2-digit code is provided in Appendix 2.3. Therefore, the sum of the capital stock of all the RUs in an SIC 1992 2-letter division surveyed by the ONS in a given year can be expressed as:

$$Total\ RU\ Investment\ Share_{siclett,year} = \frac{\sum_{j \in siclett} Investment_{j,year}}{Investment_{siclett,year}}$$

$$\sum_{j \in siclett} K_{\ j,year} = K_{\ siclett,year} \times Total\ RU\ Investment\ Share_{siclett,year}$$

where *j* represents an individual RU, *K* represents capital stock, and *siclett* represents the SIC 1992 2-letter division.

2. We divide the capital stock among the RUs in the same SIC 1992 2-letter division. We use the RU-level variable "total purchases of goods and services (*totpurch*)" to allocate a share of this capital stock to each RU. Gilhooly (2009) points out that *totpurch* is likely to be positively associated with the capital stock. In addition, as in Gilhooly (2009), we

[32] The aggregate capital stock series is from the Volume Index of Capital Services (VICS) dataset constructed by the ONS. For detailed information about the VICS, please refer to Wallis and Dey-Chowdury (2007).

use employment to refine the allocation. A RU i's share of capital stock in a given year is given by:

$$Capital\ Share_{\ i,year} = \left[\frac{totpurch_{\ i,year}}{\sum_{m\in sic3d} totpurch_{m,year}}\right] \times \left[\frac{\sum_{m\in sic3d} employment_{m,year}}{\sum_{j\in siclett} employment_{j,year}}\right]$$

where *m* represents RU and *sic3d* is the SIC 1992 3-digit sub-division that RU *i* belongs to (e.g., within the DA division (Food, beverage, and tobacco), 15.1 sub-division = Production, processing and preservation of meat and meat products, 15.2 sub-division = Processing and preserving of fish and fish products).

3. $K_{i,0}$ for RU *i* is:

$$K_{i,0} = Capital\ Share_{\ i,year} \times \sum_{j\in siclett} K_{j,year}$$

where *year* is RU i's first period of observation in the ARD.

Appendix 2.3. Manufacturing sector classification

Manufacturing sector	SIC 1992 2-digit code	SIC 1992 2-letter code	SIC 1992 2-letter division description	SIC 2007 2-digit code
Food	15,16	DA	Food, beverages, tobacco	10-12
Textiles	17-19	DB, DC	Textile and leather products	13-15
Chemicals	24	DG	Chemicals, man-made fibers	20,21
Metal manufacture	27	DJ	Basic metals and metal products	24
Metal products	28	DJ	Basic metals and metal products	25
Engineering	29	DK	Machinery and equipment	26-30
	30-33	DL	Electrical and optical equipment	
	34-35	DM	Transport equipment	

Appendix 2.4. Number of observations lost in data cleaning

	Number of observation remaining after this step	Number of observations lost in this step
Initial sample	100702	-
Step 1	89834	10868
Step 2	86544	3290
Step 3	23928	62616
Step 4	22964	964

The total number of observations lost in data cleaning is 77738. The shares of the numbers of observations lost in step 1, step 2, step 3, and step 4 in the total number of observations lost in the sample selection are 14.0%, 4.2%, 80.5%, and 1.2%, respectively. Therefore, the majority of the observations are lost in step 3 in which we discard the RUs with less than five consecutive observations.

Appendix 2.5. Descriptive statistics

Table A2.1. Distribution of observations by year

Year	Full sample	Chemicals	Engineering	Food	Metal manufacture	Metal products	Textiles
1997	1235	171	464	278	100	77	145
1998	1421	196	539	320	110	95	161
1999	1644	222	627	364	130	120	181
2000	1878	252	720	429	138	141	198
2001	2180	279	838	485	158	190	230
2002	2114	287	804	471	144	199	209
2003	2051	268	793	444	144	205	197
2004	1896	249	736	406	134	194	177
2005	1734	221	681	372	127	172	161
2006	1531	213	589	340	116	140	133
2007	1425	195	542	347	104	118	119
2008	1094	154	415	284	82	77	82
2009	878	120	342	233	60	60	63
2010	728	97	272	207	51	46	55
2011	613	82	241	184	32	36	38
2012	542	67	213	175	26	30	31
Total	22964	3073	8816	5339	1656	1900	2180

The engineering sector has the largest number of observations, followed by the food sector, the chemicals sector, the textiles sector, the metal products sector, and the metal manufacture sector. There were comparatively fewer observations for the first four years (1997-2000) and the last four years (2009-2012) because of our requirement for five consecutive observations. Between 2001 and 2008, the number of RUs in our sample gradually decreased. The fall was especially pronounced in 2008. From 2009 onwards, the ARD is constructed from a new ONS survey, the Annual Business Survey. This may have affected the number of RUs in the years near 2009.

Table A2.2. Distribution of observations by the number of consecutive years

No. of years	No. of RU-year observations	% of total RU-year observations	No. of RUs	% of total RUs
5	4320	18.81	864	28.7
6	3498	15.23	583	19.4
7	3003	13.08	429	14.3
8	2176	9.48	272	9.0
9	1809	7.88	201	6.7
10	1540	6.71	154	5.1
11	1694	7.38	154	5.1
12	1200	5.23	100	3.3
13	689	3	53	1.8
14	616	2.68	44	1.5
15	435	1.89	29	1.0
16	1984	8.64	124	4.1
Total	22964	100	3007	100

In Table A.2.2, we can observe that the number of RUs generally decreases if we require a higher number of consecutive years of observations. A high proportion (28.7%+19.4%+14.3%+9.0%=71.4%) of the RUs in the sample do not survive more than 8 years, which is half of the sample period. However, there is a non-negligible proportion (4.1%) of RUs that survive the whole sample period of 16 years.

Table A2.3. Summary statistics of key variables

Variable	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
$I_{i,t}/K_{i,t-1}$	0.074	0.101	0.016	0.045	0.098
$\Delta k_{i,t}$	-0.024	0.093	-0.080	-0.049	0.005
$\Delta y_{i,t}$	0.016	0.357	-0.147	0.025	0.191
$(k_{i,t} - y_{i,t})$	0.183	0.762	-0.295	0.181	0.668

As the capital stock growth term $\Delta k_{i,t}$ is related to the investment rate $I_{i,t}/K_{i,t-1}$ by $\Delta k_{i,t} \approx I_{i,t}/K_{i,t-1} - \delta_i$, where δ_i denotes the RU-specific rate of depreciation, the mean of $\Delta k_{i,t}$ is smaller than the mean of $I_{i,t}/K_{i,t-1}$. $\Delta k_{i,t}$ has a negative mean, which suggests that the average RU-level capital stock is decreasing over the sample period. Furthermore, the median of $\Delta k_{i,t}$ is also negative. This is consistent with the results in Driver and Temple (2013), which show that the capital stock growth rate of the aggregate U.K. manufacturing industry was slow between 1997-1999, and has turned negative since 2000. Driver and Temple (2013) argue that the low and recently negative U.K. manufacturing capital stock growth rates may be because the Information and Communications Technology (ICT) assets are forming an increasingly large share of U.K. manufacturing capital stock and these ICT assets tend to be short-lived and have very high depreciation rates. As the error correction term $(k_{i,t} - y_{i,t})$ has the highest standard error, it shows greater variation than the other three variables.

Table A2.4. Share of total investment in the full sample, by sector (unit: %)

Year	Chemicals	Engineering	Food	Metal manufacture	Metal products	Textiles
1997	17.6	47.9	24.9	4.7	2.7	2.1
1998	22.5	42.2	27.4	3.1	2.8	2.0
1999	24.7	39.5	28.2	3.4	2.1	2.1
2000	23.5	44.8	25.5	3.1	1.9	1.3
2001	24.3	48.5	21.7	2.8	1.5	1.1
2002	24.9	43.8	26.2	2.0	1.8	1.3
2003	23.9	40.0	29.4	2.5	2.6	1.6
2004	27.3	44.1	22.5	3.4	2.0	0.7
2005	24.2	42.1	26.2	4.0	2.7	0.8
2006	23.4	42.9	26.6	4.9	2.0	0.2
2007	25.4	37.7	30.4	3.6	2.2	0.8
2008	22.6	46.2	23.6	4.3	2.5	0.8
2009	18.2	50.4	25.9	2.4	2.3	0.8
2010	14.3	58.9	22.1	2.1	1.4	1.2
2011	18.3	54.7	20.5	3.8	2.0	0.7
2012	20.2	47.0	25.0	3.8	3.0	1.0

In Table A2.4, we can observe that in most of the years over the sample period, the engineering sector has the highest share of investment, followed by the food sector, the chemicals sector, the metal manufacture sector, the metal products sector, and the textiles sector. In a typical year, the engineering sector has an about 40-50% share of investment, the chemicals and the food sector both have an about 20-30% share of investment, and the metal manufacture, metal products, and food sectors each have a below 5% share of investment.

Table A2.5. Share of total output in the full sample, by sector (unit:%)

Year	Chemicals	Engineering	Food	Metal manufacture	Metal products	Textiles
1997	16.1	39.4	33.0	3.4	3.9	4.2
1998	17.8	39.7	31.5	3.2	4.0	3.7
1999	18.0	40.7	30.9	3.0	3.7	3.7
2000	16.4	42.3	32.8	2.6	3.0	2.9
2001	19.9	41.7	30.4	2.5	3.0	2.5
2002	20.7	40.1	31.1	2.5	3.2	2.3
2003	18.7	44.2	29.1	2.4	3.3	2.3
2004	20.6	42.7	28.0	4.0	2.9	1.7
2005	20.9	42.8	28.3	3.4	3.1	1.6
2006	20.7	42.9	28.6	3.3	3.2	1.2
2007	12.2	48.8	30.6	4.3	2.8	1.3
2008	13.3	48.8	30.6	3.2	2.6	1.5
2009	16.0	42.7	35.0	2.0	2.7	1.5
2010	14.7	45.3	33.8	2.8	2.0	1.4
2011	13.1	46.9	33.6	2.8	2.2	1.3
2012	13.7	46.3	34.0	2.6	2.2	1.3

In Table A2.5, we can observe that, in all years, the engineering sector has the highest share of output, the food sector has the second largest, and the chemicals sector has the third largest. This pattern is similar to the pattern for investment observed in Table A2.4. The metal manufacture, metal products, and food sectors had similar shares of output before 2003. Since 2003, the share of food sector has begun to fall below those of the metal manufacture and metal products sectors. In a typical year, the engineering sector has an about 40-50% share of output, the food sector has an about 30-35% share of output, the chemicals sector has an about 15-20% share of output, and the metal manufacture, metal products and food sectors each have a below 5% share of output.

Table A2.6. Share of total capital stock in the full sample, by sector (unit: %)

Year	Chemicals	Engineering	Food	Metal manufacture	Metal products	Textiles
1997	22.9	37.4	25.9	5.6	3.8	4.3
1998	22.7	38.5	25.9	5.0	4.3	3.7
1999	22.5	37.8	27.6	4.5	4.0	3.6
2000	21.9	40.9	27.1	3.7	3.5	2.9
2001	24.1	41.0	25.4	3.6	3.2	2.7
2002	24.8	41.2	25.5	3.1	3.2	2.3
2003	23.9	42.7	24.8	3.2	3.1	2.2
2004	24.7	41.9	25.0	3.5	3.0	1.9
2005	22.4	43.0	25.8	3.4	3.5	1.8
2006	22.7	42.1	26.6	3.8	3.3	1.5
2007	19.3	42.7	29.5	3.5	3.2	1.7
2008	18.7	43.1	29.7	3.6	3.2	1.6
2009	19.1	44.1	28.7	3.1	3.3	1.6
2010	18.6	44.1	29.6	3.4	2.6	1.7
2011	18.8	45.9	27.9	3.3	2.6	1.6
2012	19.7	43.1	29.5	3.5	2.7	1.5

In Table A2.6, we can observe that, in all years, the engineering sector has the highest share of the capital stock, the food sector has the second largest, and the chemicals sector has the third largest. This pattern for the capital stock is similar to those for investment and output observed in Tables A2.4 and A2.5. In most of the years, the metal manufacture sector has a higher share of the capital stock than the metal products sector, and the food sector has the lowest share of the capital stock. In a typical year, the engineering sector has an about 40-50% share of the capital stock, the food sector has an about 30-35% share of the capital stock, the chemicals sector has an about 15-20% share of the capital stock, and the metal manufacture, metal products and food sectors each have a below 5% share of the capital stock.

Table A2.7. Comparing the full sample with the aggregate data of the six sectors

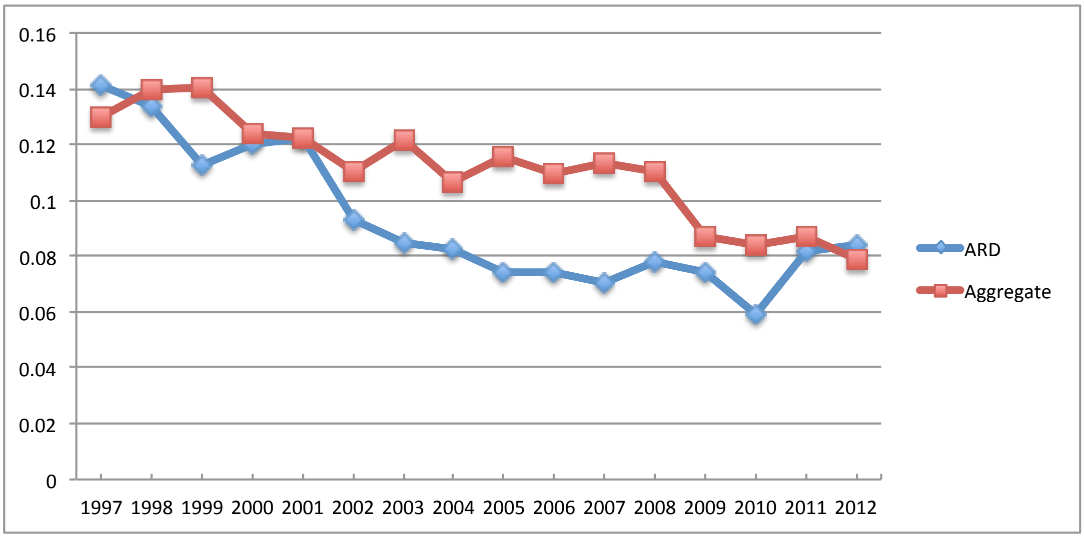
Year	Total investment of full sample	% of aggregate investment	Total output of full sample	% of aggregate output	Total capital stock of full sample	% of aggregate capital stock
1997	3609791	24.5	24481418	24.3	33906860	15.8
1998	3999521	25.0	27511756	27.1	38253724	17.6
1999	4047790	27.7	33068338	32.4	44347784	20.3
2000	4549149	33.4	40001780	38.3	54572004	24.9
2001	5665242	44.4	46248620	44.7	64244592	29.4
2002	4798853	43.6	48029824	47.9	65774488	30.5
2003	4152460	38.8	47219724	47.2	65018608	30.5
2004	4715099	45.8	51149800	50.1	62914268	29.7
2005	4302902	42.0	49730736	48.5	58861536	27.9
2006	3998556	39.8	48827596	46.4	54966280	26.1
2007	4039189	41.6	52204664	49.3	53854636	25.6
2008	3629992	35.9	46629616	45.2	49539060	23.5
2009	3086202	35.6	37894856	40.5	43095620	20.6
2010	2473668	29.3	38125008	38.4	36851848	-
2011	3332499	36.1	37312140	36.5	35254212	-
2012	2814369	28.5	33444708	32.7	31986108	-

Notes: Total investment, output and capital stock are in £ thousands (2005 constant prices). The ONS aggregate capital stock data are available until 2009.

In Table A2.7, we can observe that our microdata sample's share of aggregate investment, aggregate output, and aggregate capital stock increased from 1997 to 2000, then remained relatively stable between 2001 to 2008, and declined from 2009 to 2012. A likely explanation for these trends is that we have fewer observations for the first four years (1997-2000) and the last four years (2009-2012) compared with the middle years (2001-2008) (see Table A2.1) as a result of our sample selection requirement of five consecutive observations.

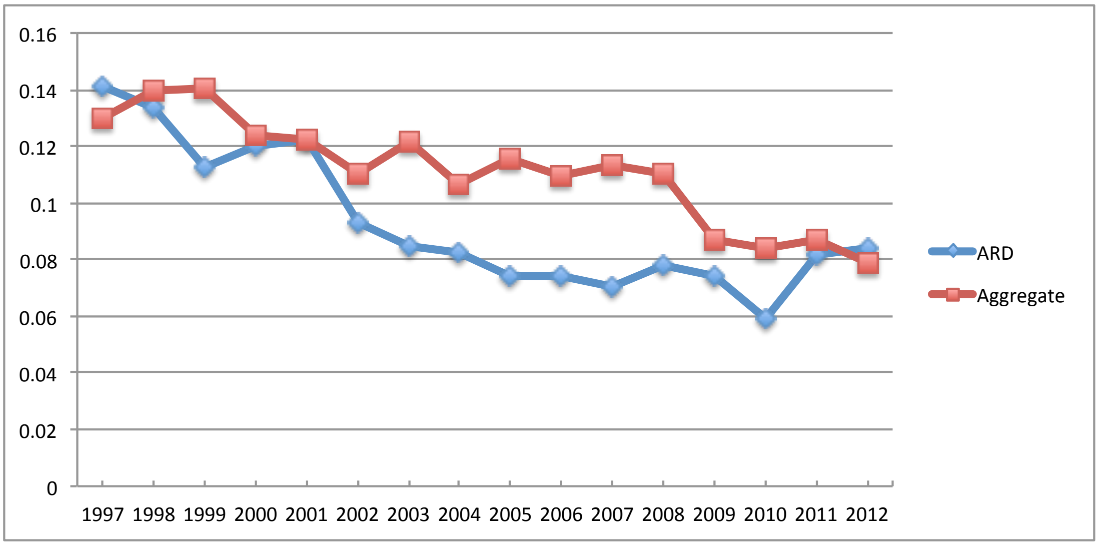
Appendix 2.6. Investment to output ratio after each data cleaning step

Figure A2.1. Investment to output ratio of the initial sample



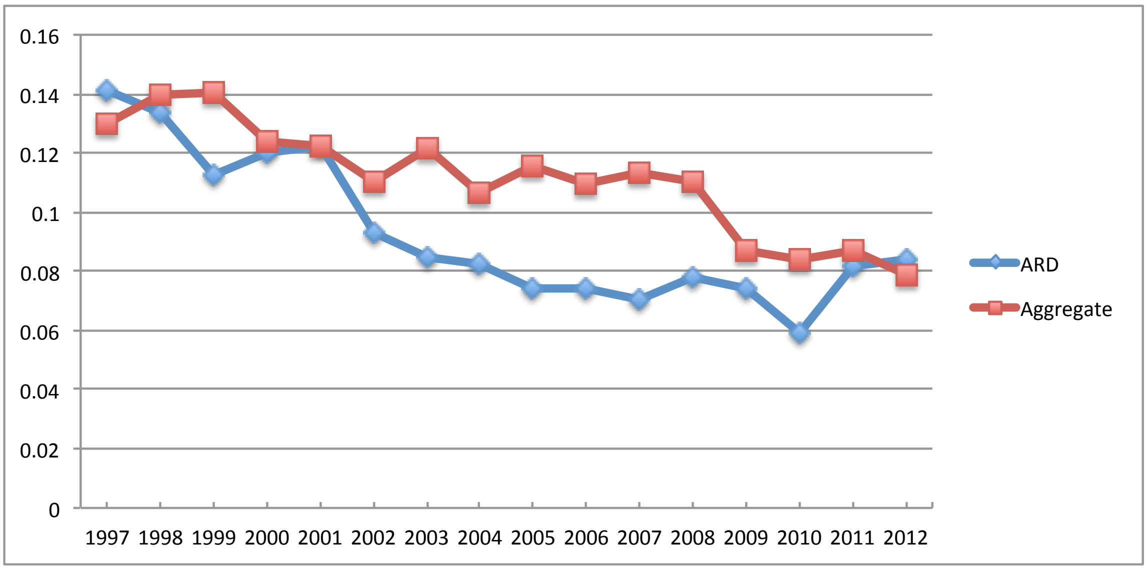
Source: Author's calculations.

Figure A2.2. Investment to output ratio after sample selection step 1



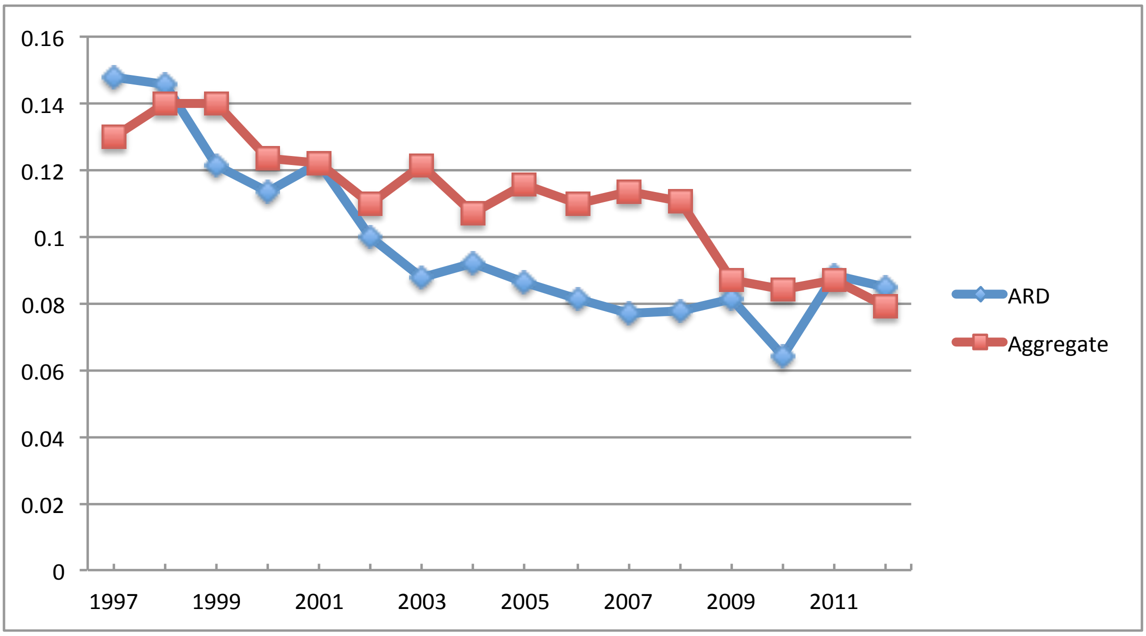
Source: Author's calculations.

Figure A2.3. Investment to output ratio after sample selection step 2



Source: Author's calculations.

Figure A2.4. Investment to output ratio after sample selection step 3



Source: Author's calculations.

Appendix 2.7. CBI Industrial Trends Survey

No.	Question	Variable Prefix	Data Series Construction
1	Are you more, or less, optimistic than you were three months ago about the general business situation in your industry? ("More", "Same" or "Less")	**BUSOPT**	BS= % citing "More"-% citing "Less"
	Question 3: Do you expect to authorize more or less capital expenditure in the next twelve months than you authorized in the past twelve months on		
3A	Buildings ("More", "Same" or "Less")	**CAPEX_B**	BS= % citing "More"-% citing "Less"
3B	Plant and machinery ("More", "Same" or "Less")	**CAPEX_PM**	BS= % citing "More"-% citing "Less"
4	Is your present level of output below capacity (i.e., are you working below a satisfactory full rate of operation)? ("Yes" or "No")	**LOWCAP**	% of firms reporting "Yes"
7	**Excluding seasonal variations, what has been the trend over the PAST THREE MONTHS with regard to**: Volume of total new orders? ("Up", "Same" or "Down")	**ORDER_P**	BS= % citing "Up"-% citing "Down"
7	**Excluding seasonal variations, what is the expected trend for the NEXT THREE MONTHS with regard to**: Volume of total new orders? ("Up", "Same" or "Down")	**ORDER_N**	BS= % citing "Up"-% citing "Down"
8	**Excluding seasonal variations, what has been the trend over the PAST THREE MONTHS with regard to**: Volume of output? ("Up", "Same" or "Down")	**OUTPUT_P**	BS= % citing "Up"-% citing "Down"
8	**Excluding seasonal variations, what is the expected trend over the NEXT THREE MONTHS with regard to**: Volume of output? ("Up", "Same" or "Down")	**OUTPUT_N**	BS= % citing "Up"-% citing "Down"
	Question 16B: What are the main reasons for any expected capital expenditure authorizations on buildings, plant or machinery over the next twelve months		
16BA	To expand capacity		% of firms reporting this option
16BB	To increase efficiency		% of firms reporting this option
16BC	For replacement		% of firms reporting this option
16BD	Other (please specify)		% of firms reporting this option
	Question 16C: What factors are likely to limit (wholly or partly) your capital expenditure authorization over the next twelve months?		
16CA	Inadequate net return on proposed investment	**INARET**	% of firms reporting this option
16CB	Shortage of internal finance	**INTFIN**	% of firms reporting this option
16CC	Inability to raise external finance	**EXTFIN**	% of firms reporting this option
16CD	Cost of finance	**FINCOST**	% of firms reporting this option
16CE	Uncertainty about demand	**UNCERT**	% of firms reporting this option

Notes: BS, Balance Statistic

Appendix 2.8. Matching fiscal quarters with calendar quarters

FY start month	FY (t) Q1	FY (t) Q2	FY (t) Q3	FY (t) Q4
1, 2	CY (t) Q1	CY (t) Q2	CY (t) Q3	CY (t) Q4
3, 4, 5	CY (t) Q2	CY (t) Q3	CY (t) Q4	CY (t+1) Q1
6, 7, 8	CY (t) Q3	CY (t) Q4	CY (t+1) Q1	CY (t+1) Q2
9, 10, 11	CY (t) Q4	CY (t+1) Q1	CY (t+1) Q2	CY (t+1) Q3
12	CY (t+1) Q1	CY (t+1) Q2	CY (t+1) Q3	CY (t+1) Q4

Notes: FY (t) is fiscal year t; CY (t) is calendar year t; Q designates quarter
For example, if a RU's fiscal year 2010 starts in October 2010, its fiscal quarters are as follows:

FY 2010 Q1: October 2010 - December 2010
FY 2010 Q2: January 2011 -March 2011
FY 2010 Q3: April 2011 - June 2011
FY 2010 Q4: July 2011 - September 2011

Based on the above table, FY 2010Q1 is matched with CY 2010Q4, FY 2010Q2 is matched with CY 2011Q1, FY 2010Q3 is matched with CY 2011Q2, and FY 2010Q4 is matched with CY 2011Q3.

Appendix 2.9. Correlations among the CBI survey variables

	Correlation Coefficients		
	$INTFIN\_MA1_{j,t}$	$ORDER\_P\_MA4_{j,t-1}$	$UNCERT\_MA4_{j,t}$
$INTFIN\_MA1_{j,t}$	1	-	-
$ORDER\_P\_MA4_{j,t-1}$	0.006	1	-
$UNCERT\_MA4_{j,t}$	-0.256	-0.040	1

References

Abel, A. B. (1983). "Optional Investment Under Uncertainty," American Economic Review 73: 228-233.

Abel, A. B. and J. C. Eberly (1999). "The Effects of Irreversibility and Uncertainty on Capital Accumulation," Journal of Monetary Economics 44: 339–377.

Anderson, T. G. and B. E. Sørenson (1996). "GMM Estimation of a Stochastic Volatility Model: A Monte Carlo Study," Journal of Business and Economic Statistics 14: 328-352.

Arellano, M. and S. R. Bond (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," Review of Economic Studies 58: 277-297.

Ayyagari, M., A. Demirguc-Kunt, and V. Maksimovic (2010). "Formal Versus Informal Finance: Evidence From China," Review of Financial Studies 23: 3048–3097.

Beck, T., A. Demirguc-Kunt, and V. Maksimovic (2005). "Financial and Legal Constraints to Firm Growth: Does Firm Size Matter?" Journal of Finance 60: 137-277.

Bean, C. R. (1981). "An Econometric Model of Manufacturing Investment in the UK," Economic Journal 91: 106–121.

Bloom, N. (2009). "The Impact of Uncertainty Shocks," Econometrica 77: 623- 685.

Bloom, N., S. R. Bond, and J. Van Reenen (2007). "Uncertainty and Investment Dynamics," Review of Economic Studies 74(2): 391-415.

Blundell, R. and S. R. Bond. (1998). "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." Journal of Econometrics 87(1): 115-143.

Bond, S. R. and J. G. Cummins (2004). "Uncertainty and Investment: An Empirical Investigation Using Data on Analysts' Profits Forecasts," Finance and Economics Discussion Series 2004-20, Board of Governors of the Federal Reserve System.

Bond, S. R., J. Elston, J. Mairesse, and B. Mulkay (2003). "Financial Factors and Investment in Belgium, France, Germany and the UK: A Comparison Using Company Panel Data," Review of Economics and Statistics 85 (1): 153–165.

Bond, S. R., D. Harhoff, and J. Van Reenen (2005). "Investment, R&D and Financial Constraints in Britain and Germany,"Annales d'Economie et de Statistique 79-80: 433-460.

Bond, S. R. and C. Meghir (1994). "Dynamic Investment Models and the Firm's Financial Policy," Review of Economic Studies 61:197–222.

Bowsher, C. G. (2002). "On Testing Overidentifying Restrictions in Dynamic Panel Data Models," Economics Letters 77: 211–20.

Caballero, R. J. (1991). "On the Sign of the Investment-Uncertainty Relationship," American Economic Review 81: 279–288.

Carpenter, R. and A. Guariglia (2008). "Cash Flow, Investment, and Investment Opportunities: New Tests Using UK Panel Data," Journal of Banking and Finance 32: 1894-1906.

Cleary, S. (1999). "The Relationship Between Firm Investment and Financial Status," Journal of Finance 54(2): 673-92.

Cobham, D. (2013). "Monetary Policy under the Labour Government, 1997–2010: The First 13 Years of the MPC," Oxford Review of Economic Policy, 29(1): 47-70.

Department for Environment, Food and Rural Affairs (DEFRA) (2014). "Food Statistics Pocketbook," available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/423616/foodpocketbook-2014report-23apr15.pdf.

Dixit, A. K. and R. S. Pindyck (1994). "Investment Under Uncertainty." Princeton, New Jersey: Princeton University Press.

Driver, C. and P. Temple (2013). "Capital Investment: What Are the Main Long Term Trends in Relation to U.K. Manufacturing Businesses, and How Do These Compare Internationally?" available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/283884/ep8-capital-investment-trends-uk-manufacturing.pdf

Fazzari, S.M., R. G. Hubbard, and B. C. Petersen (1988). "Financing Constraints and Corporate Investment," Brookings Papers on Economic Activity 1988 (1): 141–195.

Gilbert, P., M. Roeder, and P. Thornley (2013). "Can the UK Afford (Not) to Produce Chemicals in 2050?" available at: http://www.mace.manchester.ac.uk/media/eps/schoolofmechanicalaerospaceandcivilengineering/research/centres/tyndall/pdf/Chemical_industry_in_the_UK_Final_Update.pdf.

Gilhooly, R. (2008). "Estimating Capital Stock at the Firm Level," VML Data Brief, Winter 2008.

Gilhooly, R. (2009). "Firm-level Estimates of Capital Stock and Productivity," Economic and Labour Market Review 3(5): 36–41.

Guariglia, A. (2008). "Internal Financial Constraints, External Financial Constraints, and Investment Choice: Evidence from a Panel of UK Firms," Journal of Banking and Finance 32: 1795-1809.

Guiso, L. and G. Parigi (1999). "Investment and demand uncertainty," Quarterly Journal of Economics 114 (1): 185–227.

Hall, R. E. and D. W. Jorgenson (1967). “Tax Policy and Investment Behaviour,” American Economic Review 57: 391-414.

Hartman, R. (1972).“The Effects of Price and Cost Uncertainty on Investment,” Journal of Economic Theory 5: 258-66.

Heaton, C. A. (Eds.) (2013). “The Chemical Industry.” New York, NY, US: Springer Science and Business Media.

Hansen, L. (1982). “Large Sample Properties of Generalized Method of Moments Estimators,” Econometrica 50(3): 1029-1054.

Hoshi, T., A. K. Kashyap, and D. Scharfstein (1991). “Corporate Structure, Liquidity and Investment: Evidence from Japanese Industrial Groups,” Quarterly Journal of Economics 106: 33–60.

Hsiao, C. (1986). “Analysis of Panel Data.” Cambridge: Cambridge University Press.

Jones, J., L. Nolan, A. Banks, P. Wales and D. Morgan (2014) “Explaining United Kingdom Investment Estimates: Past, Present and Future,” available at: http://www.ons.gov.uk/ons/guide-method/method-quality/ons-statistical-continuous-improvement/business-investment---explaining-uk-investment-estimates--past--present---future.pdf.

Jorgenson, D.W. (1963). “Capital Theory and Investment Behavior,” American Economic Review 53: 247–259.

Kaplan, S. N. and L. Zingales (1997). “Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?” Quarterly Journal of Economics 112: 169-216.

Kitson, M. and J. Michie (1996).“Britain’s Industrial Performance since 1960: Underinvestment and Relative Decline,” Economic Journal, 106 (434): 196-212.

Kitson, M. and J. Michie (1997). “Does Manufacturing Matter?” International Journal of the Economics of Business, 4(1): 71-95.

Kitson, M. and J. Michie (2014). “The Deindustrial Revolution: The Rise and Fall of UK Manufacturing, 1870-2010,” Working Paper No. 459, Center for Business Research, University of Cambridge.

Leahy, J. V. and T. M. Whited (1996). “The Effect of Uncertainty on Investment: Some Stylised Facts,” Journal of Money, Credit and Banking 28: 64–83.

Modigliani, F. and Merton M. (1958). “The Cost of Capital, Corporation Finance, and the Theory of Investment,” American Economic Review 48: 261-297.

Myers, S. C. (1984). “The Capital Structure Puzzle,” Journal of Finance 39 (3): 575-592.

Myers, S. C. and N. S. Majluf (1984). "Corporate Financing and Investment Decisions When Firms Have Information Investors Do Not Have," Journal of Financial Economics 13 (2): 187-221.

Nickell, S. (1981). "Biases in Dynamic Models with Fixed Effects," Econometrica 49: 1417-1426.

Nordas, H. (2004). "The Global Textile and Clothing Industry post the Agreement on Textiles and Clothing," WTO Discussion Paper No. 5.

Office for National Statistics (ONS) (2012). "Annual Respondents Database, 1973-2008: Secure Access." Colchester, Essex: UK Data Archive.

Office for National Statistics (ONS) (2016). "U.K. National Accounts: A Short Guide," available at: http://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/nationalaccounts

Nickell, S., S. Redding, and J. Swaffield (2008). "The Uneven Pace of Deindustrialisation in the OECD," The World Economy 31(9): 1154-1184.

Roodman, D. (2009a). "A Note on the Theme of Too Many Instruments," Oxford Bulletin of Economics and Statistics 71(1): 135–158.

Roodman, D. (2009b). "How to Do Xtabond2: An Introduction to Difference and System GMM in Stata," Stata Journal 9(1): 88-136.

Wallis, G. and S. Dey-Chowdhury (2007). "Volume of Capital Services: Estimates for 1950 to 2006," Economic and Labour Market Review 1(12): 37-47.

Windmeijer, F. (2005). "A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators," Journal of Econometrics 126: 25–51.

Chapter 3

Forecasting U.K. Manufacturing Investment Using CBI Survey Data

3.1. Introduction

Manufacturing investment is a volatile component of GDP and can therefore be an important driver of short-term business cycle fluctuations. In times of crisis, accurate manufacturing investment forecasts may be important to economic recovery because they can help policymakers to predict business cycle turning points and to implement timely stimulus measures to revitalize the economy. Consequently, there have been considerable efforts among the economists to build more reliable manufacturing investment forecasting models. In this chapter, we attempt to develop forecasting models for U.K. manufacturing investment making use of the CBI survey data. There are several advantages of using business survey data for forecasting manufacturing investment. First, business surveys collect forward-looking information by asking firms about their expectations of future economic activity. Second, survey data contain qualitative information related to investment spending, such as business confidence and capacity utilization, which is otherwise not measured by official quantitative statistics. Third, survey data are usually published with a short time lag.

We start our analysis by providing a qualitative assessment of the path of U.K. manufacturing investment over the period 1970-2012 and examine the trends in manufacturing output, the ratio of manufacturing investment to manufacturing output, and the relative price of manufacturing investment goods. We also study the CBI

Industrial Trends Survey evidence, for the manufacturing industry as a whole, which provides valuable additional information pertaining to corporate investment such as expected trends in orders and output, and perceptions about financing constraints and demand uncertainty. Moreover, we analyze the manufacturing investment forecasting record of the CBI over the recent crisis period and conclude that the CBI investment forecasts were lagging behind the economic developments during the financial crisis.

Next, we follow Bean (1981) and Bond et al. (2003) to develop an error correction model that can be used for forecasting U.K. manufacturing investment. We adopt the general-to-specific approach to determine a more parsimonious model specification within the error correction framework, and use the automatic model selection program Autometrics (see Doornik, 2009) to guide our analysis. The baseline model retains the previous period's investment growth term in addition to the error correction term representing the deviation of investment from its long-run equilibrium. However, the selected baseline specification has poor out-of-sample forecast properties. When we include additional CBI survey variables in the baseline model, there is an improvement in the out-of-sample forecast properties in most cases. Survey measures of business optimism and expected future orders are found to be particularly useful in this context.

The remainder of the chapter is laid out as follows. Section 3.2 reviews the existing literature. Section 3.3 studies the macroeconomic trends in U.K. manufacturing investment. Section 3.4 explores the CBI survey evidence. Section 3.5 examines the CBI forecasting record. Section 3.6 discusses the estimation strategy. Section 3.7 presents the results of the baseline model. Section 3.8 introduces additional CBI survey variables into the baseline model. Section 3.9 presents and discusses the estimation results of the models with the CBI survey variables. Finally, section 3.10 concludes.

3.2. Literature Review

A number of earlier studies in the literature have investigated the use of business survey data for investment forecasting. For instance, Abberger (2005) finds that the capacity utilization measure derived from the Ifo institute's business survey has predictive value for business investment in Germany. Cassidy et al. (2012) show that the information on firms' expected investment spending from the Australian Bureau of Statistics' (ABS) quarterly survey of Private New Capital Expenditure and Expected Expenditure can assist in forecasting business investment growth in Australia, but should be used in conjunction with other quantitative and qualitative information in order to reduce the forecast errors. Osterholm (2013) examines the usefulness of survey data from Sweden's Economic Tendency Survey for forecasting short-term investment growth in the manufacturing industry, the investment goods industry, the construction industry, and the total business sector. His results suggest that survey data are informative about future changes in investment and can thus be used to improve investment forecasts.

Specifically for the U.K., Britton et al. (1999) first estimates simple regression equations of the official business investment data on survey responses to questions on firms' investment intentions from the British Chambers of Commerce (BCC) Quarterly Economic Survey and the CBI Industrial Trends Survey, and then use these equations to generate business investment forecasts. Larsen and Newton-Smith (2001) use survey measures of investment intentions from the BCC Quarterly Economic Survey and the CBI Industrial Trends Survey to build a survey-based forecasting model for business investment, and find that this model has better business investment forecast performance at longer forecast horizons than the Bank of England's macroeconometric model for business investment. Barnes and Ellis (2005) analyze the statistical correlations between responses from various business surveys, such as the 3i Enterprise Barometer Survey and the BCC Quarterly Economic Survey, and business investment. They find that survey indicators such as investment intentions, capacity utilization, and general business optimism have high correlations with the future business investment growth rate. While previous research concentrates on the use of survey data to forecast U.K. business investment, of which manufacturing investment is a part, to the best of our knowledge, our study is the first attempt in the literature to assess the forecasting potential of survey data specifically for U.K. manufacturing investment.

3.3. Trends in Manufacturing Investment

In this section, we analyze the trends in U.K. manufacturing investment over the sample period 1970-2012, with a particular focus on the recent financial crisis. Appendix 3.1 gives the sources for the data series discussed in this section.

We first examine U.K. manufacturing investment (I_t) in 2010 prices in Figure 3.1. The level of manufacturing investment exhibited different trends over two sub-periods 1970-1998 and 1999-2012. During the first sub-period, manufacturing investment displayed sharp cyclical fluctuations around a trend that was gently rising. In the second sub-period, manufacturing investment was on a downward trend.

Increased competition from Chinese manufacturing firms after China's entry into the World Trade Organization in 2001 may be an important cause for the decline of the U.K. manufacturing industry in the 2000s. Between 1998 and 2008, manufacturing investment shrank by a total of 35.3%. In 2009, after the failure of Lehman Brothers, manufacturing investment was 16.9% lower than its level in 2008, the largest annual drop since 1970. In 2010, it fell by another 6.6%. During 2011-2012, manufacturing investment started to recover, although in 2012 it was still 13.2% below its 2008 level. By regressing the natural logarithm of manufacturing investment (in millions) on a constant and a linear trend, we can estimate the growth rate of manufacturing investment in the two sub-periods. The respective coefficients (p-values) on the trend term, which can be interpreted as the average growth rates of manufacturing investment, for the first and second sub-periods are 0.011 (0.000) and -0.039 (0.000).

Figure 3.2 shows manufacturing output in 2010 prices (Y_t). Since the early 1980s, manufacturing output had been steadily rising. This upward trend ended in around 2000. In 2008, there was a small 2.7% contraction in manufacturing output compared to its level in 2007. In 2009, manufacturing output declined sharply by 10.2% from its 2008 level. The peak to trough fall between 2007 and 2009 was 13.2%, higher than the peak to trough fall of 5.3% in the early 1990s recession but smaller than the peak to trough fall of 14.6% in the early 1980s downturn.

Manufacturing investment in 2010 prices as a share of manufacturing output in 2010 prices (I_t/Y_t) is presented in Figure 3.3. Similar to the level of the manufacturing investment series (Figure 3.4), the ratio of manufacturing investment to manufacturing output also exhibited distinct trends over the two sub-periods 1970-

1998 and 1999-2012. For the first sub-period, the ratio was on a modest upward trend with cyclical fluctuations. In 1998, the ratio reached a peak of 17.5%. For the second sub-period, the ratio was trending downwards. In 2009, it declined to 10.5%, down from 11.3% in 2008. In 2010, it further fell to 9.4%. In 2011 and 2012, the ratio stayed at around 10.0%. The cumulative fall between 2008 and 2010 was 1.9 percentage points, which was smaller in comparison with the falls during the previous recessions. In the early 1980s and the early 1990s downturns, the peak to trough falls were 3.7 and 3.2 percentage points, respectively.

The relative price of investment goods bought by the manufacturing industry (P_t) is calculated as the ratio of the manufacturing investment implicit price deflator to the manufacturing output implicit price deflator, and is plotted in Figure 3.4 with the relative price in 2010 normalized to unity. All else equal, a decline in the relative price of investment goods tends to raise the desired capital stock and thereby investment expenditure.[1] In the 1970s, the average level of the relative price was about 1.10 (i.e. about 10% higher than the relative price in 2010). The relative price fell sharply in the late 1970s and again in the mid-1990s, giving an average level in the 1980s and 1990s of about 0.97. This fall in the average relative price is consistent with the gentle rise in the ratio of manufacturing investment to output in the period 1970-1998, as shown in Figure 3.3. In the early 2000s, the relative price remained more or less constant around 0.95. In 2005, the ratio was at a historical low of 0.85. During the recent credit crunch, it dropped from 0.95 in 2007 to 0.88 in 2009. The ratio was at a level of around 0.94 in 2011 and 2012.

[1] According to equation (3.6) in section 3.5.2, the desired ratio of investment to output is negatively related to the real user cost of capital. Based on equation (3.8) in the same section, the relative price of investment goods is a component of the real user cost of capital.

In our later regression analysis, we apply a natural logarithm transformation to the abovementioned variables. The summary statistics of the variables we used in the estimation are reported in Table 3.1.

3.4. CBI Industrial Trends Survey

The quarterly CBI Industrial Trends Survey asks manufacturing firms in the U.K. questions pertaining to their investment behavior, and can provide useful information about influences on corporate investment that is otherwise not available from the published ONS data. This section studies CBI survey responses for the aggregate manufacturing industry with an emphasis on the recent financial crisis. Most of the survey responses are standardized in the form of a balance statistic, which equals the percentage responding an increase (e.g., “up” or “more”) minus the percentage reporting a decrease (e.g., “down” or “less”). The precise wording of each question and further information on the construction of the data series are presented in Appendix 3.2.

Question 1 concerns the change in business optimism over the previous three months (***BUSOPT***) (Figure 3.5). This is one of the most widely publicized survey questions in the media. The balance started its rapid decline in 2007Q3, and fell for seven consecutive quarters. In 2009Q1, after the failure of Lehman Brothers, the survey balance reached a trough of -64%, the lowest point since 1980Q3. However, it was higher compared with the troughs in the mid-1970s recession (-75%) and the early 1980s recession (-70%). Similarly, the decline in confidence between 2008Q4 and 2009Q1 was the largest quarterly fall since 1980Q3. After 2009Q1, the confidence balance rose steadily. It reached positive territory in 2009Q4, for the first time since 2007Q3. In 2011Q3, amid growing concerns over debt sustainability in the euro area, business sentiment deteriorated for the first time in two years since 2009Q3. In 2011Q4, the balance reached a trough of -30%. The balance recovered to its pre-crisis level in 2012.

Question 3 asks about capital expenditure intentions for the next year relative to the past year (Figure 3.6). The trends for buildings (***CAPEX_B***) and plant and machinery (***CAPEX_PM***) capital expenditure intentions are broadly similar. For both *CAPEX_B* and *CAPEX_PM* series, we compare the means in two sub-periods 1972Q1-1998Q4 and 1999Q1-2012Q4 in Table 3.2. The *t*-test results suggest that the average in the first sub-period is significantly higher than that in the second sub-period for both series. This is consistent with the declining trends in both the level of manufacturing investment (Figure 3.1) and the ratio of manufacturing investment to manufacturing output (Figure 3.3) from 1999 onwards. Beginning in 2007Q3, as the state of the economy worsened, both survey balances started to fall. In 2008Q4, the rate of decline accelerated rapidly after the bankruptcy of Lehman Brothers. The quarterly falls for buildings and plant and machinery balances were 20 and 14 percentage points, respectively. In 2009Q1, both balances reached their historical lows. The balances for buildings and plant and machinery were -56% and -57%, respectively, considerably lower than their troughs in the previous recessions. Since 2012, both balance series have returned to their pre-crisis levels.

Question 4 asks firms whether their present output is below capacity (***LOWCAP***) (Figure 3.7). Firms with excess production capacity tend to have lower incentive to invest in additional capital. The percentage of firms working below capacity began to rise sharply after 2008Q4, and reached a peak of 76% in 2009Q2. It stayed at a high level of around 70% during the rest of 2009, which implies that the capacity utilization rate was low at the height of the crisis in 2009. The percentage started to fall in 2010, and returned to its pre-crisis level at around 50% in 2011.

Question 7 assesses the short-term trends in the volume of total new orders. Figure 3.8 presents the trend in the volume of new orders over the previous three months balance series (***ORDER_P***). Between 2008Q1 and 2009Q1, the orders balance fell by 54 percentage points, the largest annual decline since the question was first introduced in 1977Q4. In 2008Q4, shortly after Lehman Brothers collapsed, the orders balance dropped to -30% from -3% in 2008Q3. The balance continued to decline for two more quarters, and arrived at -47% in 2009Q2, which was its lowest level in almost three decades. However, this was still higher than the historical low of -61% during the early 1980s downturn. The orders balance began to increase after 2009Q2, and remained positive in 2010 and 2011. In 2011Q2, as the state of economy in the euro area worsened, the orders balance started to decline again. It fell to a local low of -15% in 2012Q1.

Figure 3.9 shows the expected trend in the volume of new orders over the subsequent three months balance series (***ORDER_N***). In Table 3.2, we report the average levels of this series in sub-periods 1977Q4-1998Q4 and 1999Q1-2012Q4. The mean of the series up to 1998Q4 is significantly higher than that of the series from 1999Q1 onwards. This finding again corroborates the downward trends in both the level of manufacturing investment (Figure 3.1) and the ratio of manufacturing investment to output (Figure 3.3) starting in 1999. Between 2008Q1 and 2009Q1, the orders expectation series recorded a steep fall of 58 percentage points. Most of the decline happened in the second half of 2008. In 2008Q3, the orders expectation balance dropped rapidly by 24 percentage points from its level in 2008Q2. In 2009Q1, the balance reached its record low of -54%. This was significantly lower than the troughs in both the early 1990s recession (-35%) and the early 1980s recession (-47%). It suggests that firms showed greater pessimism about future orders at the height of the current recession than in the previous recessions. The orders expectation balance showed a strong recovery after 2009Q1. In 2011Q4, it was affected by the economic instability in the euro area, and dropped to a local low of -10%. Since 2012Q2, the balance has stayed positive.

Question 8 deals with the short-term trends in the volume of output. Figure 3.10 illustrates the balance series for the trend in the volume output over the previous three months (***OUTPUT_P***). In the recent financial crisis, the balance experienced a rapid fall of 41 percentage points between 2008Q1 and 2009Q1. In 2008Q4, it fell to -29% from -1% in 2008Q3, the largest single quarter fall since the question was introduced in 1975Q3. It continued to decline sharply for two more quarters, reaching a series low of -53% in 2009Q2. This was lower than its troughs in the early 1980s recession (-49%) and the early 1990s recession (-43%), and consistent with the low level of the orders over the previous three months balance statistic (Figure 3.8) around the same time. The output balance rose steadily since then, and turned positive in 2010Q1. In 2011Q2, with the spread of the euro crisis, it began to fall quickly again. This corresponds to the drop in orders over the previous three months balance statistic (Figure 3.8) at the same time. In 2012Q4, the output balance was at a trough of -3%.

The expected trend in the volume of output over the subsequent three months balance series (***OUTPUT_N***) is presented in Figure 3.11. In Table 3.2, we compute the average values of this balance series in the two sub-periods 1975Q3-1998Q4 and

1999Q1-2012Q4. The t-statistic indicates that the mean of the series in the first sub-period is significantly higher than that of the series in the second sub-period, which is again consistent with the break in the trend for both the level of manufacturing investment (Figure 3.1) and the share of manufacturing investment in manufacturing output (Figure 3.3) starting in 1999. In the recent credit crisis, the balance started to fall in 2008Q1. In 2008Q4, it fell by 24 percentage points from 2008Q3, the largest single quarter decline since 1980Q3. It also reached a series low of -43% in 2008Q4. This was considerably lower than the trough in the early 1990s crisis (-30%), but similar to the trough of the early 1980s downturn (-41%). The balance picked up since 2008Q4, and became positive in 2009Q4. It stayed positive until 2011Q4. As the euro zone debt crisis unfolded, the balance fell to a trough of -11% in 2011Q4.

Question 16B examines investment motivations. The series in Figure 3.12 are the proportions of firms indicating particular reasons.[2] Before 2008, increasing efficiency was cited as the most important reason for investment, followed by replacement and expanding capacity.[3] Starting in 2008Q3, the percentage citing increasing efficiency fell sharply. In 2009Q2, it reached a record low of 46%. In 2010Q2, the increasing efficiency series began to rise steadily and arrived at 64% in 2012Q4. However, this was still considerably lower than the pre-crisis level of the series. The steep fall in the percentage citing expanding capacity commenced in 2008Q2. In 2009Q2, the percentage fell to 14%, its lowest point since 1981Q2. The expanding capacity series seems to be related to the business cycle. In the early 1980s and early 1990s recessions, it reached local lows of 9% and 16%, respectively. After 2009Q2, the

[2] Firms can select more than one reason for expected capital expenditure authorizations.

[3] If a firm wants to invest to expand capacity, it is likely that its current capital stock is considered too low relative to the desired level. Hence, the expanding capacity motivation is closely related to the role of the error correction term in our econometric model (3.11) in section 3.5.2. The error correction term $(i - y)$ represents the deviation of capital or investment from its steady state target level.

percentage increased gradually. Since 2011, it has remained at a level of around 40%, higher than its pre-crisis level. In 2011Q4, it even reached a series high of 47%. Earlier periods when the proportion of firms reporting a desire to expand capacity was high were often also periods of high investment such as the late 1980s and the late 1990s (see Figures 3.1 and 3.3). However, the record high levels of this series in late 2010 and early 2011 were not associated with high levels of actual investment. This suggests that some other unusual factors might have been important in keeping actual investment low, such as unusually high levels of uncertainty and unusual difficulties in financing investment. The percentage citing replacement as a motivation for investment remained relatively steady at around 50% both before and during the crisis.

The answers to Question 16B give more insight into the investment behavior of manufacturing firms during the crisis. In 2008, output contracted as demand declined rapidly. As a result, many firms reported working below capacity (Figure 3.7), and fewer firms planned to invest (Figure 3.6), particularly for reasons related to increasing efficiency and expanding capacity (Figure 3.12). In early 2009, as the economic downturn quickly gathered pace after the bankruptcy of Lehman Brothers, firms expected a further deterioration in demand and scaled back their plans for enhancing efficiency and expanding capacity to new low levels. Since 2010, as the state of the economy improved, output has grown due to higher demand. Hence, more firms reported wanting to invest to increase efficiency and expand capacity to cope with the rise in demand.

Question 16C attempts to identify factors limiting firm investment over the next twelve months (Figure 3.13).[4] The two most commonly cited factors are "uncertainty about demand" and "inadequate net return on proposed investment." This highlights that demand expectations greatly affect the incentive to invest. From the late 1980s to 2007, the proportion of firms citing inadequate net return (***INARET***) stayed steady in the range of 40% to 50%. This percentage fell sharply in the course of the crisis. In 2008Q4, the percentage was 41%. In 2009Q1, it decreased to 29%, a rapid decline of 12 percentage points. This marked the largest quarterly fall since the question was first asked in 1979Q4. Since 2009Q1, the percentage stayed at around 30% to 40% and did not recover to its pre-crisis level.

Conversely, the percentage of firms citing "uncertainty about demand" (***UNCERT***) increased sharply in the crisis. The rise started in 2008Q2, and the percentage was at a historically high level of 69% in 2009Q1. This was considerably higher than the peaks in the early 1980s downturn (55%) and the early 1990s downturn (60%). The percentage started to decline after 2009Q1, and was at a trough of 41% in 2010Q4. In 2012, the percentage was around 50%-60%. Since 2008Q2, the percentage of firms citing demand uncertainty has been consistently higher than the percentage citing inadequate return. This suggests that demand uncertainty may be the most important factor restraining investment during the crisis.

Before 2008, the proportion citing "shortage of internal finance" (***INTFIN***) stayed at a level of around 20%. In 2008Q4, it started to increase and reached a peak of 31% in 2009Q2. The percentage stabilized at a level of around 20%-30% in 2009Q3-

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[4] Firms can cite more than one factor restraining investment.

2012Q4, somewhat higher than its pre-crisis level. At the start of the current recession, the percentage selecting “inability to raise external finance” (***EXTFIN***) also spiked up. Before 2008, the percentage stayed at a level of around 5%. In 2008Q4, it increased by 13 percentage points from 3% in 2008Q3, to a record high of 16%. The series had never reached 10% before that. Since 2009, the percentage has stayed relatively steady at around 10%. The trends in these two series suggest that financial constraints faced by manufacturing firms also contributed to the low level of investment during the crisis. Financial constraints became especially severe after the collapse of Lehman Brothers in September 2008, as is evident from the rapid rises in the two percentages in late 2008.

The proportion citing “cost of finance” (***FINCOST***) rose strongly in the early 1990s, and was at a historical peak of 26% in 1990Q4. It has fallen to around 5% level since then, and showed no significant movement in the period 2008-2012.

3.5. CBI Manufacturing Investment Forecasts

As shown by the ONS data and the CBI survey evidence in sections 3.3 and 3.4, the Great Recession had a large negative effect on U.K. manufacturing investment. In recent years, considerable resources have been devoted by various national and international organizations to forecasting manufacturing investment. In the U.K., the CBI produces quarterly manufacturing investment forecasts primarily based on an econometric model provided by Oxford Economics. This section analyzes the CBI forecasting record in the recent financial crisis period 2007-2012. The CBI manufacturing investment forecasts are sourced from its quarterly publication *CBI Economic and Business Outlook* and are reported in the form of year-on-year percentage change in constant prices. The CBI publishes its forecasts in January/February (Q1), April/May (Q2), August/September (Q3), and November/December (Q4). In our analysis, a Year (T-1) forecast is defined as one that is made in the previous calendar year. For example, a Year (T-1) Q1 forecast for the calendar year 2007 was made in 2006Q1. A Year (T-2) forecast is made two calendar years previously. For example, a Year (T-2) Q1 forecast for the calendar year 2007 was made in 2005Q1.

Figure 3.14 illustrates the CBI forecasts and compares these with the outturns for the annual aggregate change in manufacturing investment. As discussed in section 3.4, the business optimism (Figure 3.5) and investment intentions (Figure 3.6) series of the CBI Industrial Trends Survey started to decline in 2007Q3, more than a year before Lehman Brothers filed for bankruptcy, and were already in severe negative territory in the first half of 2008. Despite these early negative signals from the CBI survey, prior to 2008Q3, the CBI predicted a small expansion in manufacturing investment in 2009. Even in 2008Q3, the CBI still expected manufacturing investment to fall only by 0.2% in 2009. It was only in 2008Q4, after the failure of Lehman Brothers, that the CBI began to make a sharp downward adjustment in its investment forecast for 2009. However, even then it only managed to predict about half of the decline in manufacturing investment that actually occurred in 2009. After learning more about the seriousness of the credit crunch in 2009 and 2010, the CBI then became too pessimistic about the prospects of recovery in 2011. In the course of 2010, the CBI only expected a small increase in manufacturing investment in 2011. The outturn for 2011 was a large rise of 12.5%. Conversely, in 2011, the CBI was too optimistic about the growth of manufacturing investment in 2012 and predicted a substantial increase in the range of 3%-6%. However, the actual growth rate in 2012 was close to zero. The CBI forecasting record suggests that it did not predict the unusual pattern of investment growth in the current downturn well. Loungani (2001) argues that forecasters do not have the necessary information such as timely data and adequate forecasting models to project recessions. With specific regard to the current crisis, Visco (2009) claims that the existing forecasting models do not take into sufficient account the links between the economy and financial markets, which played a key role in the development of the Great Recession.

We use the Pearson's correlation coefficient to examine the degree of linear association between the CBI forecasts and the actual outcomes. The results are summarized in Table 3.3. The correlation coefficient for Year (T-2) Q4 forecasts is very small and lower than 0.5. On the other hand, Year (T-1) Q1, Year (T-1) Q2, Year (T-1) Q3, and Year (T-1) Q4 forecasts all have correlation coefficients higher than 0.5. In particular, Year (T-1) Q4 forecasts have a high positive correlation coefficient of 0.91. Our results show that the CBI tends to generate a more accurate forecast when it attempts to predict the annual growth rate of manufacturing investment over a shorter forecast horizon.

Furthermore, we use statistical measures to compare the properties of these different forecasts in the recession period 2007-2012. The forecast error is defined as the outturn minus the forecast. The first statistical measure used is the mean forecast error (MFE). It is the arithmetic average of all forecast errors over the evaluation period and measures the average forecast bias. For example, a positive MFE over the evaluation period would imply that the forecasting model has a downward forecast bias and under-predicts the actual growth on average. Forecasts are said to be unbiased if the MFE is zero. The MFEs of the CBI forecasts over different forecast horizons are shown in Table 3.4. Year (T-2) Q4, Year (T-1) Q1, Year (T-1) Q2, and Year (T-1) Q3 forecasts all have negative MFEs, which implies that these forecasts tend to be biased upwards. On the other hand, Year (T-1) Q4 forecasts have a positive MFE, suggesting that they tend to have a downward bias. The second statistical measure used is the root mean square forecast error (RMSFE). It is the square root of the arithmetic average of the squared forecast errors. RMSFE measures the average error size irrespective of the sign, and is sensitive to large forecast errors. Therefore, it can be used to assess the forecast precision. The RMSFEs of the CBI forecasts over different forecast horizons are also reported in Table 3.4. Year (T-1) Q4 forecasts have the lowest RMSFE, and therefore appear to be the most accurate.

3.6. Methodology

3.6.1. Model Specification

In this section, we follow the methodology proposed in Bean (1981) and Bond et al. (2003) to derive an error correction specification for aggregate manufacturing investment. According to the neoclassical investment model proposed in Jorgenson (1963), assuming that there are no adjustment costs or frictions and profit-maximizing firms have a constant returns to scale, constant elasticity of substitution production function, the desired capital stock can be expressed as:

$$k_t = y_t - \sigma r_t + \lambda \quad (3.1)$$

where k_t is the natural logarithm of the desired capital stock, y_t is the natural logarithm of output, r_t is the natural logarithm of the real user cost of capital, σ is the elasticity of substitution between labour and capital in the production function, and λ is a constant. The standard capital accumulation formula says:

$$K_{t+1} = (1-\delta)K_t + I_t \quad (3.2)$$

where δ is the depreciation rate and I_t is gross investment. In period t, firms produce with a level of capital stock K_t and spend I_t on capital investment. In the next period $t+1$, the total available capital stock K_{t+1} is the sum of the depreciated amount of capital inherited from period t and investment I_t. Rearranging equation (3.2) gives:

$$I_t = w_t K_t + \delta K_t \quad (3.3)$$

where $w_t = (K_{t+1} - K_t)/K_t$ is the growth rate of capital.

At the steady state, we assume that w_t is constant and equals w. By taking logarithms on both sides of (3.3), we can then derive the steady state relationship between investment and capital:

$$i_t = k_t + \log(w + \delta) \quad (3.4)$$

However, as one can observe from Figures 3.1-3.3, for the U.K. manufacturing industry, the steady state growth rate of capital w may have experienced a structural break in 1999. To allow for such a structural break, we re-write (3.4) as:

$$i_t = k_t + \log(h + (D1999)g + \delta) \quad (3.5)$$

where h and g are some constants, and $D1999$ is a dummy variable which equals one after 1998, i.e. years 1999-2012, and equals zero otherwise. Therefore, the steady growth rate of capital takes two values: h for the sub-period 1970-1998 and $h + g$ for the sub-period 1999-2012.

It is difficult to accurately measure the aggregate capital stock in the economy. To avoid the use of the possibly problematic capital stock data, Bean (1981) substitutes (3.4) into (3.1) and derives a log-linear long-run condition relating investment to output and the real user cost of capital. Generalizing this approach to allow for a break in 1999 in the steady state growth rate gives:

$$i_t - y_t = \log(h + (D1999)g + \delta) + \lambda - \sigma r_t \quad (3.6)$$

There are various adjustment costs or frictions which prevent firms from transitioning to a new desired level of capital stock immediately. To account for the dynamic adjustment of the capital stock, we follow Bean (1981) and Bond et al. (2003) and adopt a general autoregressive-distributed lag (ADL) model:

$$i_t = \alpha_0 + \alpha_1 D1999 + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 i_{t-3} + \alpha_5 y_t + \alpha_6 y_{t-1} + \alpha_7 y_{t-2} + \alpha_8 y_{t-3} + \alpha_9 r_t + \alpha_{10} r_{t-1} + \alpha_{11} r_{t-2} + \alpha_{12} r_{t-3} + e_t \quad (3.7)$$

where e_t is an error term. The lag length in our GUM is initially set to three as annual data are used and the sample period is relatively short. Equation (3.7) relates investment (i_t) to output (y_t) and the real user cost of capital (r_t), all in natural logarithms.

According to the Hall and Jorgenson (1967) formulation, the real user cost of capital R_t is determined by the real interest rate or cost of finance c_t, the depreciation rate δ, the relative price of investment goods P_t, the tax rate on corporate income T_t, the present value of current and expected future tax savings due to investment allowances Z_t, and the expected rate of change in the relative price of investment goods π_t:

$$R_t = P_t(c_t + \delta - \pi_t)\frac{1 - Z_t}{1 - T_t} \quad (3.8)$$

It is however challenging to measure c_t, δ, π_t, Z_t, and T_t. For simplicity, we assume that the natural logarithms of $(c_t + \delta - \pi_t)$ and (1- Z_t)/(1- T_t) are either stable or trending over the sample period, and absorb these components of the real user cost of capital into a constant and trend terms. Hence, we use explicitly only the relative price of investment goods P_t component of R_t and re-write (3.7) as:

$$i_t = \beta_0 + \beta_1 D1999 + \beta_2 i_{t-1} + \beta_3 i_{t-2} + \beta_4 i_{t-3} + \beta_5 y_t + \beta_6 y_{t-1} + \beta_7 y_{t-2} + \beta_8 y_{t-3} + \beta_9 p_t + \beta_{10} p_{t-1} + \beta_{11} p_{t-2} + \beta_{12} p_{t-3} + \beta_{13} t + \beta_{14} st1999 + e_t \quad (3.9)$$

where p_t is the natural logarithm of the relative price of investment goods, t is a linear trend term and $st1999$ is a split trend term which equals zero until 1998 and increases from one to fourteen over the period 1999-2012. The split trend term aims to capture the break in 1999 in the trend for the ratio of manufacturing investment to output (see Figure 3.3). For convenience, we re-parameterize (3.9) as:

$$\begin{aligned}\Delta i_t = {} & \beta_0 + \beta_1 D1999 - (\beta_4 + \beta_3)\Delta i_{t-1} - \beta_4 \Delta i_{t-2} + \beta_5 \Delta y_t - (\beta_7 + \beta_8)\Delta y_{t-1} \\ & - \beta_8 \Delta y_{t-2} + \beta_9\, \Delta p_t - (\, \beta_{11} + \ \beta_{12})\Delta p_{t-1} - \beta_{12} \Delta p_{t-2} \\ & + (\beta_2 + \beta_3 + \beta_4 - 1) i_{t-1} + (\beta_5 + \beta_6 + \ \beta_7 + \beta_8) y_{t-1} \\ & + (\, \beta_9 + \beta_{10} + \beta_{11} + \beta_{12}) p_{t-1} + \beta_{13} t + \beta_{14} st1999 + e_t \quad (3.10)\end{aligned}$$

Bean (1981) was the first paper to exploit the steady state relationship between investment and output, and introduce the error correction framework into the empirical investment literature. Assuming as in equation (3.6) that the long-run elasticity of investment with respect to output is one (i.e., $(\beta_5 + \beta_6 + \ \beta_8 + \beta_7)/(1 - \beta_2 - \beta_3 - \beta_4) = 1$), we follow Bean (1981) and nest the steady state relationship (3.6) within (3.10):

$$\begin{aligned}\Delta i_t = {} & \gamma_0 + \gamma_1 D1999 + \gamma_2 \Delta i_{t-1} + \gamma_3 \Delta i_{t-2} + \gamma_4\, \Delta y_t + \gamma_5 \Delta y_{t-1} + \gamma_6 \Delta y_{t-2} \\ & + \ \gamma_7\, \Delta p_t + \gamma_8 \Delta p_{t-1} + \gamma_9 \Delta p_{t-2} + \gamma_{10}(i_{t-1} - y_{t-1}) + \gamma_{11} p_{t-1} \\ & + \gamma_{12} t + \gamma_{13} st1999 + e_t \quad (3.11)\end{aligned}$$

The coefficients of the first-differenced terms represent short-run investment elasticities, and the coefficients of the level terms represent long-run investment elasticities. The error correction term $(i_{t-1} - y_{t-1})$ reflects the deviation of investment from its long-run path. If the term $(i_{t-1} - y_{t-1})$ is positive (negative), investment was above (below) its long-term equilibrium in the previous year and, all else being equal, is expected to decrease (increase) in the current year. Therefore, the coefficient on the error correction term captures the rate at which investment re-equilibrates to its long-run relationship with output, and is expected to have a negative sign.

In year $t - 1$, a genuine *ex-ante* forecast of investment growth in year t could only be made based on information available from year $t - 1$ and earlier. Therefore, to obtain a specification that could be used for forecasting the growth rate of manufacturing investment, we keep only lagged explanatory variables in equation (3.11) and derive the baseline forecasting model:

$$\Delta i_t = \eta_0 + \eta_1 D1999 + \eta_2 \Delta i_{t-1} + \eta_3 \Delta i_{t-2} + \eta_4 \Delta y_{t-1} + \eta_5 \Delta y_{t-2} + \eta_6 \Delta p_{t-1} + \eta_7 \Delta p_{t-2} + \eta_8 (i_{t-1} - y_{t-1}) + \eta_9 p_{t-1} + \eta_{10} t + \eta_{11} st1999 + e_t \quad (3.12)$$

3.6.2. Model Selection Strategy

Parsimony is a desirable property for forecasting models. A complicated forecasting model whose number of parameters is large relative to the number of observations may explain the random fluctuations in the past manufacturing investment data well but fail to identify a stable underlying relationship that is useful for predicting future manufacturing investment. A parsimonious forecasting model with a small number of parameters reduces this problem of overfitting. Empirical studies have shown that when selecting between competing models, a parsimonious model tends to have better forecasting performance and is thus preferred (Ledolter and Abraham, 1981; Chatfield, 1996; Armstrong, 2001).

In this chapter, we apply the general-to-specific (GETS) modeling approach to trim equation (3.12) down to a parsimonious version, which adequately represents the underlying data using as few parameters as possible. This modeling strategy uses statistical tests to remove insignificant variables and obtain a reduced model that includes only the significant predictors of Δi_t.[5] In recent years, Hoover and Perez (1999), Hendry and Krolzig (2001, 2005), and Doornik (2009) have developed multi-path GETS specification search algorithms and written computer programs to automate the GETS model selection procedures. We use Autometrics embodied in the software package Oxmetrics to implement the GETS modeling process.

According to Doornik (2009), the Autometrics algorithm consists of three main steps:

1. General Unrestricted Model (GUM) Formulation: The starting point of the GETS modeling strategy is formulating an initial GUM, which must contain a sufficiently large set of potentially relevant variables and their suitable lags so that it can capture the key aspects of the data generation process. The specification of the GUM is based on available economic theory, empirical evidence, and inference. In our case, we use equation (3.12) as our GUM.

2. Pre-search: Statistical tests are carried out to exclude highly insignificant variables from the forecasting model at a loose significance level. The purpose of this

[5] For an overview of the GETS methodology, see Hendry (1995), Mizon (1995), Hendry (2003), and Campos et al. (2005).

step is to derive a smaller GUM and speed up the search process. The new GUM will be used as the baseline GUM for the next step.

3. Model Selection: Autometrics relies on a multi-path tree-search method to identify and eliminate insignificant variables in a systematic way. To ensure that the reduced model preserves the error correction framework, we take more control over the model selection process by forcing Autometrics to retain the error correction term $(i_{t-1} - y_{t-1})$ and the constant term in the final specification. A terminal model retains the important determinants of Δi_t and usually passes a battery of diagnostic checks: the Godfrey (1978) Lagrange multiplier test for residual autocorrelation up to two lags (**AR 1-2 test**) with the null hypothesis of no autocorrelation, the Engle (1982) test for autoregressive conditional heteroscedasticity (ARCH) up to one lag (**ARCH 1-1 test**) with the null hypothesis of no ARCH effects in the residuals, the Jarque and Bera (1987) test for normality of regression residuals (**Normality test**) with the null hypothesis of normality, the White (1980) test for heteroscedasticity in the residuals using squares (**Hetero test**) with the null hypothesis of homoscedasticity, the White (1980) test for heteroscedasticity in the residuals using squares and cross-products (**Hetero-X test**) with the null hypothesis of homoscedasticity, and the Ramsey (1969) regression specification test using squares and cubes (**RESET23 test**) with the null hypothesis that the functional form is correctly specified. We use the default 5% significance level for these tests. There may be more than one valid terminal model, and we choose the terminal model whose forecasts have the lowest RMSFE as our final model.

3.6.3. Static One-step-ahead Forecasts

Our data are divided into the in-sample and the out-of-sample portions. The in-sample portion consists of data prior to 2007 and is used for model selection and initial parameter estimation. The out-of-sample portion consists of data over the financial crisis period 2007-2012, and is used to generate static one-step-ahead forecasts of the annual growth rate of manufacturing investment Δi_t. For each estimated reduced specification, the static one-step-ahead investment forecast for year t is computed as:

$$\widehat{\Delta i_t} = \hat{\mu}' x_t \quad (3.13)$$

where $\hat{\mu}$ is the vector of the regression coefficients of the reduced model estimated based on the in-sample data and x_t is the vector of the actual data of all the (lagged) explanatory variables included in the reduced model. The Chi-square and Chow (1960) forecast tests are applied to test the null hypothesis that the parameters of the forecasting model are constant across the in-sample and the out-of-sample forecast periods. To evaluate the average forecast bias, we calculate the MFE. In addition, we use the RMSFE to measure forecast accuracy.

3.7. Baseline Results

For our baseline specification, the in-sample period is from 1973 to 2006, and the out-of-sample period used for one-step-ahead forecasts is from 2007 to 2012. The final reduced specification selected by Autometrics is presented in column 1 of Table 3.5. It retains Δi_{t-1} and the split trend term in addition to the two variables that we force Autometrics to keep (i.e., the constant and the error correction term). The inclusion of the split trend term in this parsimonious model is not surprising because equation (3.12) can be re-parameterized to make $(i_t - y_{t-1})$ as the dependent variable and the ratio of manufacturing investment to manufacturing output starts to exhibit a downward trend from 1999 onwards (see Figure 3.3).[6] The retention of Δi_{t-1} shows that investment growth in the previous year is an important predictor of investment growth in the current year. The coefficient on the error correction term $(i_{t-1} - y_{t-1})$ is -0.523, implying that about half of the disequilibrium in investment from its long-run path is corrected each year. This parsimonious model has acceptable within-sample diagnostic statistics and all the retained explanatory variables are statistically significant.

Column 1 of Table 3.5 also summarizes the simulated forecast results using the reduced model for the baseline specification. The forecasts considered are for annual growth rates of manufacturing investment. The Chi-square and Chow forecast tests do not reject the hypothesis of parameter constancy for this model. It would however have under-predicted investment growth in all years except 2009. In particular, it would have only predicted a modest decrease of 5.6% in 2009, when manufacturing investment in fact fell by 18.5%. The MFE is 0.0299, indicating that the forecasts are biased downwards. The RMSFE is 0.0884. The simulated forecasts using this baseline specification perform less well than the forecasts made in real time by the CBI and published in quarter 4 of year $t-1$ (see Table 3.4 and Figure 3.14).

By including the split trend term in our forecasting model, we are imposing the restriction that the downward trend in the ratio of investment to output from 1999 onwards in the in-sample period will continue on its course in the out-of-sample forecasting period. Therefore, the negative coefficient on the split trend term may

[6] There is no material difference between Figure 3.3 and the graph of the ratio of manufacturing investment in the current year to manufacturing output in the previous year (available upon request). Both exhibit downward trends from 1999 onwards.

cause the forecasts from this model to have a downward bias. In column 2 of Table 3.5, we drop the split trend term to assess whether the exclusion of the split trend term improves the forecast performance. All the coefficients remain significant. However, the Chi-square forecast test rejects the null hypothesis that there is no structural change in this model across the in-sample and the out-of-sample periods. This model without the split trend term would have over-predicted investment growth in all years. In particular, it would have missed the substantial fall in investment in 2009 and would have predicted that investment would grow by 9.0% in 2009. The absolute value of the MFE is almost four times that of the model in column 1. The RMSFE is 0.1490, which is also considerably higher than that of the model with the split trend term in column 1 (0.0884). Therefore, the baseline model produces less biased and more accurate forecast results with the inclusion of the split trend term.

In columns 3, 4, and 5 of Table 3.5, we estimate the baseline model with the split trend term over three shorter in-sample periods: 1974-2006, 1980-2006, and 1978-2006.[7] The explanatory variables remain statistically significant at the 5% level when the baseline model is estimated over these three in-sample periods. Similar to the post-sample forecast results in column 1, the out-of-sample forecasts in columns 3-5 would have all under-predicted manufacturing investment growth in all years except 2009. In 2009, the out-of-sample forecasts in column 1 and columns 3-5 would all have only predicted a modest decline in the range of 5%-6% in manufacturing investment, considerably lower than the actual decrease of 18.5%.

[7] In subsequent analysis, we will introduce the CBI variables to the baseline model. As some CBI survey questions were introduced after 1973, several models with the CBI survey variables have shorter estimation periods. To allow for better comparison, we estimate the baseline model over these shorter estimation periods here in columns 3-5.

3.8. Incorporating the CBI Survey Information

Out-of-sample forecasts are widely used in the literature to evaluate the reliability of a forecasting model because they can detect structural breaks in the forecasting model (Welch and Goyal, 2008) and are less susceptible to data mining than in-sample tests (White, 2000). Therefore, it is common in the forecasting literature to employ the out-of-sample forecasting "horse race" (i.e., forecasting competition) with a number of different forecasting models to identify the best performing models based on criteria such as RMSFE and MFE (see for example, Oliner et al., 1995; Tevlin and Whelan, 2003; Rapach and Wohar, 2007). In this section, we follow the literature and apply this horse race approach to compare the forecasting ability of augmented error correction models which use different CBI survey measures as additional explanatory variables. First, we construct different forecasting models by adding different explanatory variables derived from the CBI survey questions to the baseline equation (3.12). Next, we compare the out-of-sample forecast performance between each individual model with the CBI survey variables and the baseline model to determine if the inclusion of these CBI survey variables improves the baseline forecast results. Finally, we conduct an out-of-sample forecasting horse race across all these models incorporating the CBI survey data to identify the CBI survey variables with the highest predictive power.

3.8.1. Motivations

In our analysis, we will consider the following CBI survey questions which are potentially useful for forecasting investment: *BUSOPT* (business optimism), *LOWCAP* (low capacity utilization), *ORDER_P* (past orders), *ORDER_N* (expected orders), *OUTPUT_P* (past output), *OUTPUT_N* (expected output), *UNCERT* (demand uncertainty), *INTFIN* (internal financial constraints), *EXTFIN* (external financial constraints), *CAPEX_B* (expected capital expenditure on buildings), and *CAPEX_PM* (expected capital expenditure on plant and machinery). We will explain the motivations for studying each of these CBI survey questions below.

BUSOPT is an indicator of business optimism about future prospects (what Keynes calls "animal spirits"), which may be affected not only by rational calculations of costs and benefits but also by irrational factors such as "habit, instinct, preference, desire, will, etc" (Keynes, 1938). Therefore, swings in business optimism could be a major cause for short-run fluctuations in investment. If firms become more confident about future economic conditions, they may be more likely to revise upwards the expected rate of return on investment and thus authorize more capital expenditure. We expect the relationship between *BUSOPT* and future investment to be positive.

LOWCAP is pertinent to capacity utilization. When a firm produces below its existing capacity, it tends to have less incentive to invest in expanding its productive capacity. Thus, the correlation between *LOWCAP* and future investment is expected to be negative.

OUTPUT_P, *OUTPUT_N*, *ORDER_P*, and *ORDER_N* are all questions related to demand conditions. According to dynamic investment models such as the traditional *q* model (Hayashi, 1982), in the presence of adjustment costs, investment spending depends on both current and expected future profitability. Among the four variables, *OUTPUT_P* and *ORDER_P* pertain to current demand, which is a determinant of current profitability. If a firm has recently experienced a rise in the volume of output or new orders, it is more likely to enjoy higher profitability and therefore have a higher demand for capital. On the other hand, *OUTPUT_N* and *ORDER_N* are related to expected future demand, which is an important factor influencing expected future profitability. If a firm has higher output or orders expectations, it is also more likely to have higher profit expectations and therefore increase its investment spending. All of these four variables *OUTPUT_P*, *OUTPUT_N*, *ORDER_P*, and *ORDER_N* are expected to have a positive correlation with future investment.

INTFIN and *EXTFIN* are both related to financial constraints. As we have discussed in section 2.2.1 of Chapter 2, due to capital market imperfections, corporate investment decisions depend not only on the cost of finance but also on quantitative financial factors such as the availability of internal finance (retained earnings) and the access to external finance (debt or equity). Therefore, financially constrained firms are likely to have lower investment spending and both *INTFIN* and *EXTFIN* are expected to be negatively related to future investment.

UNCERT pertains to demand uncertainty. As we have explained in section 2.2.2 of Chapter 2, the real options theory asserts that firms will defer or cancel investment plans under more uncertain conditions since higher uncertainty increases the option value of waiting for further information. According to this theory, the relationship between *UNCERT* and future investment is expected to be negative.

CAPEX_B and *CAPEX_PM* are survey measures of capital expenditure intentions. Corporate investment decisions are highly complex as they are determined by many factors. *CAPEX_B* and *CAPEX_PM* can be considered as summary statistics of all the factors influencing investment spending and therefore capture the information contained not only in the survey questions that we discussed above but also in other determinants of investment that we have not considered (Roman and Vasquez, 2013). *CAPEX_B* and *CAPEX_PM* are both expected to be positively linked with future investment.

3.8.2. Models with the CBI Survey Variables

Following the practice in Chapter 2, for every survey question *CBI*, we first calculate five different four-quarter moving averages:

1. CBI_MA4_{t-1}: four-quarter moving average for the period ending in quarter 4 of calendar year $t-1$;
2. CBI_MA3_{t-1}: four-quarter moving average for the period ending in quarter 3 of calendar year $t-1$;
3. CBI_MA2_{t-1}: four-quarter moving average for the period ending in quarter 2 of calendar year $t-1$;
4. CBI_MA1_{t-1}: four-quarter moving average for the period ending in quarter 1 of calendar year $t-1$;
5. CBI_MA4_{t-2}: four-quarter moving average for the period ending in quarter 4 of calendar year $t-2$.

Next, we construct a forecasting model by adding these five moving averages together to the baseline equation (3.12):

$$\Delta i_t = \omega_0 + \omega_1 D1999 + \omega_2 \Delta i_{t-1} + \omega_3 \Delta i_{t-2} + \omega_4 \Delta y_{t-1} + \omega_5 \Delta y_{t-2} + \omega_6 \Delta p_{t-1} + \omega_7 \Delta p_{t-2} + \omega_8 (i_{t-1} - y_{t-1}) + \omega_9 p_{t-1} + \omega_{10} t + \omega_{11} st1999 + \omega_{12} CBI\_MA4_{t-1} + \omega_{13} CBI\_MA3_{t-1} + \omega_{14} CBI\_MA2_{t-1} + \omega_{15} CBI\_MA1_{t-1} + \omega_{16} CBI\_MA4_{t-2} + \varepsilon_t \quad (3.13)$$

Autometrics is then used to simplify equation (3.13) and derive a parsimonious model retaining only the significant moving averages. Using the steps outlined above, we build different forecasting models, each using one of the CBI survey questions discussed in section 3.8.1.

3.9. Results of Models with the CBI Survey Variables

3.9.1. Business Optimism

In column 1 of Table 3.6, we present the reduced model using the survey question related to business optimism (*BUSOPT*). The in-sample period is 1974-2006 because $BUSOPT\_MA4_{t-2}$ in the GUM is only available from 1974 onwards. For comparison, we report the baseline forecasting model estimated over this shorter sample period in column 3 of Table 3.5. This reduced model in column 1 of Table 3.6 passes all the diagnostic tests. However, significance at the 5% level is not obtained for the error correction coefficient. $BUSOPT\_MA4_{t-1}$ survives the reduction process. The coefficient on $BUSOPT\_MA4_{t-1}$ is 0.00385. This positive coefficient indicates that the proportion of firms that report being more optimistic about the general business situation over the four quarters of the previous year is positively correlated with investment growth in the current year. This is in line with the results of Barnes and Ellis (2005), which show that survey indicators of confidence about future profitability and optimism about the general business situation have predictive power for investment growth. As the standard deviation of $BUSOPT\_MA4_{t-1}$ is 19.645, a one standard deviation increase in $BUSOPT\_MA4_{t-1}$ predicts an increase of 0.00385×19.645=0.0756 in Δi_t. Because one standard deviation of Δi_t is 0.0983, a one standard deviation increase in $BUSOPT\_MA4_{t-1}$ predicts a 0.0756÷0.0983=0.770 standard deviations increase in Δi_t.

Column 1 of Table 3.6 also reports the out-of-sample forecasts of this reduced model over 2007-2012. This specification passes both the Chi-square and Chow tests of parameter stability. In terms of point forecasts, this model would have forecast around half of the fall in investment in 2009, a sizeable improvement from the baseline model reported in column 3 of Table 3.5, and similar to the forecast published by the CBI in quarter 4 of 2008 (see Figure 3.14). In addition, it would have produced investment projections for 2010 and 2011 close to the outturns. This model also would have forecast manufacturing investment growth reasonably well for the remaining years. It also has a lower MFE in absolute value and a lower RMSFE compared with the baseline model. This indicates that the investment forecasts of this model with the CBI survey variable pertaining to business confidence are less biased and more accurate than those of the baseline model. The simulated forecasts from this specification are more accurate than the published CBI forecasts from quarter 4 of year $t-1$ (lower RMSFE), although they have a larger bias (higher MFE in absolute value).

3.9.2. Investment Intentions

There are two CBI survey questions related to capital expenditure intentions on buildings (*CAPEX_B*) and plant and machinery (*CAPEX_PM*). Since the trends for *CAPEX_B* and *CAPEX_PM* are broadly similar (see Figure 3.6), we add the five moving averages of *CAPEX_B* together with the five moving averages of *CAPEX_PM* to equation (3.12) to form the GUM. The in-sample period is 1974-2006. In column 2 of Table 3.6, the reduced model selected by Autometrics retains $CAPEX\_PM\_MA4_{t-1}$, the linear trend term, and the split trend term. The coefficient on $CAPEX\_PM\_MA4_{t-1}$ is 0.00386, which indicates that a higher proportion of firms over the four quarters of the previous year anticipating to authorize more investment on plant and machinery is associated with stronger investment growth in the current year. Britton et al. (1999), Barnes and Ellis (2005), and Cassidy et al. (2012) also find survey indicators of investment plans or intentions to be useful for predicting future movements in investment. As the standard deviation of $CAPEX\_PM\_MA4_{t-1}$ is 17.318, a one standard deviation increase in $CAPEX\_PM\_MA4_{t-1}$ predicts a 0.680 standard deviations increase in Δi_t. This model would have predicted a large fall in investment in 2009. However, it would have been too pessimistic in both 2010 and 2011, forecasting a 15.7% decrease in investment in 2010 and only a 2.4% increase in investment in 2011.

Since the inclusion of the trend terms in this specification may cause these forecasts to be biased downwards, we explore an alternative specification in column 3 of Table 3.6 by dropping both the linear trend and the split trend terms from the model reported in column 2 of Table 3.6. All the remaining variables stay significant at the 5% level and all the diagnostic tests are passed. In 2009, this model would have managed to forecast only 21% of the actual decline in investment. This model has slightly lower absolute MFE and RMSFE values than the model with the trend terms in column 2 of Table 3.6, but performs less well than the model which uses the survey measure of business optimism (column 1 of Table 3.6) in this out-of-sample forecasting exercise.

3.9.3. Capacity Utilization

In column 4 of Table 3.6, we show the reduced model using the capacity utilization survey question (*LOWCAP*). The in-sample period is 1974-2006. This model keeps $LOWCAP\_MA4_{t-1}$, $LOWCAP\_MA3_{t-1}$, and the split trend term. It is likely that firms producing at or close to their capacity are more willing to invest in expanding their production capacity. The coefficients on $LOWCAP\_MA3_{t-1}$ and $LOWCAP\_MA4_{t-1}$ have opposite signs, and their sum is insignificantly different from zero at the 5% level.[8] This implies that a fall in the proportion of firms reporting that they had excess capacity in quarter 4 of the previous year in relation to the same quarter of the year before is associated with stronger investment growth in the current year. This is consistent with Abberger (2005) and Barnes and Ellis (2005), according to which the relationship between capacity utilization and future investment growth is negative. As the standard deviations of $LOWCAP\_MA3_{t-1}$ and $LOWCAP\_MA4_{t-1}$ are 10.323 and 10.335, respectively, one standard deviation increases in both $LOWCAP\_MA3_{t-1}$ and $LOWCAP\_MA4_{t-1}$ together predict a 0.218 standard deviations decrease in Δi_t.

In terms of point forecasts, this model would have predicted about 60% of the decrease in manufacturing investment in 2009. However, it was too pessimistic in 2010 and would have predicted another sharp decline in investment. In 2011, it would have failed to predict the strong investment growth of more than 10%.

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[8] The Wald test statistic for the null hypothesis that the sum of the coefficients on $LOWCAP\_MA4_{t-1}$ and $LOWCAP\_MA3_{t-1}$ is zero is $\chi^2(1)=2.955$ with a *p*-value of 0.086.

In column 5 of Table 3.6, we drop the split trend term from this specification. The error correction coefficient becomes statistically insignificant at the 5% level. This model would have missed the large fall in manufacturing investment in 2009 and predicted a small increase of 3.2%. It would have been too optimistic in 2008 and 2012, predicting an investment growth rate much higher than the outturn. The absolute MFE and RMSFE of this model are close in magnitude to those of the model with the split trend term in column 4 of Table 3.6.

3.9.4. Past Orders

We report the estimates of the reduced model using the survey question pertaining to the trend in orders over the past three months (*ORDER_P*) in column 6 of Table 3.6. The in-sample period is 1980-2006. For comparison, the estimates of the baseline model over this shorter time period are presented in column 4 of Table 3.5. This parsimonious model retains $ORDER\_P\_MA4_{t-1}$ and the split trend term. The coefficient on $ORDER\_P\_MA4_{t-1}$ is 0.00362. This positive coefficient suggests that a higher proportion of firms reporting higher volumes of new orders over the past three months, in quarters 1, 2, 3, and 4 of the previous year, predicts stronger investment growth in the current year. This is in line with the results of Osterholm (2013), which show that the survey data concerning orders received in the past three months have information value for predicting future manufacturing investment in Sweden. As the standard deviation of $ORDER\_P\_MA4_{t-1}$ is 16.83, a one standard deviation increase in $ORDER\_P\_MA4_{t-1}$ predicts a 0.620 standard deviations increase in Δi_t. The White (1980) heteroscedasticity test using squares rejects the null hypothesis of homoscedasticity. This model would have forecast about half of the large decline in manufacturing investment in 2009. However, it would have under-predicted investment growth for the remaining years in the post-sample period.

In column 7 of Table 3.6, we present a variant specification without the split trend term. For the post-sample forecasts, this specification does not pass the Chi-square forecast test, suggesting a likely structural change in the parameters after the start of the financial crisis in 2007. In both 2008 and 2012, this model would have projected a high investment growth rate of more than 10%. However, the actual growth rates were only 1.9% and 0.6% in 2008 and 2012, respectively. In 2009, it would have captured only 19% of the actual fall in investment. This model also has higher absolute MFE and RMSFE compared with the model with the split trend term in column 6 of Table 3.6.

3.9.5. Expected Orders

The parsimonious specification using the question on the expected trend in orders over the next three months (*ORDER_N*) is reported in column 1 of Table 3.7. The in-sample period is 1980-2006. This reduced model keeps $ORDER\_N\_MA4_{t-1}$ with the expected positive coefficient. The coefficient on $ORDER\_N\_MA4_{t-1}$ is 0.00604. The positive coefficient indicates that the percentage of firms reporting higher expected orders over the next three months, in quarters 1, 2, 3 and 4 of the previous year, is positively correlated with current year investment growth. This is again consistent with Osterholm (2013), which finds that the survey data on the expected orders received within the next three months exhibits predictive power for short-term investment growth in Sweden. As the standard deviation of $ORDER\_N\_MA4_{t-1}$ is 13.088, a one standard deviation rise in $ORDER\_N\_MA4_{t-1}$ predicts a 0.804 standard deviations increase in Δi_t. However, this model does not pass the RESET test, suggesting that the model is likely to have a misspecified functional form. This model would have been over-optimistic in 2008, predicting a high investment growth rate of 6.2%. On the other hand, it would have been too pessimistic in 2010, forecasting a large fall of 14.4% in 2010 while the outturn was only -6.8%. For 2009, this model would have managed to predict only 38% of the decrease in investment.

3.9.6. Past Output

In column 2 of Table 3.7, we present the reduced model using the question about the trend in the volume of output over the past three months (*OUTPUT_P*). The in-sample period is 1978-2006. For reference, we also estimate the baseline model over this shorter time period and report the results in column 5 of Table 3.5. In column 2 of Table 3.7, the reduced model retains $OUTPUT\_P\_MA4_{t-1}$, $OUTPUT\_P\_MA3_{t-1}$, and the split trend term. The coefficient on $OUTPUT\_P\_MA4_{t-1}$ (0.00895) and the coefficient on $OUTPUT\_P\_MA3_{t-1}$ (-0.00494) have opposite signs and their sum is positive. The findings suggest that both a rise in the proportion of firms reporting stronger output growth in quarter 4 of the previous year compared with the same quarter in the year before that, and a higher proportion of firms reporting stronger output growth over the four quarters of the previous year, predict an increase in investment in the current year. This is in line with the results of Osterholm (2013), according to which the survey measure of the production volume in the past three months contains information about the future path of manufacturing investment. The standard deviations of $OUTPUT\_P\_MA3_{t-1}$ and $OUTPUT\_P\_MA4_{t-1}$ are 15.366 and 16.830 respectively. Therefore, one standard deviation increases in both $OUTPUT\_P\_MA3_{t-1}$ and $OUTPUT\_P\_MA4_{t-1}$ together predict a 0.553 standard deviations increase in Δi_t. For the out-of-sample forecasts, this model would have anticipated 78% of the decrease in investment in 2009. However, it would have under-predicted investment growth in all the remaining years.

In column 3 of Table 3.7, we drop the split trend term. This model fails the Chi-square test at the 5% level, indicating that its parameters are not constant across the in-sample and the post-sample periods. The out-of-sample forecasts have a clear upward forecast bias. In 2007, 2008, 2011, and 2012, it would have projected an investment growth rate much higher than the actual outcome. In 2009, it would only have anticipated 19% of the fall in investment. Compared with the model in column 2 of Table 3.7, this model has both a higher absolute MFE and a higher RMSFE.

3.9.7. Expected Output

In column 4 of Table 3.7, we present the estimates of the reduced model using the question related to the expected trend in output over the next three months (*OUTPUT_N*). The in-sample period is 1978-2006. This reduced model keeps $OUTPUT\_N\_MA4_{t-1}$ and the split trend term. The coefficient on $OUTPUT\_N\_MA4_{t-1}$ is 0.00568. This positive coefficient shows that a higher percentage of firms reporting higher expected orders over the four quarters of the previous year is linked with stronger investment growth in the current year. This is consistent with Osterholm (2013), according to which the survey data on the production volume within the next three months can help predict the future trend of manufacturing investment. Since the standard deviation of $OUTPUT\_N\_MA4_{t-1}$ is 12.174, a one standard deviation increase in $OUTPUT\_N\_MA4_{t-1}$ predicts that Δi_t will increase by 0.703 standard deviations. This model would have been able to forecast most of the decline in investment in 2009. However, it would have under-predicted investment growth in all the remaining years, especially in 2010 and 2011.

In column 5 of Table 3.7, we exclude the split trend term. All the variables in this variant specification remain statistically significant. This reduced model would have over-estimated the investment growth in 2007, 2008, and 2012. In 2009, it would have only been able to predict 22% of the reduction in investment.

3.9.8. Factors Limiting Investment

We also considered three survey questions on the possible reasons for limiting investment expenditure: demand uncertainty (*UNCERT*), internal financial constraints (*INTFIN*), and external financial constraints (*EXTFIN*). For each of the three questions, the reduced model drops all five moving averages and has the same specification as the selected baseline model reported in column 1 of Table 3.5.

3.9.9. All Selected CBI Survey Variables

In addition, we include all nine CBI survey variables selected by Autometrics in the aforementioned reduced models (i.e., $BUSOPT\_MA4_{t-1}$, $CAPEX\_PM\_MA4_{t-1}$, $LOWCAP\_MA4_{t-1}$, $LOWCAP\_MA3_{t-1}$, $ORDER\_P\_MA4_{t-1}$, $ORDER\_N\_MA4_{t-1}$, $OUTPUT\_P\_MA4_{t-1}$, $OUTPUT\_P\_MA3_{t-1}$, and $OUTPUT\_N\_MA4_{t-1}$) in equation (3.12) to form the GUM. The in-sample period is 1979-2006. The estimates of the parsimonious specification selected by Autometrics are reported in column 6 of Table 3.7. This reduced model keeps Δy_{t-1}, $CAPEX\_PM\_MA4_{t-1}$, the dummy variable for the sub-period 1999-2012, and the split trend term. This implies that $CAPEX\_PM\_MA4_{t-1}$ contains most of the information present in the other eight lagged

CBI variables useful for explaining manufacturing investment growth over the in-sample period. There is evidence of heteroscedasticity in the residuals as the White (1980) test for heteroscedasticity using squares and cross-products rejects the null hypothesis of homoscedasticity. The differences in the retained explanatory variables between this specification and the specification in column 2 of Table 3.6 are likely due to different estimation sample periods. If we estimate the specification in column 6 of Table 3.7 over the longer time period 1974-2006, both Δy_{t-1} and the dummy variable for the sub-period 1999-2012 become insignificant. For the out-of-sample forecasts, the Chi-square forecast test rejects the null hypothesis of no structural break in the coefficients in 2007. This model has a downward forecast bias and would have under-predicted investment growth rate in all years during the post-sample period.

3.9.10. Additional Explanatory Variable

The reduced baseline model presented in column 1 of Table 3.5 contains the past year's investment growth term Δi_{t-1}. However, after we introduce the CBI survey variables, the reduced models selected by Autometrics in Tables 3.6 and 3.7 all drop Δi_{t-1}. To explore whether the past investment growth term Δi_{t-1} provides additional useful information about future investment growth beyond that contained in the CBI survey variables, we add Δi_{t-1} to the specifications with survey variables presented in Tables 3.6 and 3.7. Among all cases, Δi_{t-1} is significant at the 5% level only when it is added to the specification with $BUSOPT\_MA4_{t-1}$ presented in column 1 of Table 3.6. The estimates of the resulting model containing both $BUSOPT\_MA4_{t-1}$ and Δi_{t-1} are shown in column 7 of Table 3.7.[9] The addition of Δi_{t-1} does not lead to an

[9] The sample period used here is 1973-2012. The sample period used in column 1 of Table 3.4 was 1974-2012 because longer lags of the *BUSOPT* variable were included in the GUM. The inclusion or exclusion of the observation for 1973 makes no material difference to the results discussed here.

improvement in the post-sample forecasts, as this model with Δi_{t-1} in column 7 of Table 3.7 has a higher RMSFE and a higher absolute MFE than the model without Δi_{t-1} in column 1 of Table 3.6.

3.9.11. Forecasting Horse Race

Finally, following Oliner et al. (1995), Tevlin and Whelan (2003), and Rapach and Wohar (2007), we consider a forecasting horse race by comparing the forecast error statistics of the different forecasting models with CBI survey variables reported in Tables 3.6 and 3.7. Judging from the sign of the MFE, all the models with the split trend term included tend to have a downward forecast bias over the out-of-sample period 2007-12, while the models without the split trend term tend to show an upward forecast bias. The model with $ORDER\_N\_MA4_{t-1}$ in column 1 of Table 3.7 has the lowest absolute MFE value, and the model with $BUSOPT\_MA4_{t-1}$ in column 1 of Table 3.6 has the second lowest. In terms of the RMSFE, the model with $BUSOPT\_MA4_{t-1}$ in column 1 of Table 3.6 is the lowest and the model with $ORDER\_N\_MA4_{t-1}$ in column 1 of Table 3.7 is the second lowest. In addition, both models would have projected a large fall in investment in 2009. Therefore, these two models provide the least biased and most accurate forecasts relative to the other models constructed. The simulated out-of-sample forecasts using the model with $BUSOPT\_MA4_{t-1}$ and the model with $ORDER\_N\_MA4_{t-1}$ are illustrated in Figure 3.15 and Figure 3.16, respectively. The improvements relating to the forecasts using our baseline specification are particularly clear for the last three years 2010-2012.

Our horse race exercise shows that the survey measures of demand growth and business optimism have the highest predictive power for aggregate manufacturing investment. In Chapter 2, using the ARD microdata for a shorter sample period, we found that the sector-level survey variables related to demand growth, demand uncertainty, and financing constraints are the most informative for explaining variation in the investment of reporting units in the manufacturing sector. However, the findings from the aggregate time series data and the microdata may not be directly comparable because we use different model specifications in the two chapters. In this chapter, we include only lagged explanatory variables in the models as the focus is on forecasting aggregate manufacturing investment. On the other hand, in Chapter 2, we use both the past and current values of explanatory variables to model the RU-level manufacturing investment. In Appendix 3.3, we estimate a model for aggregate manufacturing investment which uses both the lagged and current values of explanatory variables and compare the results further with those for the microdata in Chapter 2.

3.9.12. Further Refinements

In this section, we aim to further refine our model and improve the out-of-sample forecasts. Previously, we assumed that the CBI survey balance statistic in each quarter of a twelve-month period has an equal effect on the growth rate of manufacturing investment, and used the four-quarter moving average of the CBI survey variables in our regression analysis. We now relax this assumption by using quarterly CBI survey variables directly in our model. Because the model with $BUSOPT\_MA4_{t-1}$ in column 1 of Table 3.6 and the model with $ORDER\_N\_MA4_{t-1}$ in column 1 of Table 3.7 have the highest forecast precision, we focus on the quarterly survey balance statistics related to business optimism and the expected trend in new orders. To designate quarterly survey variables, we end the variable name with the quarter number. For example,

$ORDER\_N\_Q1_{t-1}$ is the balance statistic of survey responses in quarter 1 of year $t-1$ related to the expected trend over the next three months in the volume of total new orders.

In column 1 of Table 3.8, we modify the model presented in column 1 of Table 3.6 by replacing the moving average variable $BUSOPT\_MA4_{t-1}$ with the four corresponding quarterly CBI survey variables $BUSOPT\_Q1_{t-1}$, $BUSOPT\_Q2_{t-1}$, $BUSOPT\_Q3_{t-1}$, and $BUSOPT\_Q4_{t-1}$. The Wald test does not reject the null hypothesis that the coefficients on these four quarterly variables are equal,[10] thereby supporting the use of the four-quarter moving average $BUSOPT\_MA4_{t-1}$ in our previous model. However, we proceed to consider other ways of using the quarterly CBI variables to investigate whether this can improve the accuracy of the post-sample forecasts. The estimated coefficients on both $BUSOPT\_Q2_{t-1}$ and $BUSOPT\_Q3_{t-1}$ are individually insignificant and the Wald test statistic does not reject the restriction that both these coefficients are zero.[11] In column 2 of Table 3.8, we drop these two insignificant variables and obtain a more parsimonious model. The coefficients on the two remaining quarterly business optimism survey variables are significant at conventional levels. Both the coefficients on $BUSOPT\_Q1_{t-1}$ and $BUSOPT\_Q4_{t-1}$ have the expected positive signs. In terms of the forecast parameter constancy test statistics, this model passes both the Chi-square and the Chow tests. It would have forecast investment growth reasonably well in most of the years, and would have predicted around half of the fall in investment in 2009. However, this model has slightly higher RMSFE and higher absolute MFE values than the model with the four-quarter moving average measure $BUSOPT\_MA4_{t-1}$ reported in column 1 of Table 3.6.

[10] The Wald test statistic is $\chi^2(3)=2.658$ with an associated p-value of 0.448.
[11] The Wald test statistic is $F(2,28)=0.178$ with an associated p-value of 0.838.

In particular, this model which uses the quarterly business optimism measures gives a less accurate forecast for 2010.

In addition, we replace the moving average variable $ORDER\_N\_MA4_{t-1}$ used in the model of column 1 of Table 3.7 with the four quarterly CBI survey variables $ORDER\_N\_Q1_{t-1}$, $ORDER\_N\_Q2_{t-1}$, $ORDER\_N\_Q3_{t-1}$, and $ORDER\_N\_Q4_{t-1}$. The modified model is shown in column 3 of Table 3.8 and the estimation period is 1979-2006.[12] The Wald test does not reject the null hypothesis that the coefficients on these four quarterly variables are equal.[13] However, this is not the only restriction that can be considered. The coefficients on $ORDER\_N\_Q1_{t-1}$, $ORDER\_N\_Q2_{t-1}$, and $ORDER\_N\_Q3_{t-1}$ are neither individually nor jointly significant at the 5% level.[14] In column 4 of Table 3.8, we drop these three insignificant variables. The coefficient on $ORDER\_N\_Q4_{t-1}$ in this more parsimonious model remains significant with the expected positive sign. This model would have impressively predicted the sharp fall in manufacturing investment in 2009. However, it would have been too optimistic about investment in 2010 and would have predicted a moderate increase of 3.6% while the outturn was -6.8%. In this case, the forecasts from the model which uses the quarterly expected orders measure $ORDER\_N\_Q4_{t-1}$ have smaller bias and greater accuracy than the forecasts from the model which uses the annualized expected orders measure $ORDER\_N\_MA4_{t-1}$ (column 1 of Table 3.7).

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[12] The sample period was 1980-2006 in column 1 of Table 3.7 because the variable $ORDER\_MA4_{t-2}$ used in the GUM is only available from 1980 onwards. The sample period is 1979-2006 in column 3 of Table 3.8 because the variable $ORDER\_N\_Q1_{t-1}$ used in the equation is only available from 1979 onwards. The sample periods in columns 4-6 of Table 3.8 are all 1978-2012 because the variable $ORDER\_N\_Q4_{t-1}$ used in these three specifications is available from 1978 onwards.

[13] The Wald test statistic is $\chi^2(3)=3.200$ with an associated p-value of 0.362.

[14] The Wald test statistic for the joint significance of $ORDER\_N\_Q1_{t-1}$, $ORDER\_N\_Q2_{t-1}$, and $ORDER\_N\_Q3_{t-1}$ is $F(3,22)=2.252$ with an associated p-value of 0.111.

In column 5 of Table 3.8, we combine the models in columns 2 and 4 by including all three quarterly variables: $BUSOPT\_Q1_{t\text{-}1}$, $BUSOPT\_Q4_{t\text{-}1}$, and $ORDER\_N\_Q4_{t\text{-}1}$. The in-sample period is 1978-2006. The coefficient on $BUSOPT\_Q4_{t\text{-}1}$ becomes negligibly small and statistically insignificant after the addition of $ORDER\_N\_Q4_{t\text{-}1}$ to the model, which implies that $ORDER\_N\_Q4_{t\text{-}1}$ subsumes most of the explanatory power of $BUSOPT\_Q4_{t\text{-}1}$ for manufacturing investment growth. This may be because expected demand is itself an important determinant of business confidence. In column 6 of Table 3.8, we drop the insignificant variable $BUSOPT\_Q4_{t\text{-}1}$. The coefficients on $BUSOPT\_Q1_{t\text{-}1}$ and $ORDER\_N\_Q4_{t\text{-}1}$ are 0.00160 and 0.00392, respectively. As the standard deviations of $BUSOPT\_Q1_{t\text{-}1}$ and $ORDER\_N\_Q4_{t\text{-}1}$ are 26.233 and 16.493, respectively, one standard deviation increases in $BUSOPT\_Q1_{t\text{-}1}$ and $ORDER\_N\_Q4_{t\text{-}1}$ predict Δi_t to increase by 0.426 and 0.658 standard deviations, respectively.

The new model would have predicted manufacturing investment growth very close to the actual outcomes over the post-sample forecast period. In 2009, it would have managed to anticipate 85% of the fall in manufacturing investment. Both its MFE (in absolute value) and its RMSFE are lower than all the other models we have discussed in Tables 3.5-3.8. Therefore, this model has the best out-of-sample forecasting performance for manufacturing investment growth over the period 2007-2012, and thus is chosen as our preferred forecasting model.

3.9.13. Structural stability

Given the exceptional scale of the Great Recession, there may have been a structural change in the investment behavior of manufacturing firms that affects the coefficients of our preferred model after the start of the recent financial crisis in 2007. However, the Chi-square and Chow (1960) tests based on the out-of-sample forecasts reported in the previous section suggest that this was not the case. To further test the stability of the parameters of our preferred model over the pre-crisis and the post-crisis periods, we interact all the explanatory variables with a financial crisis dummy variable (*CRISIS*), which equals one after the onset of the crisis in 2007, i.e. years 2007-2012, and zero otherwise. The regression estimates over the sample period 1978-2012 are presented in Table 3.9. None of the coefficients on (*CRISIS*)*($i_{t-1} - y_{t-1}$), (*CRISIS*)*$BUSOPT\_Q1_{t-1}$, (*CRISIS*)*$ORDER\_N\_Q4_{t-1}$, and *CRISIS* is individually significant at conventional levels. The Wald test also does not reject the joint hypothesis of zero coefficients on all four of these interactions with the crisis dummy.[15] Therefore, we do not find significant evidence of a structural break in 2007 in our preferred forecasting model.

3.9.14. Comparison with CBI Forecasts

In this section, we compare the out-of-sample forecasts using our preferred model in column 6 of Table 3.8 with the published CBI forecasts. Since our preferred model makes use of the fourth quarter CBI survey responses published in October, we choose the CBI Year (T-1) Q4 forecasts published in November/December for the fairest comparison. However, it should be noted that the preferred econometric model used in this comparison has been chosen after observing the outturns for investment growth over the period 2007-2012. In real time, it may not have been clear that this specification would be the preferred forecasting model. In Figure 3.17, we plot the simulated forecasts using our model and the published CBI forecasts. For 2007, the CBI predicted an increase of 2.7% in investment and our model would have predicted

[15] The Wald test statistic is $F(4,27)=0.144$ with an associated *p*-value of 0.964.

a lower investment growth rate of 1.1%. The outturn was 5.3%. For 2008, the CBI anticipated investment to remain at around the same level as 2007. Our model would have predicted that investment grew by 1.4%, close to the actual outcome of 1.9%. For 2009, the CBI forecasters were only able to forecast about half of the very large fall in investment, while our model would have been able to predict 85% of the decrease. For 2010, the CBI anticipated another large decline of 9.3% in investment. Our model would have produced a forecast of -6.1%, which is much closer to the outturn of -6.8%. For 2011, the CBI underestimated the recovery in investment and projected an increase of 4.2% in investment, while our model would have projected that investment rose by 9.9%. The outturn was 11.8%. For 2012, the CBI projected a small rise of 1.1% in investment. Our preferred model would have given a forecast very close to the outcome of -0.6%. The RMSFE of the CBI Year (T-1) Q4 forecasts is 0.0502, which is more than twice that of the simulated forecasts using our preferred model (0.0221). The CBI Year (T-1) Q4 forecasts also have a MFE (0.0100) that is twice that of our simulated forecasts (0.0050). Therefore, our model would have yielded more accurate and less biased forecasts of the annual growth rate in manufacturing investment than the published CBI forecasts over the recent credit crunch period.

3.9.15. Shorter Estimation Periods

In column 1 of Table 3.5, the main estimation period for the baseline model is from 1973 onwards. However, the estimation periods are shorter for some models with CBI survey variables in Tables 3.6-3.8 because some CBI survey questions were only introduced after 1973. In particular, the estimation periods for the models using *ORDER_P* and *ORDER_N* are reduced to 1980-2006. However, as we can observe from Figures 3.1-3.13, there is a lot of time variation in manufacturing investment, manufacturing output, the relative price of investment goods, and the responses to various CBI survey questions throughout the sample period, even if we only consider the shorter period after 1980. Therefore, despite the relatively shorter sample periods, we can still exploit the rich time variation in our data by estimating the time series forecasting models in Tables 3.6-3.9 and draw valuable conclusions. Furthermore, for our preferred forecasting model in column 6 of Table 3.8, the estimation period is from 1978 onwards, which is only five years shorter than the main estimation period of the baseline model.

3.9.16. Endogeneity

An explanatory variable is endogenous if it is correlated with the error term. [16] In the presence of endogenous explanatory variables, the OLS estimator is biased and inconsistent. In our case, it is possible that a shock to current investment also affects current output and the current relative price of investment goods. Similarly, it is possible that shocks to past investment also caused changes in past output and past relative prices of investment goods. However, provided that the error term in our specification is not serially correlated, it is unlikely that the lagged values of these explanatory variables are correlated with the shock to investment growth in year t. That is, with serially uncorrelated errors, we reduce the risk that our OLS estimates are biased as a result of endogeneity by using only lagged explanatory variables in our forecasting specifications. The results of the residual autocorrelation tests (AR 1-2 tests) are consistent with the hypothesis of no serial correlation in the error terms of

[16] I would like to thank Professor Alessandra Guariglia for her comments on endogeneity.

our models, and thus that endogeneity is unlikely to be a serious concern for the results presented in this chapter.

3.10. Conclusions and Policy Implications

In this chapter, we build econometric models to forecast U.K. manufacturing investment using the CBI survey data. We first investigate the investment forecasting record of the CBI, and find that CBI forecasters may have been late in realizing the severe impact of the financial crisis on U.K. manufacturing investment. In spite of the early negative signals from its own Industrial Trends Survey, the CBI did not predict a large decrease in manufacturing investment in 2009 until after the collapse of Lehman Brothers in September 2008. We then proceed to estimate an error correction forecasting model. The baseline model does not perform well in the out-of-sample forecasts and would not have been able to predict the sharp decline in U.K. manufacturing investment in the Great Recession. Subsequently, we introduce the CBI survey variables to our baseline model. The CBI survey measures related to business optimism and expected future orders are found to be particularly useful in improving the post-sample forecasts. In addition, we compare the simulated forecasts using our best-performing model with the published CBI forecasts and show that our model produces more accurate and less biased forecasts over the period 2007-2012.

The results have significant policy implications. As we find that the forecasting models augmented with the CBI survey variables generally have better out-of-sample forecasting properties than the baseline forecasting model, this supports the idea that business survey data could provide extra information about future movements in manufacturing investment beyond that already contained in more conventional economic variables. Hence, in order to generate more accurate forecasts of manufacturing investment, forecasters and policymakers may want to make more efforts to utilize survey data in their forecasting models. In addition, because the survey indicators of business confidence and expected future orders are found to have the highest forecasting power and they provide forward-looking information not captured by official statistical data, the government may want to pay close attention to these two indicators when assessing the outlook for aggregate manufacturing investment and making policy decisions. For instance, a deterioration in either the business confidence or expected orders survey balance statistics may signal a sharp slowdown in manufacturing investment in the future if no offsetting policy action is taken. If policymakers could identify this news from these survey indicators early, they could design timely policy responses to stimulate manufacturing investment.

Table 3.1. Summary statistics

Variable	Mean	Standard Deviation	25% Percentile	Median	75% Percentile
Δi_t	-0.00478	0.09830	-0.08487	-0.01854	0.07782
Δy_t	0.00375	0.03742	-0.00862	0.00722	0.02058
Δp_t	-0.00245	0.04609	-0.02361	0.00210	0.01789
$i_{t-1}-y_{t-1}$	-2.021	0.144	-2.107	-2.022	-1.908
p_t	-0.0119	0.0695	-0.0598	-0.0243	0.0271

Notes: Lower-case letters denote natural logarithms.

Table 3.2. Mean values for different sub-periods

Series	Sub-period 1	M1	Sub-period 2	M2	*t*-statistic
Expected capital expenditure on building (CAPEX_B)	1972Q1-1998Q4	-15.4	1999Q1-2012Q4	-23.2	4.168 [0.000]
Expected capital expenditure on plant and machinery (CAPEX_PM)	1972Q1-1998Q4	2.8	1999Q1-2012Q4	-13.6	6.438 [0.000]
Expected orders (ORDER_N)	1977Q4-1998Q4	7.3	1999Q1-2012Q4	-0.2	2.950 [0.002]
Expected output (OUTPUT_N)	1975Q3-1998Q4	2.2	1999Q1-2012Q4	-3.0	1.904 [0.030]

Notes: M1 is the mean of the data series in sub-period 1, and M2 is the mean of the data series in sub-period 2. *T*-statistic is from the two-sample unequal variance *t*-test with the null hypothesis that M1=M2 and the alternative hypothesis that M1>M2. *P*-values are reported in square brackets.

Table 3.3. Correlation coefficients between the CBI forecasts and the outturns (sample period: 2007-2012)

Forecast Type	Correlation Coefficient
Year (T-2) Q4	0.24
Year (T-1) Q1	0.53
Year (T-1) Q2	0.69
Year (T-1) Q3	0.54
Year (T-1) Q4	0.91

Table 3.4. Forecast error analysis (sample period: 2007-2012)

Forecast Type	MFE	RMSFE
Year (T-2) Q4	-0.0312	0.0955
Year (T-1) Q1	-0.0289	0.0924
Year (T-1) Q2	-0.0245	0.0803
Year (T-1) Q3	-0.0260	0.0830
Year (T-1) Q4	0.0100	0.0502

3.5. Baseline forecasting models

Dependent Variable: Δi_t

	(1)	(2)	(3)	(4)	(5)
In-Sample Period	1973-2006	1973-2006	1974-2006	1980-2006	1978-2006
$i_{t-1}-y_{t-1}$	-0.523*** (0.127)	-0.439*** (0.134)	-0.508*** (0.131)	-0.591*** (0.148)	-0.621*** (0.138)
Δi_{t-1}	0.454*** (0.140)	0.506*** (0.151)	0.471*** (0.144)	0.516*** (0.154)	0.541*** (0.142)
Constant	-1.017*** (0.251)	-0.866*** (0.266)	-0.988*** (0.258)	-1.142*** (0.286)	-1.198*** (0.268)
Split Trend st1999	-0.0164** (0.0063)		-0.0157** (0.0064)	-0.0183** (0.0067)	-0.0193*** (0.0063)
R-Squared	0.470	0.349	0.468	0.521	0.571
AR1-2 Test	1.248 [0.303]	0.990 [0.384]	1.365 [0.273]	1.013 [0.380]	0.580 [0.568]
ARCH 1-1 Test	0.124 [0.727]	1.285 [0.265]	0.211 [0.649]	1.114 [0.301]	0.016 [0.899]
Normality Test	2.332 [0.312]	2.024 [0.364]	2.097 [0.351]	2.143 [0.342]	2.440 [0.295]
Hetero Test	0.966 [0.467]	0.967 [0.441]	0.906 [0.506]	1.928 [0.126]	1.960 [0.116]
Hetero-X Test	0.797 [0.623]	0.833 [0.538]	0.790 [0.629]	1.765 [0.150]	1.843 [0.125]
RESET23 Test	0.427 [0.657]	0.170 [0.844]	0.334 [0.719]	0.832 [0.449]	1.115 [0.345]
Observations	34	34	33	27	29

Continued on next page

Table 3.5 continued

	(1)	(2)	(3)	(4)	(5)
2007 Outturn	0.0525	0.0525	0.0525	0.0525	0.0525
Forecast	-0.0290	0.0732	-0.0306	-0.0248	-0.0231
Forecast Error	0.0815	-0.0207	0.0831	0.0773	0.0756
2008 Outturn	0.0192	0.0192	0.0192	0.0192	0.0192
Forecast	-0.0019	0.1283	0.0005	0.0066	0.0097
Forecast Error	0.02111	-0.1090	0.0187	0.0126	0.0095
2009 Outturn	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853
Forecast	-0.0589	0.0901	-0.0556	-0.0577	-0.0578
Forecast Error	-0.1264	-0.2754	-0.1298	-0.1277	-0.1275
2010 Outturn	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681
Forecast	-0.1227	0.0247	-0.1235	-0.1302	-0.1338
Forecast Error	0.0546	-0.0928	0.05542	0.0622	0.0657
2011 Outturn	0.1180	0.1180	0.1180	0.1180	0.1180
Forecast	-0.0263	0.1340	-0.0261	-0.0207	-0.0188
Forecast Error	0.1443	-0.0160	0.1441	0.1387	0.1368
2012 Outturn	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058
Forecast	-0.0105	0.1843	-0.0049	-0.0020	0.0006
Forecast Error	0.00468	-0.1901	-0.0010	-0.0038	-0.0064
MFE	0.0299	-0.1173	0.0284	0.0265	0.0256
RMSFE	0.0884	0.1490	0.0894	0.0871	0.0867
χ^2 Forecast Test	8.122 [0.229]	19.394 [0.004]	8.124 [0.229]	8.356 [0.213]	8.789 [0.186]
Chow Forecast Test	1.146 [0.361]	2.257 [0.064]	1.153 [0.358]	1.175 [0.354]	1.245 [0.318]

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets.

Table 3.6. Forecasting models with CBI survey variables

Dependent Variable: Δi_t

	(1) BUSOPT	(2) CAPEX	(3) CAPEX (No Trend)	(4) LOWCAP	(5) LOWCAP (No Trend)	(6) ORDER_P	(7) ORDER_P (No Trend)
In-Sample Period	1974-2006	1974-2006	1974-2006	1974-2006	1974-2006	1980-2006	1980-2006
i_{t-1}-y_{t-1}	-0.097 (0.104)	-0.462*** (0.103)	-0.269** (0.098)	-0.327*** (0.135)	-0.199 (0.143)	-0.417*** (0.116)	-0.260** (0.119)
BUSOPT_MA4$_{t-1}$	0.00385*** (0.00059)						
CAPEX_PM_MA4$_{t-1}$		0.00386 *** (0.00059)	0.00411*** (0.00062)				
LOWCAP_MA4$_{t-1}$				-0.0218*** (0.0051)	-0.0237*** (0.0057)		
LOWCAP_MA3$_{t-1}$				0.0197*** (0.0053)	0.0217*** (0.0059)		
ORDER_P_MA4$_{t-1}$						0.00362*** (0.00067)	0.00391*** (0.00077)
Constant	-0.166 (0.206)	-0.986*** (0.216)	-0.525** (0.194)	-0.503** (0.242)	-0.272 (0.256)	-0.794*** (0.224)	-0.506** (0.233)
Trend		0.00504*** (0.00157)					
Split Trend st1999		-0.0234*** (0.0073)		-0.0164*** (0.0057)		-0.0163*** (0.0054)	
R-Squared	0.626	0.744	0.637	0.596	0.476	0.684	0.561
AR1-2 Test	0.211 [0.811]	0.692 [0.510]	0.369 [0.695]	0.996 [0.383]	2.268 [0.123]	0.333 [0.721]	0.823 [0.452]
ARCH 1-1 Test	0.275 [0.604]	1.099 [0.303]	0.050 [0.825]	0.334 [0.567]	0.730 [0.399]	0.474 [0.498]	0.005 [0.947]
Normality Test	0.187 [0.911]	2.012 [0.366]	3.046 [0.218]	0.400 [0.819]	0.807 [0.668]	1.211 [0.546]	2.375 [0.305]
Hetero Test	0.528 [0.716]	1.445 [0.229]	1.169 [0.346]	1.015 [0.452]	0.837 [0.553]	2.622 [0.049]	0.905 [0.478]
Hetero-X Test	0.845 [0.530]	1.403 [0.245]	0.915 [0.486]	1.013 [0.482]	0.778 [0.638]	1.750 [0.153]	0.893 [0.503]
RESET23 Test	0.934 [0.405]	0.410 [0.668]	3.089 [0.061]	2.040 [0.150]	0.753 [0.481]	1.195 [0.322]	1.087 [0.355]
Observations	33	33	33	33	33	27	27

Continued on next page

Table 3.6 continued

	(1) BUSOPT	(2) CAPEX	(3) CAPEX (No Trend)	(4) LOWCAP	(5) LOWCAP (No Trend)	(6) ORDER_P	(7) ORDER_P (No Trend)
2007 Outturn	0.0525	0.0525	0.0525	0.0525	0.0525	0.0525	0.0525
Forecast	0.0209	-0.0118	0.0313	-0.0284	0.0659	-0.0075	0.0715
Forecast Error	0.0315	0.0643	0.0212	0.0809	-0.0134	0.0600	-0.0190
2008 Outturn	0.0192	0.0192	0.0192	0.0192	0.0192	0.0192	0.0192
Forecast	0.0416	-0.0384	0.0326	-0.0662	0.0491	-0.0009	0.1048
Forecast Error	-0.0224	0.0576	-0.0134	0.0854	-0.0299	0.0201	-0.0855
2009 Outturn	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853
Forecast	-0.0929	-0.1342	-0.0391	-0.1060	0.0315	-0.0909	0.0344
Forecast Error	-0.0924	-0.0511	-0.1462	-0.0793	-0.2168	-0.0945	-0.2198
2010 Outturn	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681
Forecast	-0.0547	-0.1568	-0.0631	-0.1884	-0.0502	-0.1703	-0.0505
Forecast Error	-0.0134	0.0888	-0.0050	0.1203	-0.0179	0.1023	-0.0176
2011 Outturn	0.1180	0.1180	0.1180	0.1180	0.1180	0.1180	0.1180
Forecast	0.1082	0.0241	0.1239	-0.0178	0.1342	0.0174	0.1482
Forecast Error	0.0098	0.0938	-0.0059	0.1358	-0.0163	0.1006	-0.0302
2012 Outturn	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058
Forecast	0.0236	-0.0625	0.0734	-0.0806	0.0970	-0.0315	0.1320
Forecast Error	-0.0294	0.0567	-0.0792	0.0748	-0.1028	0.0257	-0.1378
MFE	-0.0194	0.0517	-0.0381	0.0697	-0.0662	0.0357	-0.0850
RMSFE	0.0432	0.0707	0.0687	0.0989	0.0994	0.0755	0.1127
χ^2 Forecast Test	2.791 [0.835]	10.211 [0.116]	7.283 [0.295]	12.641 [0.049]	10.197 [0.117]	9.501 [0.147]	15.916 [0.014]
Chow Forecast Test	0.403 [0.871]	0.878 [0.524]	1.050 [0.414]	1.159 [0.356]	1.312 [0.284]	1.206 [0.339]	1.888 [0.124]

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets.

Table 3.7. Forecasting models with CBI survey variables

Dependent Variable: Δi_t

	(1) ORDER_N	(2) OUTPUT_P	(3) OUTPUT_P (No Trend)	(4) OUTPUT_N	(5) OUTPUT_N (No Trend)	(6) ALL CBI VARIABLES	(7) BUSOPT (With Δi_{t-1})
In-Sample Period	1980-2006	1978-2006	1978-2006	1978-2006	1978-2006	1979-2006	1973-2006
i_{t-1}-y_{t-1}	-0.163 (0.099)	-0.374*** (0.123)	-0.208 (0.125)	-0.416*** (0.105)	-0.265** (0.111)	-0.775*** (0.126)	-0.183 0.109
Δy_{t-1}						-1.069* (0.596)	
Δi_{t-1}							0.258** (0.120)
ORDER_N_MA4$_{t-1}$	0.00604*** (0.00085)						
OUTPUT_P_MA4$_{t-1}$		0.00895*** (0.00259)	0.0107*** (0.0029)				
OUTPUT_P_MA3$_{t-1}$		-0.00494** (0.00251)	-0.00636** (0.00281)				
OUTPUT_N_MA4$_{t-1}$				0.00568*** (0.00091)	0.00627*** (0.00104)		
CAPEX_PM_MA4$_{t-1}$						0.00784*** (0.00149)	
BUSOPT_MA4$_{t-1}$							0.00315*** (0.00059)
Constant	-0.358* (0.193)	-0.715*** (0.239)	-0.408 (0.246)	-0.838*** (0.203)	-0.567** (0.217)	-1.502*** (0.246)	-0.343 (0.217)
Split Trend 1999		-0.0159*** (0.0054)		-0.0164*** (0.0050)		-0.0476*** (0.0111)	
Intercept Dummy D1999						0.244*** (0.063)	
R-Squared	0.703	0.713	0.610	0.736	0.624	0.829	0.666
AR1-2 Test	0.367 [0.697]	0.176 [0.840]	0.335 [0.719]	0.085 [0.919]	0.223 [0.802]	0.881 [0.430]	0.347 [0.710]
ARCH 1-1 Test	0.728 [0.402]	0.936 [0.342]	0.622 [0.437]	0.000 [0.996]	0.0181 [0.894]	0.760 [0.391]	0.082 [0.776]
Normality Test	2.327 [0.313]	0.523 [0.770]	0.879 [0.644]	4.610 [0.100]	4.796 [0.091]	5.280 [0.071]	1.600 [0.449]
Hetero Test	0.759 [0.563]	1.738 [0.151]	0.905 [0.509]	2.573 [0.048]	1.348 [0.281]	2.058 [0.092]	0.908 [0.504]
Hetero-X Test	0.595 [0.704]	1.342 [0.295]	0.786 [0.633]	1.672 [0.165]	1.153 [0.362]	3.977 [0.010]	0.890 [0.548]
RESET23 Test	4.425 [0.024]	0.523 [0.600]	0.840 [0.445]	2.85 [0.078]	1.701 [0.214]	0.631 [0.542]	0.360 [0.701]
Observations	27	29	29	29	29	28	34

Continued on next page

Table 3.7 continued

	(1) ORDER_N	(2) OUTPUT_P	(3) OUTPUT_P (No Trend)	(4) OUTPUT_N	(5) OUTPUT_N (No Trend)	(6) ALL CBI VARIABLES	(7) BUSOPT (With Δi_{t-1})
2007 Outturn	0.0525	0.0525	0.0525	0.0525	0.0525	0.0525	0.0525
Forecast	0.0326	0.0014	0.0815	0.0022	0.0865	-0.0565	0.0189
Forecast Error	0.0199	0.0510	-0.0291	0.0502	-0.0340	0.1090	0.0335
2008 Outturn	0.0192	0.0192	0.0192	0.0192	0.0192	0.0192	0.0192
Forecast	0.0615	-0.0181	0.0836	-0.0130	0.0965	-0.0980	0.0693
Forecast Error	-0.0423	0.0373	-0.0644	0.0322	-0.0773	0.1172	-0.0501
2009 Outturn	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853	-0.1853
Forecast	-0.0701	-0.1446	-0.0346	-0.1618	-0.0403	-0.2554	-0.0546
Forecast Error	-0.1152	-0.0407	-0.1508	-0.0236	-0.1451	0.0701	-0.1307
2010 Outturn	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681	-0.0681
Forecast	-0.1435	-0.1652	-0.0442	-0.2216	-0.1051	-0.2521	-0.0670
Forecast Error	0.0755	0.0972	-0.0239	0.1535	0.0370	0.1841	-0.0011
2011 Outturn	0.1180	0.1180	0.1180	0.1180	0.1180	0.1180	0.1180
Forecast	0.0953	0.0269	0.1580	-0.0103	0.1243	-0.0676	0.1086
Forecast Error	0.0227	0.0911	-0.0400	0.1283	-0.0063	0.1856	0.0094
2012 Outturn	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058	-0.0058
Forecast	0.0232	-0.0341	0.1249	-0.0795	0.0853	-0.2081	0.0768
Forecast Error	-0.0290	0.0283	-0.1307	0.0737	-0.0911	0.2022	-0.0826
MFE	-0.0114	0.0440	-0.0731	0.0691	-0.0528	0.1447	-0.0369
RMSFE	0.0612	0.0635	0.0885	0.0909	0.0795	0.1526	0.0679
χ^2 Forecast Test	6.956 [0.325]	6.764 [0.343]	10.058 [0.122]	15.703 [0.015]	8.757 [0.188]	66.246 [0.000]	7.588 [0.270]
Chow Forecast Test	1.149 [0.366]	0.584 [0.740]	0.913 [0.502]	1.209 [0.334]	1.165 [0.355]	1.533 [0.214]	0.899 [0.508]

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets.

Table 3.8. Further refinements

Dependent Variable: Δi_t

	(1)	(2)	(3)	(4)	(5)	(6)
In-Sample Period	1973-2006	1973-2006	1979-2006	1978-2006	1978-2006	1978-2006
$i_{t-1}-y_{t-1}$	-0.111 (0.109)	-0.122 (0.100)	-0.139 (0.103)	-0.106 (0.105)	-0.096 (0.095)	-0.096 (0.093)
$BUSOPT\_Q1_{t-1}$	0.00109* (0.00061)	0.00128** (0.00047)			0.00160** (0.00062)	0.00160*** (0.00057)
$BUSOPT\_Q2_{t-1}$	0.000554 (0.000991)					
$BUSOPT\_Q3_{t-1}$	-0.000158 (0.001199)					
$BUSOPT\_Q4_{t-1}$	0.00215** (0.00082)	0.00222*** (0.00056)			0.000002 (0.001305)	
$ORDER\_Q1_{t-1}$			0.00117 (0.00112)			
$ORDER\_Q2_{t-1}$			0.00185 (0.00180)			
$ORDER\_Q3_{t-1}$			-0.00021 (0.00170)			
$ORDER\_Q4_{t-1}$			0.00343*** (0.00120)	0.00491*** (0.00071)	0.00389** (0.00187)	0.00392*** (0.00072)
Constant	-0.188 (0.216)	-0.206 (0.199)	-0.312 (0.205)	-0.227 (0.205)	-0.194 (0.189)	-0.195 (0.183)
R-Squared	0.648	0.643	0.745	0.683	0.759	0.759
AR1-2 Test	1.509 [0.2340]	1.842 [0.177]	0.882 [0.429]	2.051 [0.151]	1.861 [0.179]	1.935 [0.167]
ARCH 1-1 Test	0.0054 [0.942]	0.046 [0.831]	0.051 [0.822]	0.385 [0.540]	0.211 [0.650]	0.208 [0.652]
Normality Test	0.932 [0.628]	0.986 [0.611]	5.354 [0.069]	0.059 [0.971]	5.285 [0.071]	5.312 [0.070]
Hetero Test	0.464 [0.897]	0.328 [0.916]	0.593 [0.798]	1.242 [0.320]	0.560 [0.798]	0.791 [0.587]
Hetero-X Test	0.858 [0.632]	0.476 [0.876]	NA†	1.463 [0.240]	0.424 [0.940]	0.751 [0.660]
RESET23 Test	4.279 [0.025]	4.161 [0.026]	3.432 [0.052]	4.991 [0.015]	2.409 [0.113]	2.517 [0.103]
Observations	34	34	28	29	29	29

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Table 3.8 continued

	(1)	(2)	(3)	(4)	(5)	(6)
2007 Outturn	-	0.0525	-	0.0525	-	0.0525
Forecast	-	0.0289	-	0.0266	-	0.0113
Forecast Error		0.0236		0.0259		0.0411
2008 Outturn	-	0.0192	-	0.0192	-	0.0192
Forecast	-	0.0257	-	0.0169	-	0.0143
Forecast Error		-0.0065		0.0023		0.0050
2009 Outturn	-	-0.1853	-	-0.1853	-	-0.1853
Forecast	-	-0.0986	-	-0.1750	-	-0.1571
Forecast Error		-0.0867		-0.0103		-0.0282
2010 Outturn	-	-0.0681	-	-0.0681	-	-0.0681
Forecast	-	0.0083	-	0.0357	-	-0.0612
Forecast Error		-0.0764		-0.1038		-0.0068
2011 Outturn	-	0.1180	-	0.1180	-	0.1180
Forecast	-	0.1020	-	0.0821	-	0.0985
Forecast Error		0.0160		0.0359		0.0195
2012 Outturn	-	-0.0058	-	-0.0058	-	-0.0058
Forecast	-	0.0123	-	-0.0365	-	-0.0055
Forecast Error		-0.0182		0.0307		-0.0003
MFE	-	-0.0247	-	-0.0032	-	0.0050
RMSFE	-	0.0492	-	0.0479	-	0.0221
χ^2 Forecast Test	-	3.738 [0.712]	-	3.775 [0.707]	-	1.022 [0.985]
Chow Forecast Test	-	0.515 [0.792]	-	0.629 [0.706]	-	0.150 [0.987]

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets. †Not enough observations.

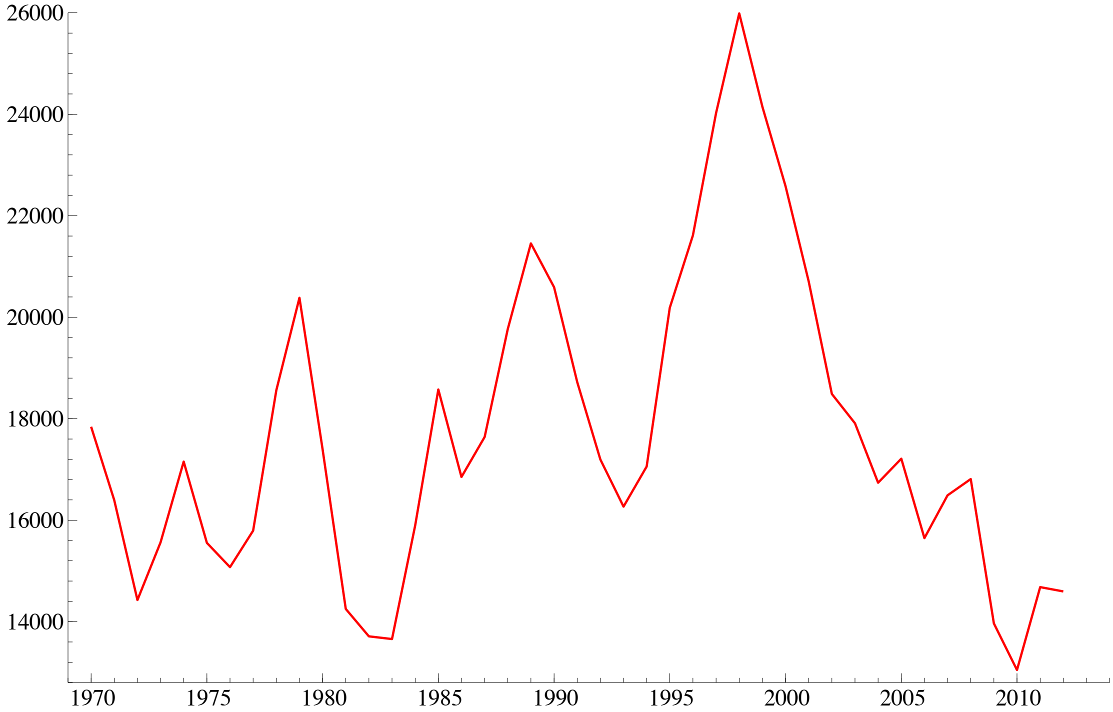
Table 3.9. Structural stability of the preferred model

Dependent Variable: Δi_t

VARIABLES	
i_{t-1}-y_{t-1}	-0.0962 (0.0903)
(CRISIS)*(i_{t-1}-y_{t-1})	0.0735 (0.649)
BUSOPT_Q1$_{t-1}$	0.00160*** (0.00055)
(CRISIS)*BUSOPT_Q1$_{t-1}$	0.000332 (0.001169)
ORDER_Q4$_{t-1}$	0.00392*** (0.00070)
(CRISIS)*ORDER_Q4$_{t-1}$	0.00121 (0.00242)
Constant	-0.195 (0.177)
CRISIS	0.180 (1.470)
R-Squared	0.794
AR 1-2 test	2.013 [0.155]
ARCH 1-1 test	0.070 [0.794]
Normality test	9.267 [0.010]
Hetero Test	0.504 [0.890]
RESET23 test	2.0577 [0.149]
Observations	35

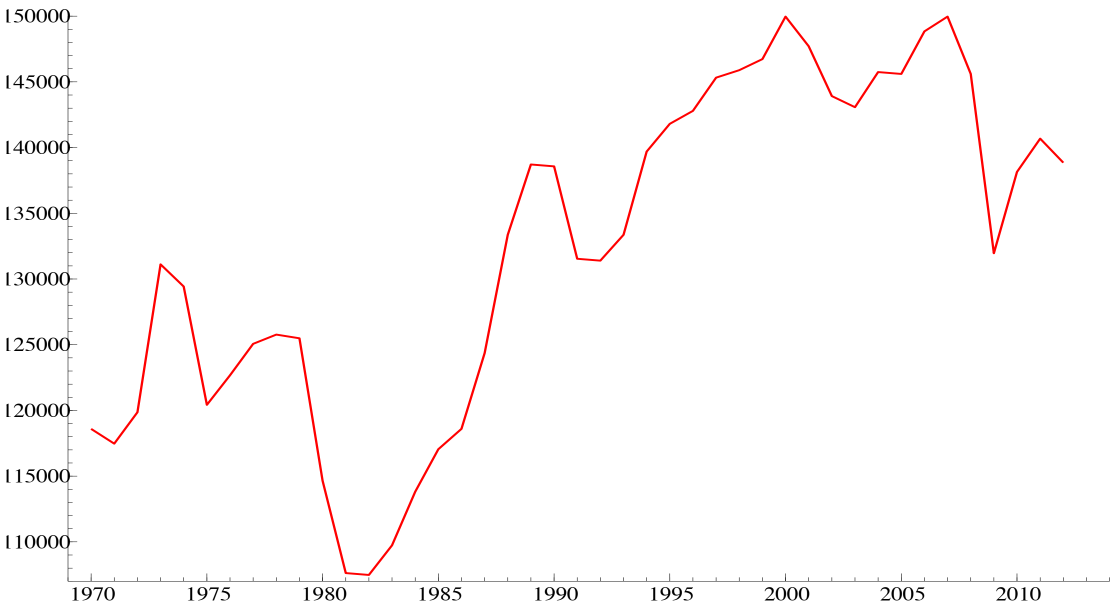
Notes: The sample period is 1978-2012.
Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets.

Figure 3.1. Manufacturing investment in 2010 constant prices (£ millions)



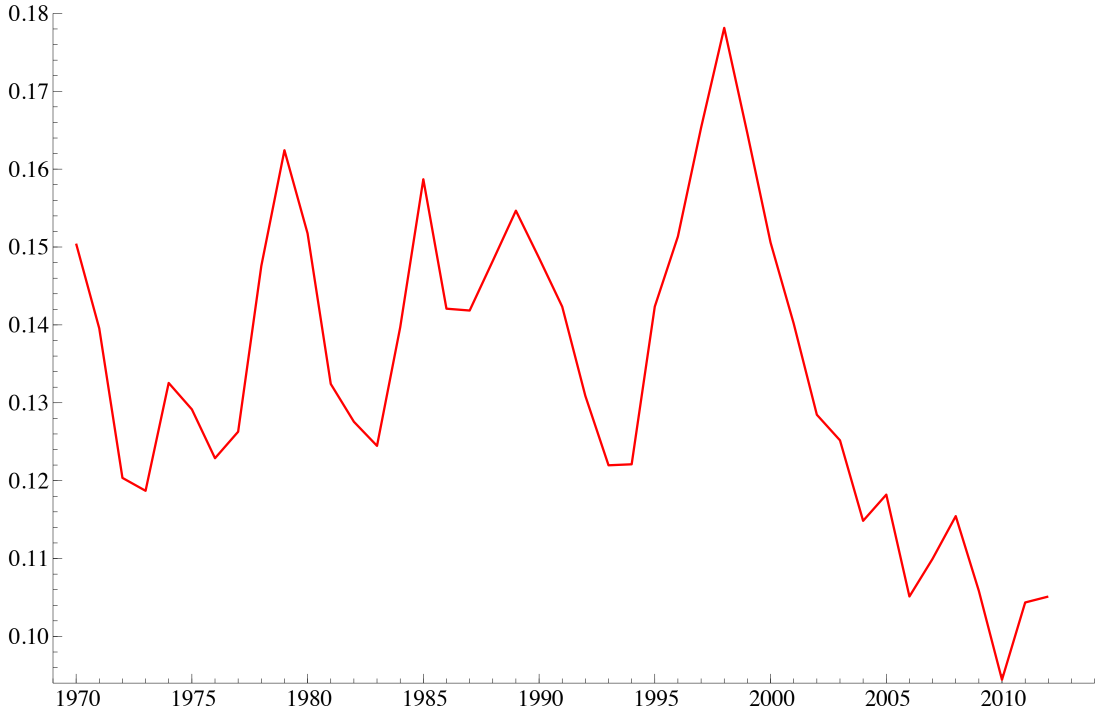
Source: Office for National Statistics.

Figure 3.2. Manufacturing output in 2010 constant prices (£ millions)



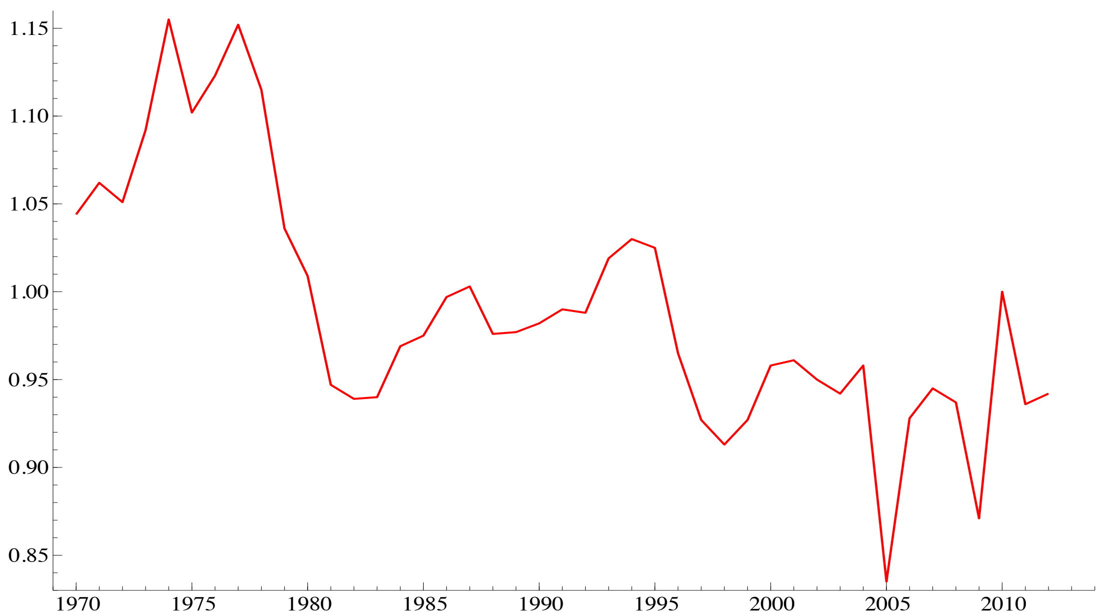
Source: Office for National Statistics.

Figure 3.3. Ratio of manufacturing investment in 2010 constant prices to manufacturing output in 2010 constant prices



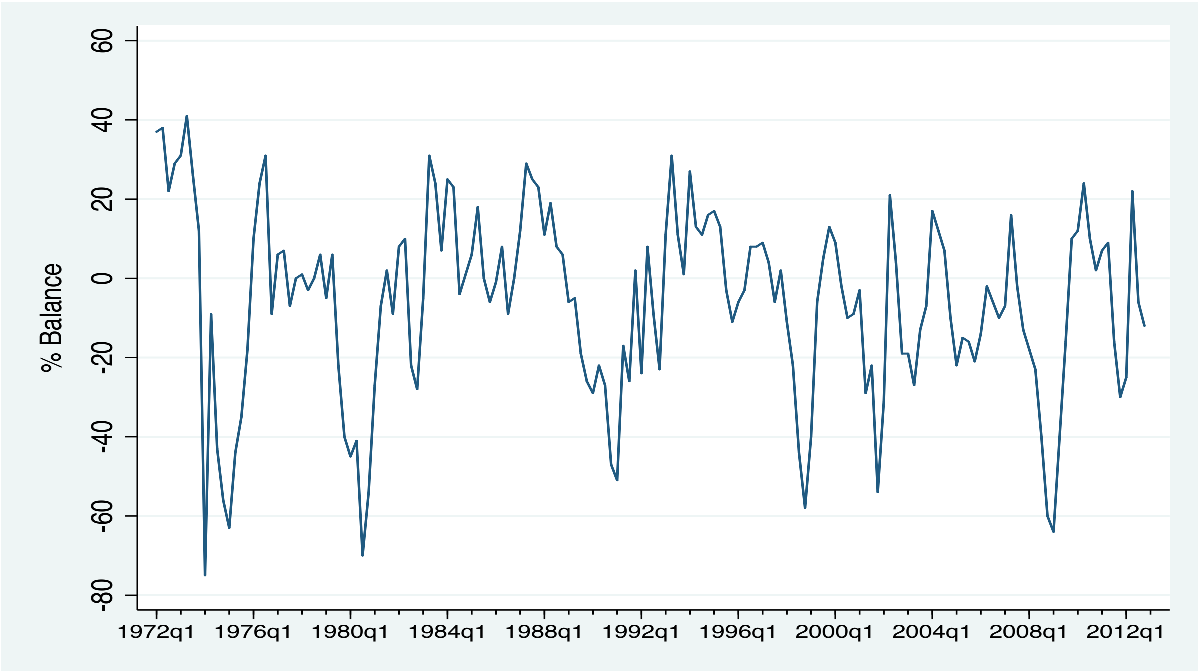
Source: Author’s calculations.

Figure 3.4. Relative price of manufacturing investment goods (Index: 2010=1.00)



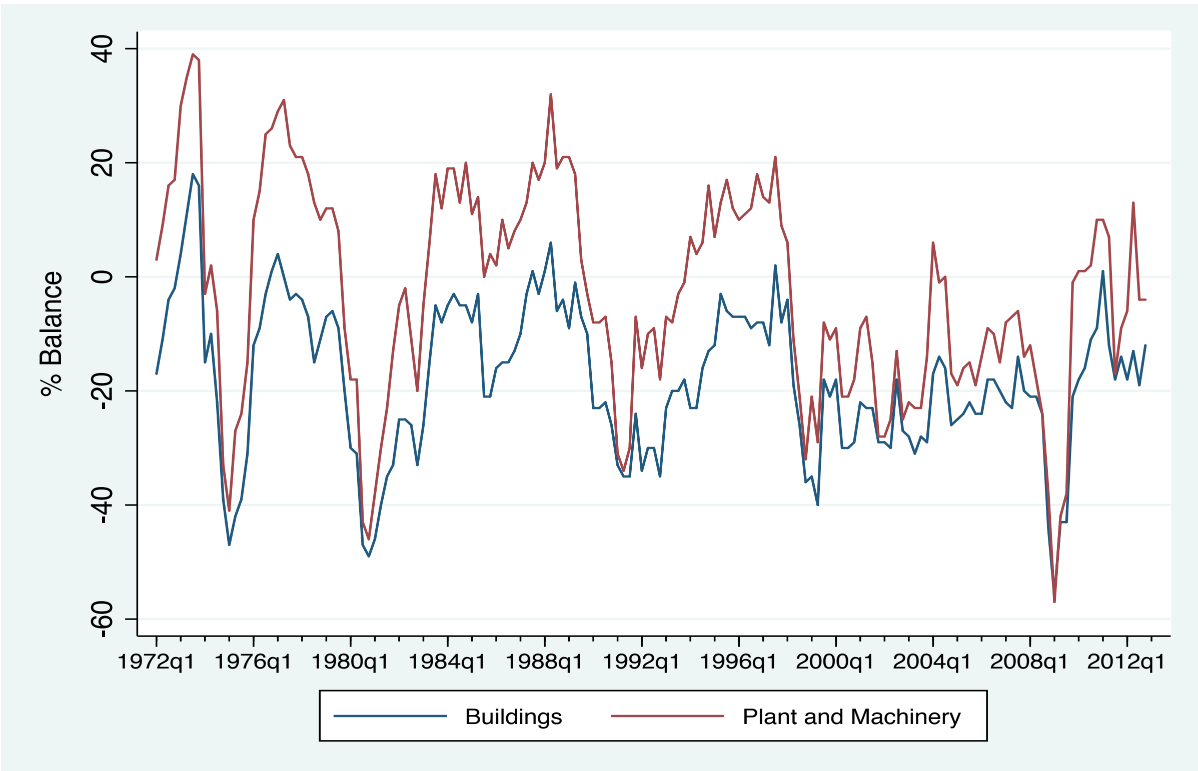
Source: Author’s calculations.

Figure 3.5. Business optimism (more /less than three months ago)



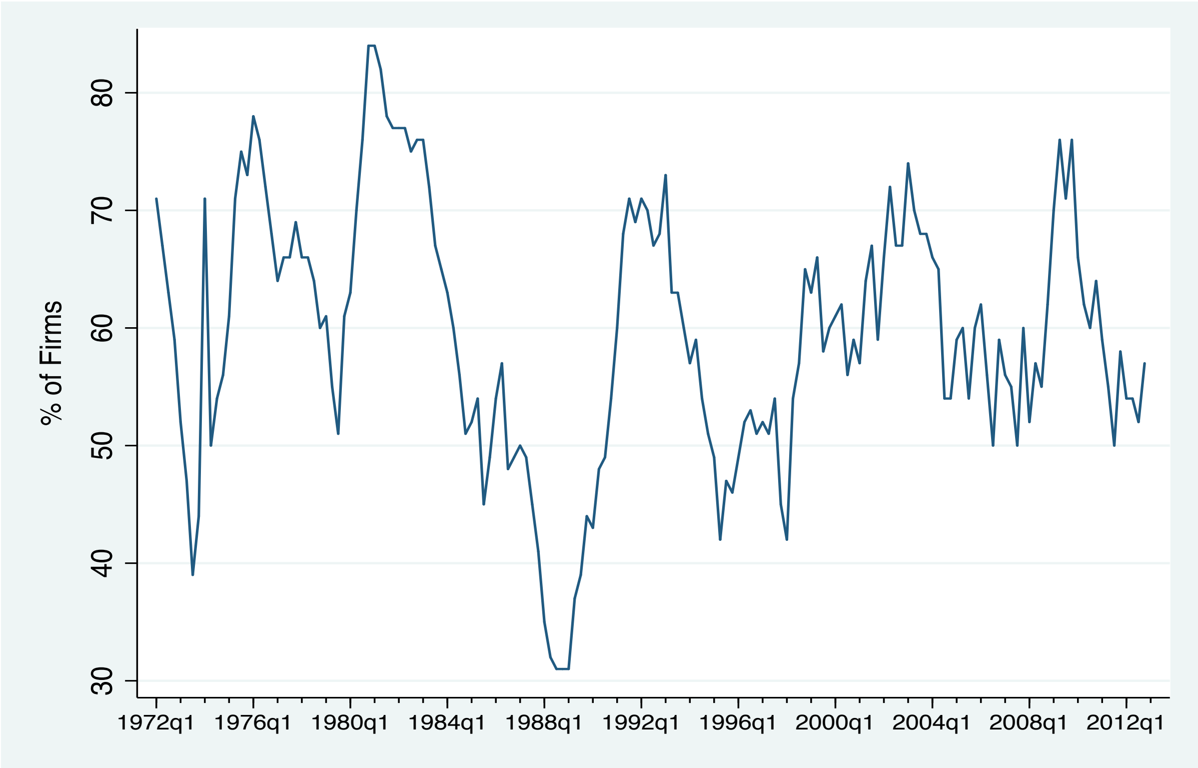
Source: CBI Industrial Trends Survey.

Figure 3.6. Investment on buildings/plant and machinery over the next twelve months compared with the past twelve months (more/less)



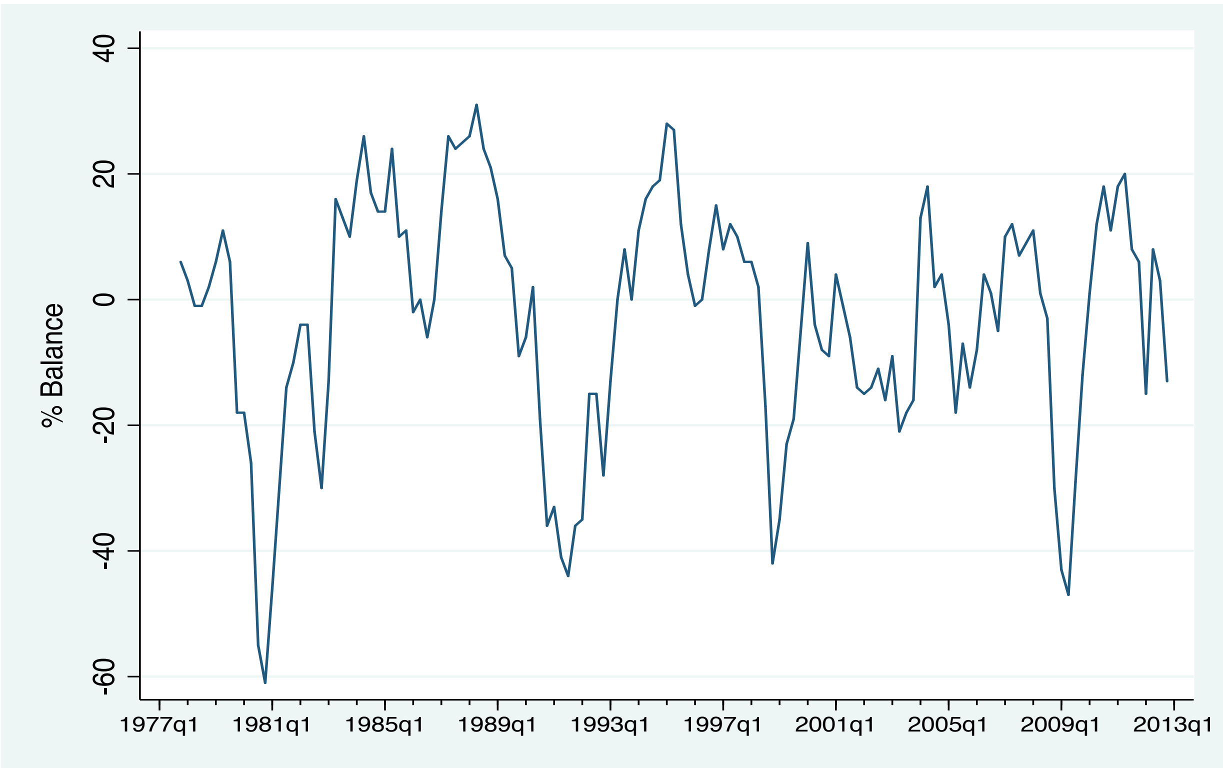
Source: CBI Industrial Trends Survey.

Figure 3.7. Level of present output below capacity



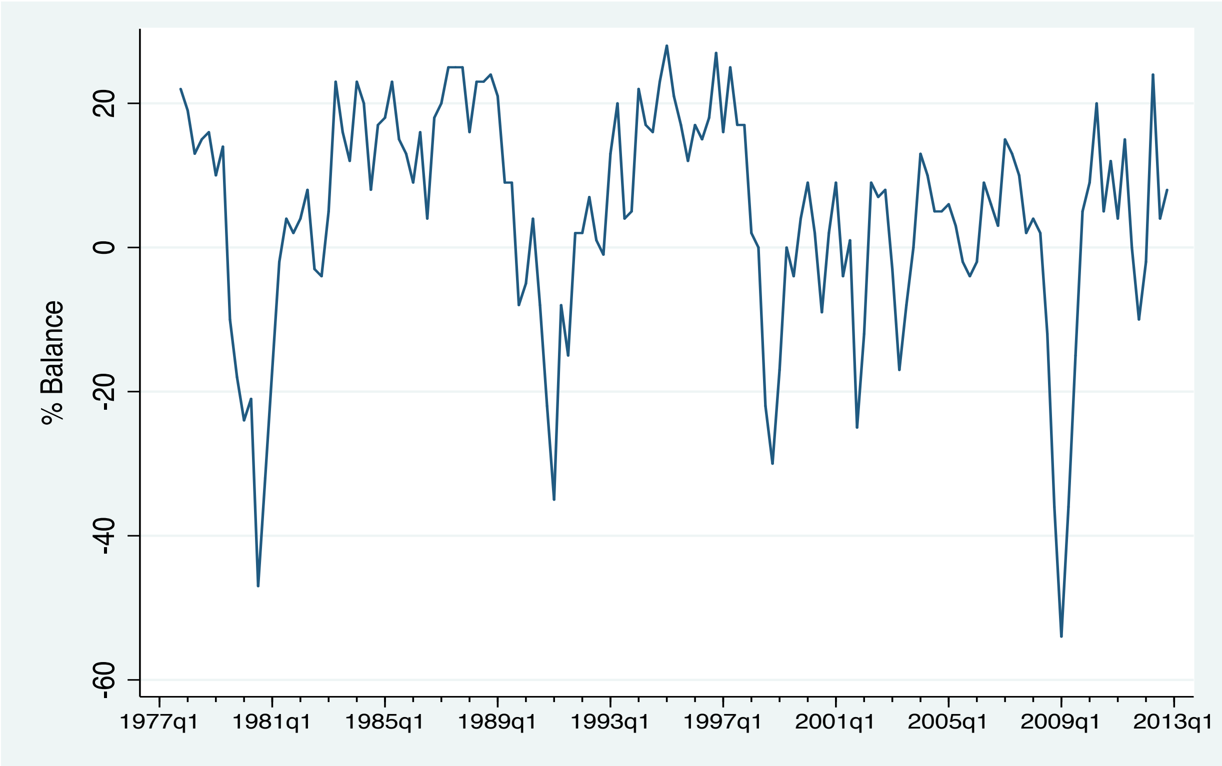
Source: CBI Industrial Trends Survey.

Figure 3.8. Volume of total new orders over the past three months (up/down)



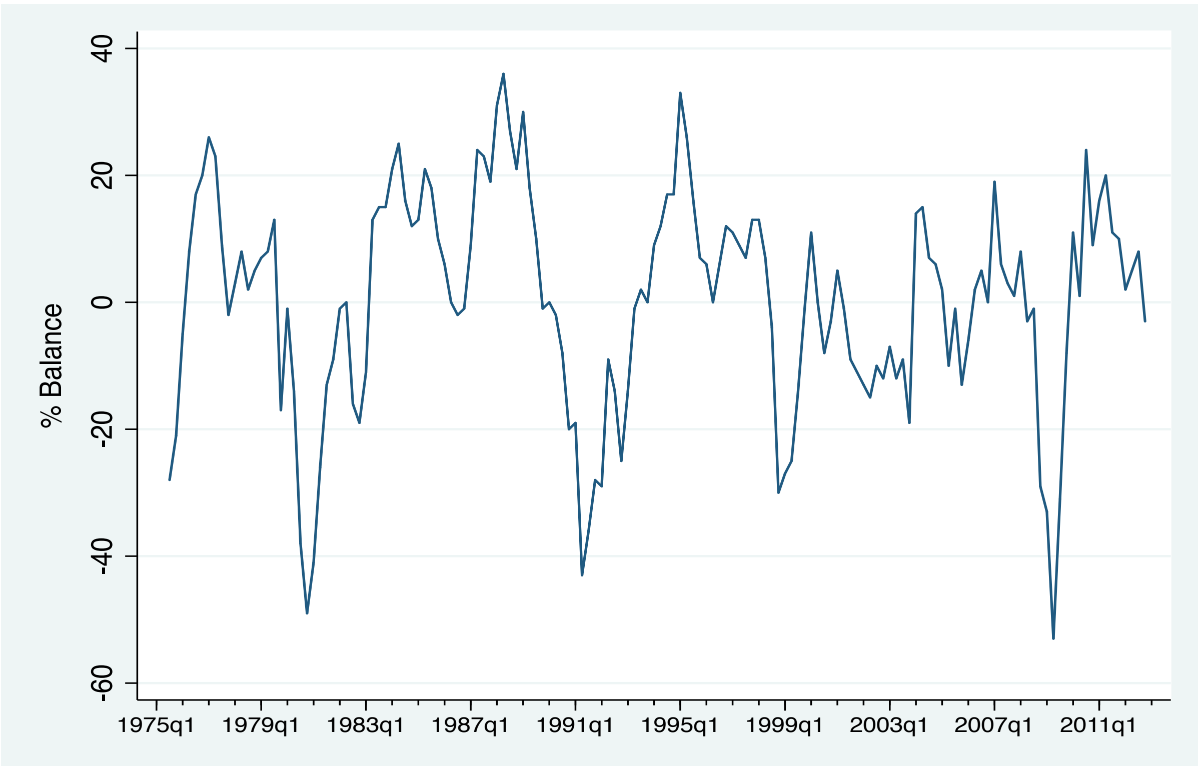
Source: CBI Industrial Trends Survey.

Figure 3.9. Volume of total new orders over the next three months (up/down)



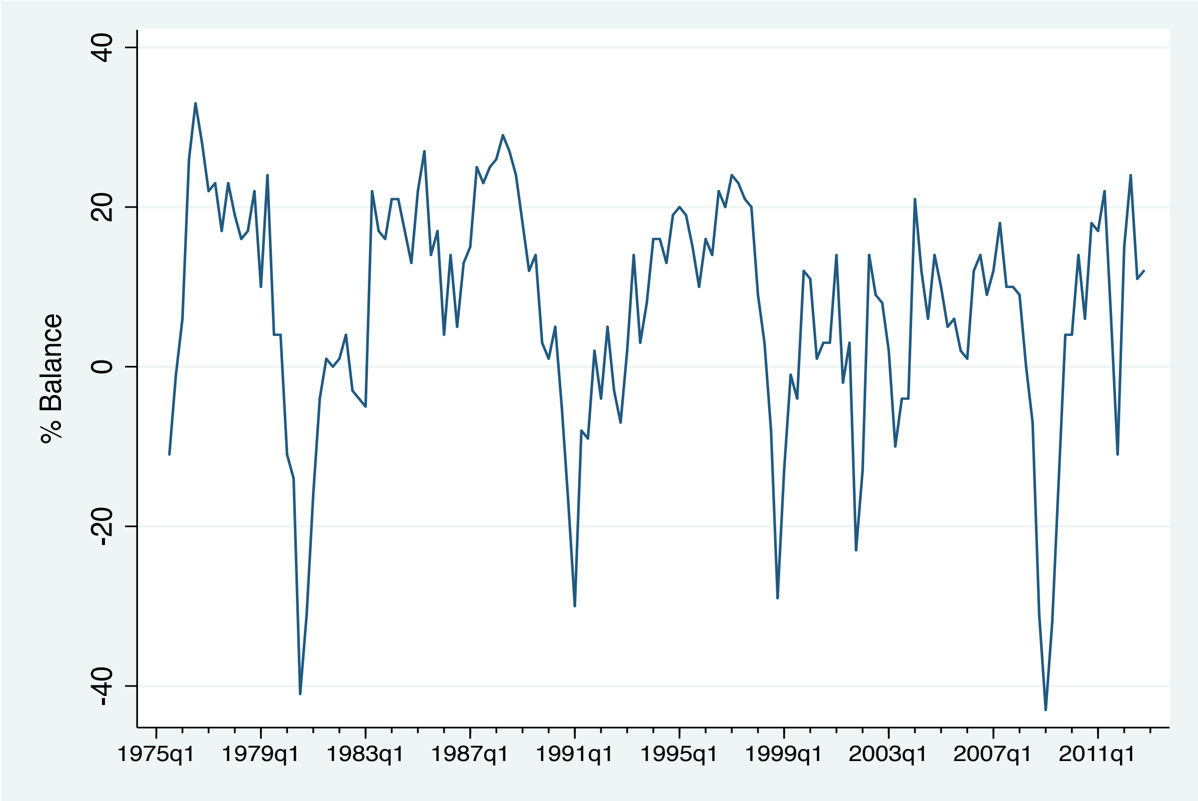
Source: CBI Industrial Trends Survey.

Figure 3.10. Volume of output over the past three months (up/down)



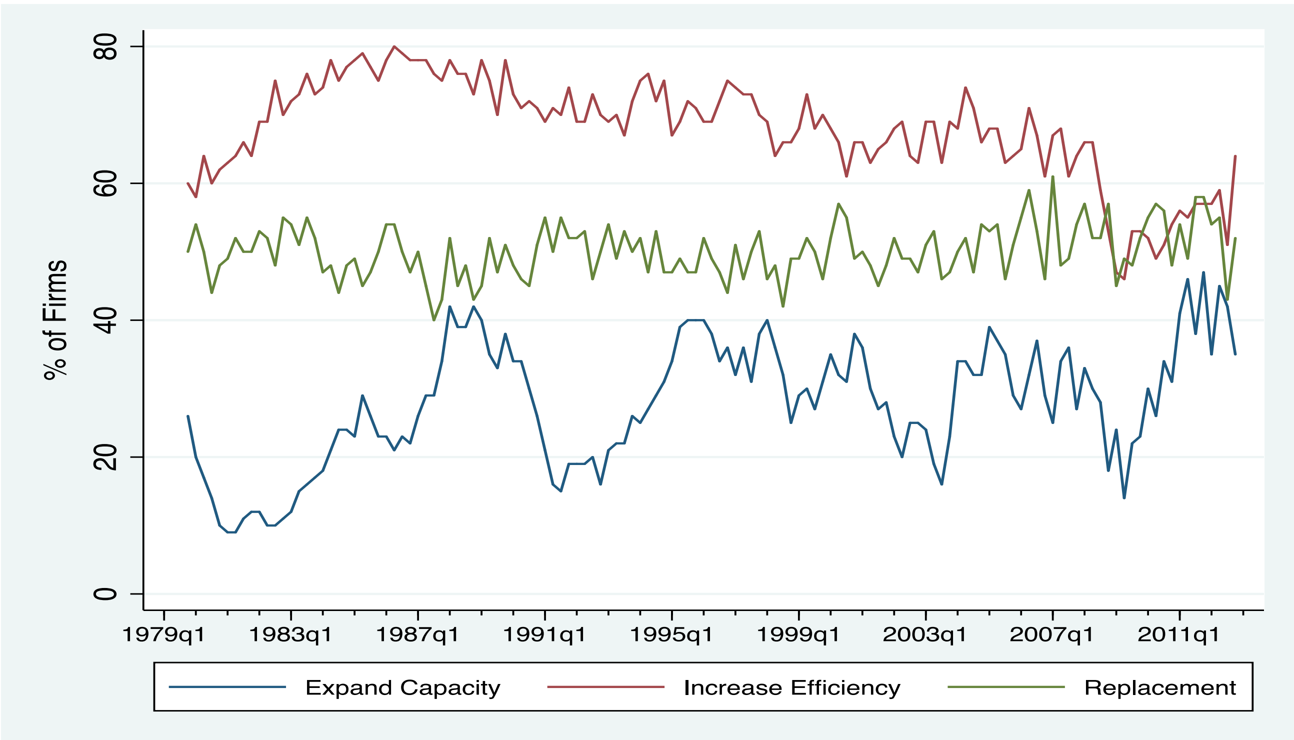
Source: CBI Industrial Trends Survey.

Figure 3.11. Volume of output over the next three months (up/down)



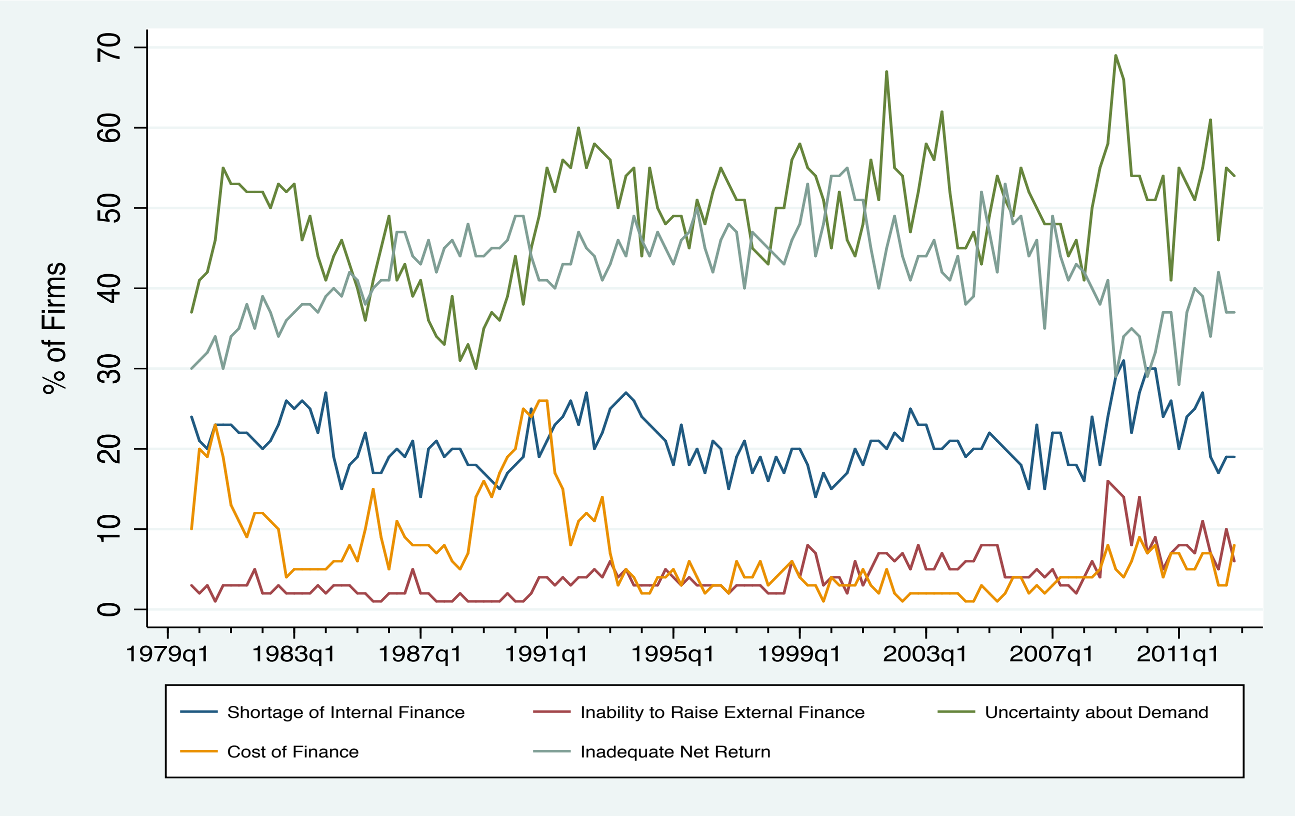
Source: CBI Industrial Trends Survey.

Figure 3.12. Investment motivations



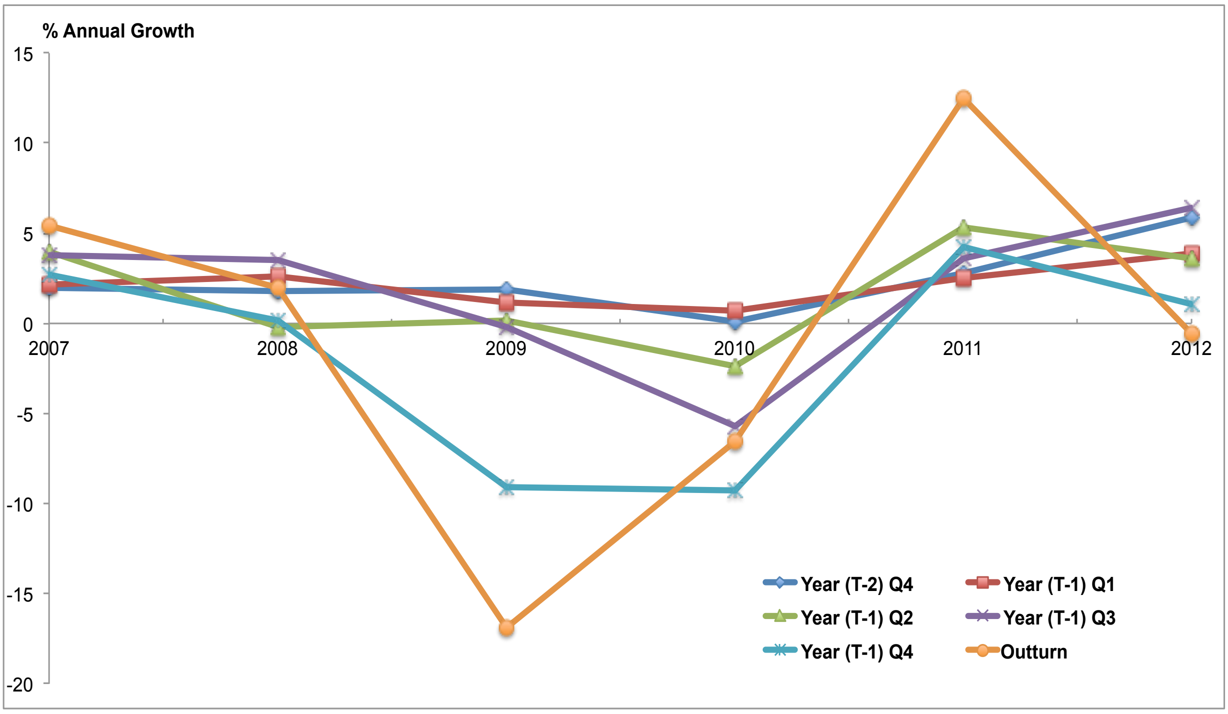
Source: CBI Industrial Trends Survey.

Figure 3.13. Factors limiting investment



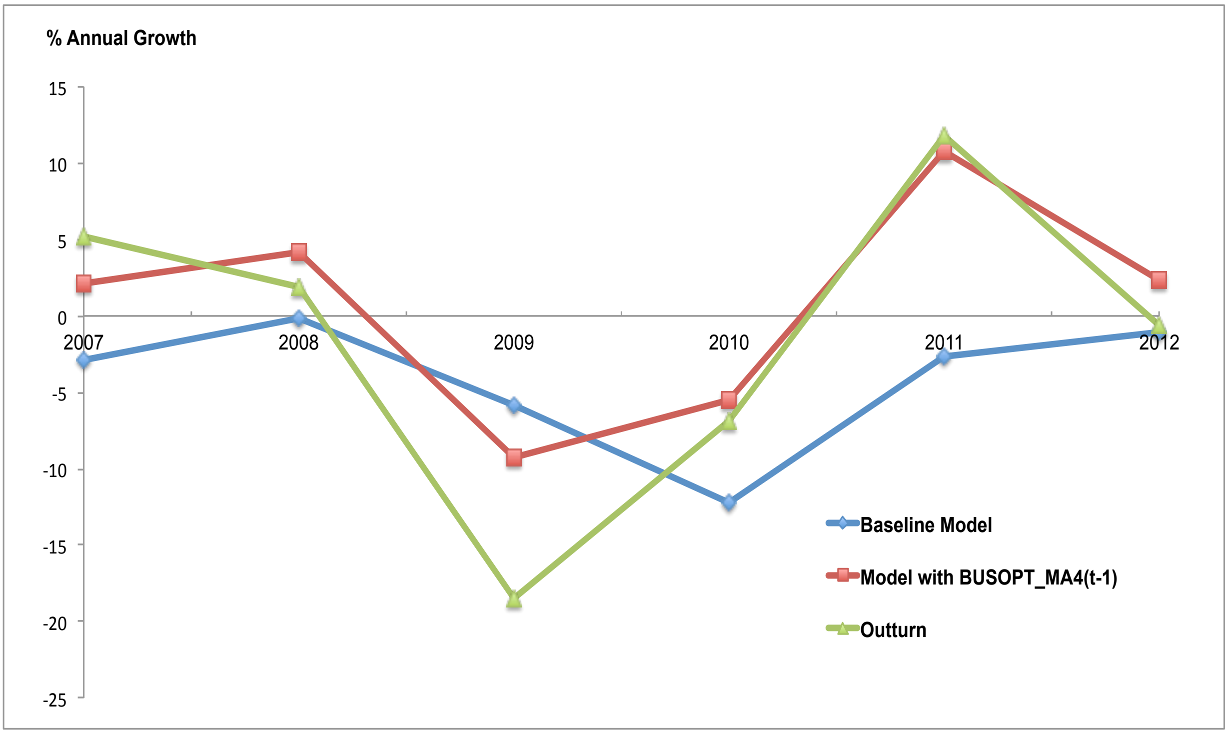
Source: CBI Industrial Trends Survey.

Figure 3.14. CBI forecasts



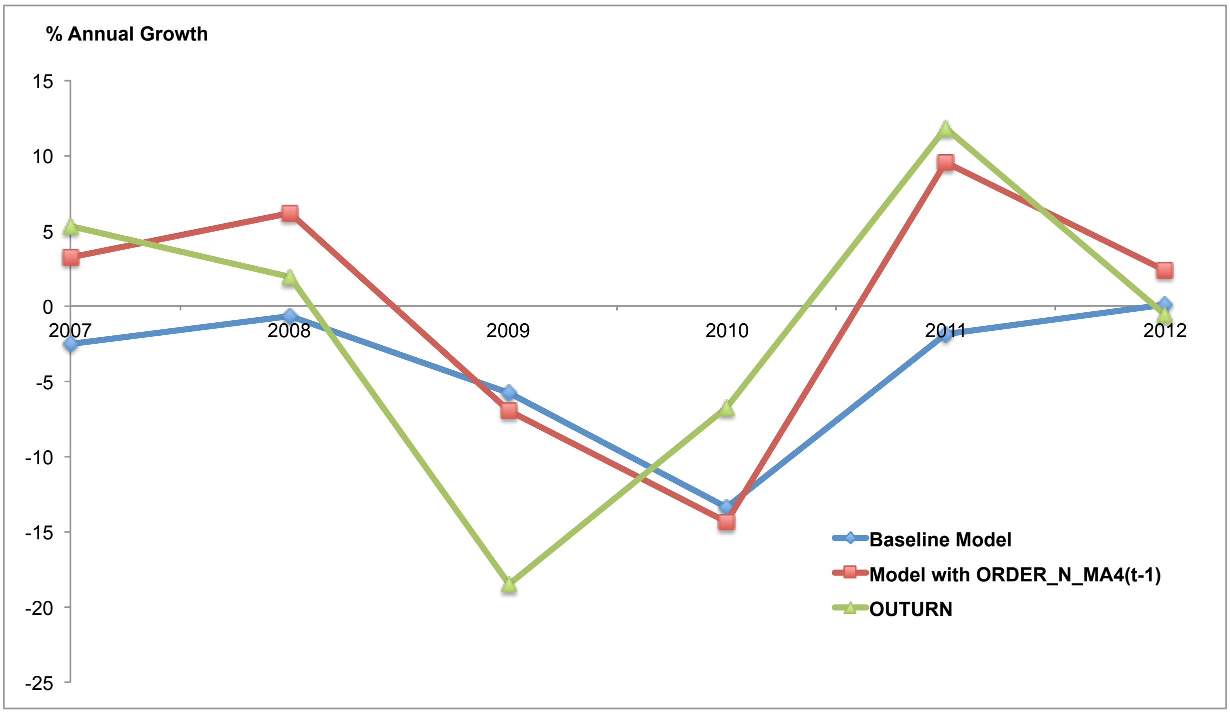
Source: CBI.

Figure 3.15. Forecasts of the model with $BUSOPT\_MA4_{t\text{-}1}$



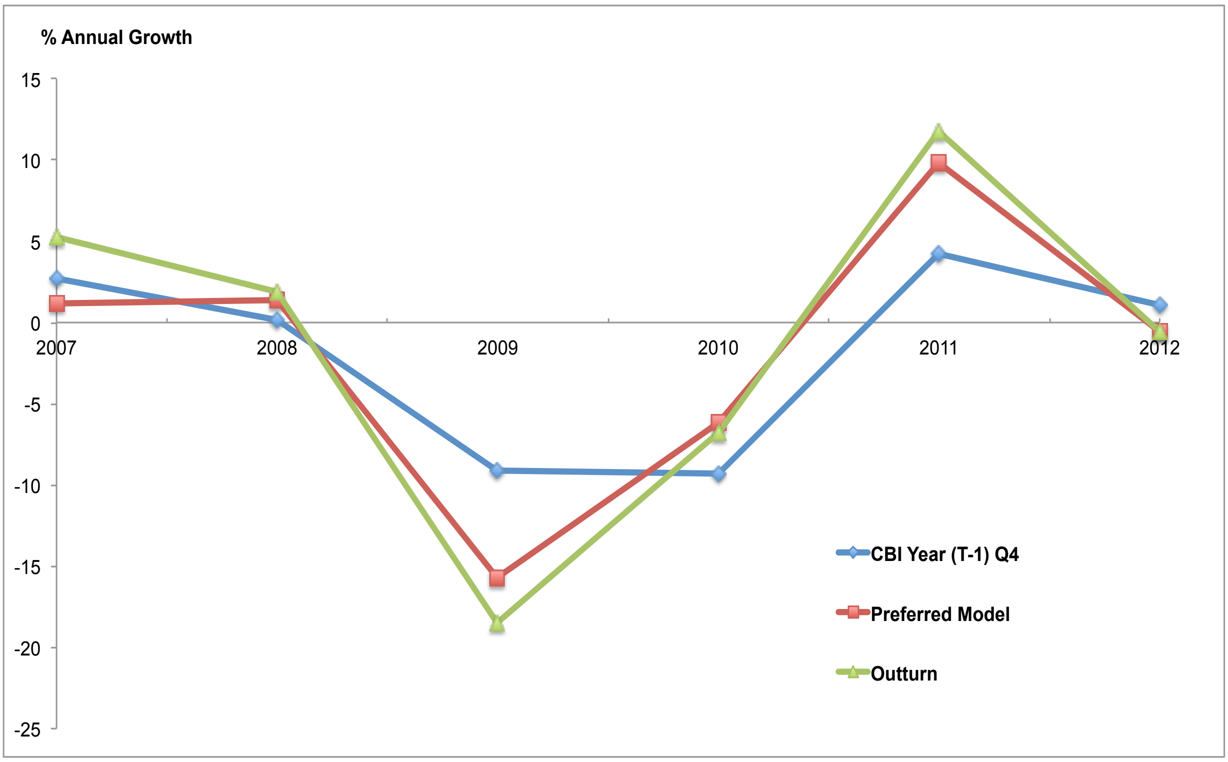
Source: Author's calculations.

Figure 3.16. Forecasts of the model with $ORDER\_N\_MA4_{t\text{-}1}$



Source: Author's calculations.

Figure 3.17 Comparing the forecasts of the CBI and the preferred model



Source: Author's calculations.

Appendix

Appendix 3.1. Data

Official ONS Data

Data	Available At:
Manufacturing investment in constant prices	1970-1996: Datastream (UKAPIN); 1997-2012: ONS Website (GAN6)
Manufacturing investment in current prices	1970-1985: ETAS 1997; 1986-1996: Datastream (UKAPGZA); 1997-2012: ONS Website (GAO2)
Manufacturing output in constant prices	1970-2012: ONS Website (K22A)
Manufacturing output in current prices	1970-1996: Datastream (UKQTPIA); 1997-2012: ONS Website (KKE3)

Notes:
ONS, Office for National Statistics.
ETAS, Economic Trends Annual Supplement.
Data codes are in parentheses.

Constructed Data Series

Manufacturing investment price deflator: ratio of manufacturing investment in current prices to manufacturing investment in constant prices.

Manufacturing output price deflator: ratio of manufacturing output in current prices to manufacturing output in constant prices.

Appendix 3.2. CBI Industrial Trends Survey

No.	Question	Variable Prefix	Data Series Construction
1	Are you more, or less, optimistic than you were three months ago about the general business situation in your industry? ("More," "Same" or "Less")	**BUSOPT**	BS= % citing "More"-% citing "Less"
	Question 3: Do you expect to authorize more or less capital expenditure in the next twelve months than you authorized in the past twelve months on		
3A	Buildings ("More," "Same" or "Less")	**CAPEX_B**	BS= % citing "More"-% citing "Less"
3B	Plant and machinery ("More," "Same" or "Less")	**CAPEX_PM**	BS= % citing "More"-% citing "Less"
4	Is your present level of output below capacity (i.e., are you working below a satisfactory full rate of operation)? ("Yes" or "No")	**LOWCAP**	% of firms reporting "Yes"
7	Excluding seasonal variations, what has been the trend over the PAST THREE MONTHS with regard to: Volume of total new orders? ("Up," "Same" or "Down")	**ORDER_P**	BS= % citing "Up"-% citing "Down"
7	Excluding seasonal variations, what is the expected trend for the NEXT THREE MONTHS with regard to: Volume of total new orders? ("Up," "Same" or "Down")	**ORDER_N**	BS= % citing "Up"-% citing "Down"
8	Excluding seasonal variations, what has been the trend over the PAST THREE MONTHS with regard to: Volume of output? ("Up," "Same" or "Down")	**OUTPUT_P**	BS= % citing "Up"-% citing "Down"
8	Excluding seasonal variations, what is the expected trend over the NEXT THREE MONTHS with regard to: Volume of output? ("Up," "Same" or "Down")	**OUTPUT_N**	BS= % citing "Up"-% citing "Down"
	Question 16B: What are the main reasons for any expected capital expenditure authorizations on buildings, plant or machinery over the next twelve months		
16BA	To expand capacity		% of firms reporting this option
16BB	To increase efficiency		% of firms reporting this option
16BC	For replacement		% of firms reporting this option
16BD	Other (please specify)		% of firms reporting this option
	Question 16C: What factors are likely to limit (wholly or partly) your capital expenditure authorizations over the next twelve months?		
16CA	Inadequate net return on proposed investment	**INARET**	% of firms reporting this option
16CB	Shortage of internal finance	**INTFIN**	% of firms reporting this option
16CC	Inability to raise external finance	**EXTFIN**	% of firms reporting this option
16CD	Cost of finance	**FINCOST**	% of firms reporting this option
16CE	Uncertainty about demand	**UNCERT**	% of firms reporting this option

Notes: BS, Balance Statistic.

Appendix 3.3. Comparing with the Results of the Microdata

A3.3.1 Aggregate Investment Model Specification

We first modify the error correction equation (3.11) to derive a model for aggregate manufacturing investment. To allow for a possible structural change in the steady state growth rate of capital after the financial crisis in 2007, we add a dummy variable $D2007$, which equals one for years 2007-2012 and zero otherwise, to equation (3.11). Therefore, our model of aggregate manufacturing investment is as follows:

$$\Delta i_t = \gamma_0 + \gamma_1 D1999 + \gamma_2 \Delta i_{t-1} + \gamma_3 \Delta i_{t-2} + \gamma_4 \Delta y_t + \gamma_5 \Delta y_{t-1} + \gamma_6 \Delta y_{t-2} + \gamma_7 \Delta p_t + \gamma_8 \Delta p_{t-1} + \gamma_9 \Delta p_{t-2} + \gamma_{10}(i_{t-1} - y_{t-1}) + \gamma_{11} p_{t-1} + \gamma_{12} t + \gamma_{13} st1999 + \gamma_{14} D2007 + e_t \quad (3.14)$$

As in Chapter 2, we annualize the CBI survey results by constructing the four-quarter moving average and study five different four-quarter moving averages for each survey question *CBI* as follows:

1. CBI_MA4_t: four-quarter moving average for the period ending in quarter 4 of calendar year t;
2. CBI_MA3_t: four-quarter moving average for the period ending in quarter 3 of calendar year t;
3. CBI_MA2_t: four-quarter moving average for the period ending in quarter 2 of calendar year t;
4. CBI_MA1_t: four-quarter moving average for the period ending in quarter 1 of calendar year t;
5. CBI_MA4_{t-1}: four-quarter moving average for the period ending in quarter 4 of calendar year $t-1$.

For each CBI question, we add these five four-quarter moving averages together to the equation (3.14) and obtain the following GUM:

$$\Delta i_t = \gamma_0 + \gamma_1 D1999 + \gamma_2 \Delta i_{t-1} + \gamma_3 \Delta i_{t-2} + \gamma_4 \Delta y_t + \gamma_5 \Delta y_{t-1} + \gamma_6 \Delta y_{t-2} + \gamma_7 \Delta p_t + \gamma_8 \Delta p_{t-1} + \gamma_9 \Delta p_{t-2} + \gamma_{10}(i_{t-1} - y_{t-1}) + \gamma_{11} p_{t-1} + \gamma_{12} t + \gamma_{13} st1999 + \gamma_{14} D2007 + \gamma_{15} CBI\_MA4_t + \gamma_{16} CBI\_MA3_t + \gamma_{17} CBI\_MA2_t + \gamma_{18} CBI\_MA1_t + \gamma_{19} CBI\_MA4_{t-1} + e_t \quad (3.15)$$

We follow the general-to-specific strategy as outlined in section 3.6 to simplify the GUM and use Autometrics to guide our model reduction process.[17] To preserve the error correction framework in the final specific model, we force Autometrics to retain

[17] Because our purpose here is to compare the results of the aggregate data and those of the microdata in Chapter 2, if there is more than one valid terminal model after the model reduction process, we select here the terminal model with the CBI survey variable whose timing is closest to the timing of the CBI variable that we found to be informative in Chapter 2 as the final parsimonious specification. For example, when using the survey question related to demand uncertainty, we choose the terminal model containing $UNCERT\_MA3_t$ as the final model presented in column 3 of Table A3.3.2 because none of the terminal models contains $UNCERT\_MA4_t$ which we found to be informative in Chapter 2 and the timing of $UNCERT\_MA3_t$ is closest to the that of $UNCERT\_MA4_t$ ($UNCERT\_MA3_t$ is the average of the survey responses over quarters 3, 2, and 1 of the current year and quarter 4 of the previous year, and $UNCERT\_MA4_t$ is the average of the survey responses over quarters 4, 3, 2, and 1 of the current year. Therefore, $UNCERT\_MA3_t$ lags $UNCERT\_MA4_t$ by only one quarter).

the constant term and the error correction term $(i_{t-1} - y_{t-1})$.

A3.3.2. Estimation Results

The estimates of the reduced models using different survey questions are presented in Tables A3.3.1 and A3.3.2. In column 1 of Table A3.3.1, the reduced model using the survey question on business optimism (*BUSOPT*) retains $BUSOPT\_MA1_t$. In column 2 of Table A3.3.1, the reduced model using the question about capacity utilization (*LOWCAP*) drops all five moving averages. In column 3 of Table A3.3.1, the reduced model using the question on capital expenditure intentions (*CAPEX*) retains $CAPEX\_B\_MA2_t$. In column 4 of Table A3.3.1, the parsimonious model using the question related the volume of output over the past three months (*OUTPUT_P*) keeps $OUTPUT\_P\_MA1_t$. In column 5 of Table A3.3.1, the reduced model using the question related to the volume of output over the next three months (*OUTPUT_N*) retains both $OUTPUT\_N\_MA3_t$ and $OUTPUT\_N\_MA4_{t-1}$. In column 6 of Table A3.3.1, the parsimonious model using the question related to the volume of orders over the past three months (*ORDER_P*) keeps $ORDER\_P\_MA1_t$. In column 7 of Table A3.3.1, the reduced model using the question related to the volume of orders over the next three months (*ORDER_N*) retains $ORDER\_N\_MA1_t$. In column 1 of Table A3.3.2, the reduced model using the survey question related to internal financing constraints (*INTFIN*) keeps $INTFIN\_MA3_t$. In column 2 of Table A3.3.2, the parsimonious model using the survey question related to external financing constraints (*EXTFIN*) retains $EXTFIN\_MA4_{t-1}$. In column 3 of Table A3.3.2, the reduced model using the survey question on demand uncertainty (*UNCERT*) keeps $UNCERT\_MA3_t$.

Finally, we include all of the CBI survey variables that are retained in the aforementioned models (i.e., $BUSOPT\_MA1_t$, $CAPEX\_B\_MA2_t$, $OUTPUT\_N\_MA3_t$, $OUTPUT\_N\_MA4_{t-1}$, $ORDER\_P\_MA1_t$, $ORDER\_N\_MA1_t$, $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$) in equation (3.14). The reduced model only retains $ORDER\_P\_MA1_t$ and is the same specification as the model reported in column 6 of Table 3.3.1. This suggests that the survey indicator of the volume of new orders is the most informative for explaining the behavior of aggregate U.K. manufacturing investment. In Chapter 2, we find that survey variables related to the volume of new orders, demand uncertainty, and financing constraints have the highest explanatory power for the RU-level manufacturing investment. To check whether the orders survey variable indeed subsumes most of the explanatory power of the CBI survey variables related to financing constraints and demand uncertainty, we add $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ to the reduced model with $ORDER\_P\_MA1_t$ presented in column 6 of Table A3.3.1. The estimates of the resulting model are presented in column 4 of Table A3.3.2. The results show that $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ are individually and jointly insignificant in the presence of $ORDER\_P\_MA1_t$.[18]

[18] The Wald test statistic for the null hypothesis that the sum of the coefficients on $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ is zero in column 4 of Table A3.3.2 is $F(3,25)=0.813$ with a *p*-value of 0.499. We also add $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ one at a time to the model containing $ORDER\_P\_MA1_t$ reported in column 5 of Table A3.3.1. $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ are all insignificant in the presence of $ORDER\_P\_MA1_t$ in their respective regressions.

There are several possible reasons for the differences in the results between the microdata sample and the aggregate time series data sample. First, the sample period of 1997-2012 used for the RU-level data in Chapter 2 is considerably shorter than the sample periods used for the aggregate time series data here. In column 5 of Table A.3.3.2, we re-estimate the aggregate manufacturing investment model from column 4 of Table A3.3.2 over the period 1997-2012. For this shorter sample period, $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ remain individually and jointly insignificant.[19]

Second, we gave equal weight to all the establishments in our microdata sample when estimating the models reported in Chapter 2. However, we implicitly give higher weight to larger establishments when using the aggregate data here. To explore whether this is responsible for some of the differences in the findings between the microdata sample and the aggregate data sample, we split our microdata sample into two sub-samples of larger and smaller RUs based on their level of employment. For each RU, we first calculate its average employment level over its years of observations in the ARD sample. For those RUs whose average employment numbers are above the median of the average employment numbers of all the RUs in its sector, we classify them as larger RUs. Conversely, for those RUs whose average employment numbers are below the median of the average employment numbers of all the RUs in its sector, we classify them as smaller RUs. In Table A3.3.3, we estimate the investment model presented in column 2 of Table 2.5 of Chapter 2 separately for the sub-samples of larger and smaller RUs. In column 1, for the sub-sample of larger RUs, we find that the CBI survey variable related to the volume of new orders is significant while the CBI survey variables related to financing constraints and demand uncertainty are insignificant. By contrast, in column 2, for the sub-sample of smaller RUs, we find that the CBI survey measure of demand uncertainty is significant while the CBI survey measures of financing constraints and the volume of new orders are insignificant. The important role for demand conditions, measured by the volume of new orders, in explaining aggregate UK manufacturing investment may thus be a reflection of the importance of demand in explaining the investment behavior of larger RUs. Conversely, the relative importance of demand uncertainty in explaining the investment behavior of smaller RUs may help to explain why we find demand uncertainty to be less important in explaining aggregate UK manufacturing investment.

Third, we exploited variation across different sectors within the manufacturing industry as well as variation over time in the panel data analysis in Chapter 2, while we are only able to exploit fluctuations over time in the time series analysis here. To compare the sectoral variation in the four CBI survey variables $ORDER\_MA4_{j,t}$, $UNCERT\_MA4_{j,t}$, $INFIN\_MA4_{j,t}$, and $EXTFIN\_MA4_{j,t}$, we regress each of these variables on a full set of year dummies and compute the R-square over the time period 1997-2012. A R-square of zero would suggest that there is only sectoral variation but no common time variation, while a R-square of one would imply that there is only

[19] The Wald test statistic for the null hypothesis that the sum of the coefficients on $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ is zero in column 5 of Table 3.3.2 is $F(3,9)=0.343$ with a p-value of 0.795. We also add $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ one at a time to the model containing $ORDER\_P\_MA1_t$ presented in column 5 of Table A3.3.1. $INTFIN\_MA3_t$, $EXTFIN\_MA4_{t-1}$, and $UNCERT\_MA3_t$ are all insignificant in the presence of $ORDER\_P\_MA1_t$ in their respective regressions.

common time variation but no sectoral variation. The *R*-squares of the regressions for $ORDER\_MA4_{j,t}$, $UNCERT\_MA4_{j,t}$, $INFIN\_MA4_{j,t}$, $EXTFIN\_MA4_{j,t}$ are 0.513, 0.154, 0.101, and 0.136, respectively. Therefore, the three CBI survey variables related to demand uncertainty, internal financing constraints, and external financing constraints have considerably more sectoral variation than the CBI survey variable related to the volume of new orders, which may explain why these three variables are more informative about manufacturing investment in the panel data analysis in Chapter 2.

A3.3.3. Endogeneity Problem

We acknowledge that our time series estimations in this appendix may suffer from endogeneity.[20] In the investment equation (3.14), both the current and lagged values of the explanatory variables appear on the right hand side. As investment, output, the relative price of investment goods, and the responses to the CBI survey questions in the past period are unlikely to be affected by a serially uncorrelated shock to investment in the current period, the lagged explanatory variables are likely to be exogenous. On the other hand, it is possible that a shock to investment in the current period causes changes in output, the relative price of investment goods, and the responses to the CBI survey questions in the current period. Therefore, the current values of explanatory variables could be endogenous. One way to overcome the potential endogeneity problem is to use an instrumental variable. However, it is often difficult to find variables that can serve as valid instruments because an instrumental variable needs to be both uncorrelated with the error term and correlated with the endogenous explanatory variable. As we find the orders survey variable to be the most informative for explaining the aggregate investment dynamics of U.K. manufacturing investment, we attempt to re-estimate the model with the orders survey variable $ORDER\_P\_MA1_t$ reported in column 6 of Table A3.3.1 using the two-stage least squares method. In this specification, the error correction term $(i_{t-1} - y_{t-1})$ is a lagged explanatory variable and is therefore likely to be exogenous. $ORDER\_P\_MA1_t$ is the average survey responses on the volume of new orders over quarter 1 of the current year and quarters 4, 3, and 2 of the previous year. Because $ORDER\_P\_MA1_{t-1}$ contains information on the volume of new orders from the current year, it may be endogenous.

To investigate this, we use $ORDER\_P\_MA4_{t-1}$ as an instrumental variable for $ORDER\_P\_MA1_{t-1}$. As $ORDER\_P\_MA4_{t-1}$ reflects the survey responses on the volume of new orders over the four quarters of the previous year, it is unlikely to be correlated with the shock to investment in the current year. On the other hand, since $ORDER\_P\_MA4_{t-1}$ and $ORDER\_P\_MA1_t$ both contain the information on the volume of new orders from quarters 2, 3, and 4 of the previous year, these two variables are correlated. Hence, we believe that $ORDER\_P\_MA4_{t-1}$ is an appropriate instrument for $ORDER\_P\_MA1_t$. In column 1 of Table A3.3.4, we present the first stage regression results, which suggest that the relationship between $ORDER\_P\_MA4_{t-1}$ and $ORDER\_P\_MA1_t$ is strongly positive. In column 2 of Table A3.3.4, we report the two-stage least squares estimates using this instrument. The results are close to those of the original OLS estimation in column 6 of Table A3.3.1, suggesting that there is not a serious endogeneity concern about these OLS estimates. The Hausman (1978) test also does not reject the null hypothesis that $ORDER\_P\_MA1_t$ is exogenous at the 5%

[20] I would like to thank Professor Alessandra Guariglia for her comments on endogeneity.

level.[21] Furthermore, as the autocorrelation test (AR1-2 test) indicates that the residuals are not serially correlated, an idiosyncratic shock to current investment is unlikely to be correlated with past investment and past output. Therefore, these lagged explanatory variables are also unlikely to be endogenous.

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[21] The Hausman test statistic for the null hypothesis that $ORDER\_P\_MA1_t$ is exogenous has a *p*-value of 0.175.

Table A3.3.1 Investment models with CBI survey variables

Dependent Variable: Δi_t

	(1) BUSOPT	(2) LOWCAP	(3) CAPEX	(4) OUTPUT_P	(5) OUTPUT_N	(6) ORDER_P	(7) ORDER_N
Sample Period	1973-2012	1973-2012	1973-2012	1977-2012	1977-2012	1979-2012	1979-2012
$i_{t-1}-y_{t-1}$	-0.123* (0.067)	-0.414*** (0.088)	-0.347*** (0.087)	-0.091 (0.066)	-0.0860 (0.0612)	-0.350*** (0.100)	-0.105* (0.055)
Δi_{t-1}	0.320*** (0.093)	0.423*** (0.089)					
Δy_t		1.670*** (0.256)		1.013*** (0.305)			
Δp_t		-0.602*** (0.198)					
$BUSOPT\_MA1_t$	0.00380*** (0.00048)						
$CAPEX\_B\_MA2_t$			0.00619*** (0.00066)				
$OUTPUT\_P\_MA1_t$				0.00394*** (0.00072)			
$OUTPUT\_N\_MA3_t$					0.00469*** (0.00097)		
$OUTPUT\_N\_MA4_{t-1}$					0.00288*** (0.00096)		
$ORDER\_P\_MA1_t$						0.00414*** (0.00056)	
$ORDER\_N\_MA1_t$							0.00643*** (0.00063)
Constant	-0.222 (0.136)	-0.817*** (0.173)	-0.633*** (0.186)	-0.190 (0.133)	-0.226* (0.1232)	-0.662*** (0.194)	-0.244** (0.111)
Trend			0.00370*** (0.00122)				
Split Trend 1999		-0.00925*** (0.00289)	-0.0164*** (0.0044)			-0.0119*** (0.0033)	
R-Squared	0.708	0.754	0.810	0.696	0.762	0.744	0.779
AR1-2 Test	1.827 [0.176]	1.433 [0.254]	0.966 [0.391]	0.098 [0.907]	0.252 [0.779]	0.020 [0.980]	0.582 [0.565]
ARCH 1-1 Test	0.004 [0.949]	0.004 [0.949]	1.437 [0.238]	0.074 [0.788]	0.002 [0.965]	0.377 [0.543]	0.789 [0.381]
Normality Test	3.246 [0.197]	0.999 [0.607]	0.675 [0.714]	0.761 [0.683]	2.322 [0.313]	1.583 [0.453]	7.179 [0.028]
Hetero Test	1.014 [0.433]	0.750 [0.674]	1.243 [0.308]	0.769 [0.600]	0.605 [0.724]	2.629 [0.039]	1.457 [0.241]
Hetero-X Test	0.808 [0.612]	0.733 [0.752]	1.132 [0.378]	0.813 [0.608]	0.594 [0.790]	1.907 [0.100]	1.128 [0.369]
RESET23 Test	0.940 [0.407]	0.046 [0.955]	2.665 [0.085]	0.640 [0.535]	1.036 [0.367]	1.082 [0.353]	4.144 [0.026]
Observations	40	40	40	36	36	34	34

Notes: Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
P-values of diagnostic tests are in square brackets.

Table A3.3.2. Investment models with CBI survey variables

Dependent Variable: Δi_t

	(1) INTFIN	(2) EXTFIN	(3) UNCERT	(4) ORDER_P, INTFIN, EXTFIN, &UNCERT	(5) ORDER_P, INTFIN, EXTFIN, &UNCERT
Sample Period	1981-2012	1981-2012	1981-2012	1981-2012	1997-2012
$i_{t-1}-y_{t-1}$	-0.418*** (0.091)	-0.314*** (0.101)	-0.535*** (0.126)	-0.419*** (0.129)	-0.222 (0.267)
Δi_{t-1}			0.345** (0.126)		
Δy_t	1.057*** (0.343)	1.675*** (0.359)			
$ORDER\_P\_MA1_t$				0.00364*** (0.00084)	0.00574** (0.00179)
$INTFIN\_MA3_t$	-0.0949*** (0.0250)			-0.00730 (0.00552)	-0.00198 (0.00899)
$EXTFIN\_MA4_{t-1}$		-0.0197*** (0.00631)		0.00830 (0.00680)	0.00902 (0.01098)
$UNCERT\_MA3_t$			-0.00632*** (0.00205)	-0.000036 (0.002165)	-0.00145 (0.00500)
Constant	-0.427*** (0.149)	-0.567*** (0.189)	-0.729** (0.282)	-0.668*** (0.217)	-0.307 (0.565)
Year Dummy 1999	-0.0949*** (0.0250)				
Trend			-0.0130*** (0.0043)		
Split Trend 1999			-0.0130*** (0.0043)	-0.0160*** (0.0046)	-0.0130 (0.0110)
R-Squared	0.692	0.571	0.631	0.802	0.770
AR1-2 Test	0.265 [0.770]	1.467 [0.249]	2.500 [0.102]	0.262 [0.771]	0.527 [0.489]
ARCH 1-1 Test	0.006 [0.940]	1.100 [0.303]	0.385 [0.540]	0.006 [0.938]	0.325 [0.578]
Normality Test	1.688 [0.430]	0.979 [0.613]	0.029 [0.986]	1.145 [0.564]	0.379 [0.827]
Hetero Test	0.313 [0.941]	0.462 [0.830]	1.149 [0.370]	0.854 [0.601]	NA†
Hetero-X Test	1.128 [0.369]	0.556 [0.818]	2.307 [0.052]	NA†	NA†
RESET23 Test	0.787 [0.466]	0.005 [0.995]	0.490 [0.618]	0.744 [0.486]	3.595 [0.084]
Observations	32	32	32	32	16

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets. †Not enough observations

Table A3.3.3. Sub-samples of larger and smaller RUs

Dependent Variable: $I_{i,t}/K_{i,t-1}$

VARIABLES	(1) Larger RUs	(2) Smaller RUs
$I_{i,t-1}/K_{i,t-2}$	0.182***	0.134***
	(0.028)	(0.032)
$\Delta y_{i,t}$	0.066***	0.032
	(0.015)	(0.020)
$\Delta y_{i,t-1}$	0.051***	0.044***
	(0.007)	(0.010)
$\Delta p_{j,t}$	-0.066***	-0.067***
	(0.015)	(0.024)
$\Delta p_{j,t-1}$	-0.042***	-0.055**
	(0.016)	(0.024)
$(k-y)_{i,t-2}$	-0.049***	-0.040***
	(0.007)	(0.011)
$p_{j,t-2}$	-0.087***	-0.060***
	(0.013)	(0.022)
$UNCERT\_MA4_{j,t}$	-0.000140	-0.000301**
	(0.000121)	(0.000142)
$ORDER\_P\_MA4_{j,t-1}$	0.000201**	0.000043
	(0.000084)	(0.000103)
$EXTFIN\_MA4_{j,t-1}$	-0.000220	-0.000333
	(0.000235)	(0.000231)
$INTFIN\_MA1_{j,t}$	-0.000111	0.000046
	(0.000153)	(0.000189)
Constant	Yes	Yes
Sector dummies	Yes	Yes
Year dummies	Yes	Yes
m1	-12.51	-10.35
	[0.000]	[0.000]
m2	-0.25	-0.76
	[0.806]	[0.446]
Hansen	0.106	0.818
Dif Hansen	0.823	0.922
Observations	9263	7687

Notes: See next page.

Notes:
Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
DIFF GMM is the first-differenced GMM estimation.
SYS GMM is the system GMM estimation.
Hansen is the Hansen test of overidentifying restrictions. P-values are reported.
Dif Hansen is the difference-in-Hansen test of the validity of the additional moment conditions used in the levels equations. P-values are reported.
m1 and m2 are tests of first-order and second-order serial correlation in the first-differenced residuals. P-values are reported in square brackets.

In both columns, the instruments used in the first-differenced equations are: $k_{i,t-2}$, $k_{i,t-3}$, $k_{i,t-4}$, $y_{i,t-2}$, $y_{i,t-3}$, and $y_{i,t-4}$, and the instruments used in the levels equations are: $\Delta y_{i,t-1}$. In both columns, $\Delta p_{i,t}$, $\Delta p_{i,t-1}$, $p_{i,t-2}$, and the CBI survey variables are treated as strictly exogenous.

Table A3.3.4. Instrumental variables estimation

	(1) Dependent Variable: $ORDER\_P\_MA1_t$	(2) Dependent Variable: Δi_t
$ORDER\_P\_MA4_{t-1}$	0.916*** (0.057)	
i_{t-1}-y_{t-1}	-30.31*** (10.25)	-0.362*** (0.101)
$ORDER\_P\_MA1_t$		0.00387*** (0.00059)
Constant	-58.65*** (19.81)	-0.686*** (0.195)
Split Trend 1999	-0.845** (0.344)	-0.0122*** (0.0034)
AR1-2 Test	3.177 [0.057]	0.005 [0.995]
ARCH 1-1 Test	0.005 [0.947]	0.781 [0.383]
Normality Test	3.265 [0.195]	1.115 [0.573]
Hetero-X Test	2.277 [0.052]	1.960 [0.091]
Observations	34	34

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
P-values of diagnostic tests are in square brackets.
The sample period is 1979-2012 in both columns.

References

Abberger, K. (2005). “The Use of Qualitative Business Tendency Surveys for Forecasting Business Investment in Germany,” Ifo Working Paper No. 13.

Armstrong, J. S. (2001) “Combining Forecasts,” in: Armstrong, J. S. (2001), Principles of Forecasting: A Handbook for Researchers and Practitioners, Kluwer Academic Publishers.

Bean, C. R. (1981). “An Econometric Model of Manufacturing Investment in the UK,” Economic Journal 91: 06–121.

Barnes, S. and C. Ellis (2005) “Indicators of Short-term Movements in Business Investment,” Bank of England Quarterly Bulletin, Spring: 30-38.

Bond, S. R., J. Elston, J. Mairesse, and B. Mulkay (2003). “Financial Factors and Investment in Belgium, France, Germany and the UK: A Comparison Using Company Panel Data,” Review of Economics and Statistics 85 (1): 153–165.

Britton, E., J. Cutler, and A. Wardlow (1999) “The Bank’s Use of Survey Data,” Bank of England Quarterly Bulletin, May: 177-182.

Campos, J., D. F. Hendry, and N. R. Ericsson (2005). “General-To-Specific Modeling,” Volume 1 and 2, Edward Elgar Publishing.

Cassidy, N., E. Doherty, and T.Gill, (2012). “Forecasting Business Investment Using the Capital Expenditure Survey,” Reserve Bank of Australia Bulletin, September 2012: 1-10.

Chatfield, C. (1996). “Model Uncertainty and Forecast Accuracy,” Journal of Forecasting 15: 495-508.

Chow, G. C. (1960). “Tests of Equality Between Sets of Coefficients in Two Linear Regressions,” Econometrica 28: 591–605.

Doornik, J. A. (2009). “Autometrics,” in: Castle, J. L. and Shephard, N. (2009), The Methodology and Practice of Econometrics, Oxford: Oxford University Press.

Ellis, C. and S. Barnes (2005). “Indicators of Short-term Movements in Business Investment,” Bank of England Quarterly Bulletin, Spring: 30-38.

Engle, R. F. (1982). “Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation,” Econometrica 50: 987–1007.

Larsen, J. D. and R. Newton-Smith (2001). “Using Surveys of Investment Intentions,” Bank of England Quarterly Bulletin, Summer: 189-194.

Godfrey, L. G. (1978). “Testing for Higher Order Serial Correlation in Regression Equations When the Regressors Include Lagged Dependent Variables,” Econometrica 46: 1303–1313.

Hall, R. E. and D. W. Jorgenson (1967). “Tax Policy and Investment Behaviour,” American Economic Review 57: 391-414.

Hausman, J. A. (1978). “Specification Tests in Econometrics,” Econometrica 46: 1251–1271.

Hayashi, F. (1982). “Tobin’s Average q and Marginal q: A Neoclassical Interpretation,” Econometrica 50: 213–224.

Hendry, D. F. (1995). “Dynamic Econometrics (Advanced Texts in Econometrics).” Oxford: Oxford University Press.

Hendry, D. F. (2003). “J. Denis Sargan and the Origins of LSE Econometric Methodology,” Econometric Theory 19: 457–480.

Hendry, D. F. and H. Krolzig (2001). “Automatic Econometric Model Selection.” London: Timberlake Consultants Press.

Hendry, D. F. and H. Krolzig (2005). “The Properties of Automatic Gets Modeling,” Economic Journal, 115: C32–C61.

Hoover, K. D. and S. J. Perez (1999). “Data Mining Reconsidered: Encompassing and the General-To-Specific Approach to Specification Search,” Econometrics Journal 2: 1–25.

Jarque, C. M. and A. K. Bera (1987). “A Test for Normality of Observations and Regression Residuals,” International Statistical Review 55: 163–172.

Jorgenson, D. W. (1963). “Capital Theory and Investment Behavior,” American Economic Review 53: 247–259.

Keynes J.M. (1938). “The General Theory and After: A Supplement,” in Moggridge, D. (1979), The Collected Writings of John Maynard Keynes, London: Macmillan for the Royal Economic Society.

Ledolter, J. and B. Abraham (1981). “Parsimony and Its Importance in Time Series Forecasting,” Technometrics 23(4): 411-414.

Loungani, P. (2001). “How Accurate Are Private Sector Forecasts? Cross-Country Evidence from Consensus Forecasts of Output Growth,” International Journal of Forecasting 17: 419−432.

Mizon, G. (1995). “Progressive Modeling of Macroeconomic Time Series: the LSE Methodology,” in Hoover, K. D. (1995), Macroeconometrics. Developments, Tensions and Prospects, Dordrecht: Kluwer Academic Publishers.

Oliner S, G. Rudebusch, and D. Sichel (1995). “New and Old Models of Business Investment: A Comparison of Forecasting Performance,” Journal of Money, Credit, and Banking 27: 806–826.

Osterholm, P. (2013). "Forecasting Business Investment in the Short Term Using Survey Data," National Institute of Economic Research Working Paper No. 131.

Visco, I. (2009). "The Financial Crisis and Economists' Forecasts," Commencement address to the students of the Master in Public Economics at the Faculty of Economics, La Sapienza University in Rome, 4 March 2009.

Welch, I., and A. Goyal (2008). "A Comprehensive Look At the Empirical Performance of Equity Premium Prediction," Review of Financial Studies 21(4): 1455-1508.

White, H. (1980). "A Heteroskedastic-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity," Econometrica 48: 817–838.

White, H. (2000). "A Reality Check for Data Snooping," Econometrica 68: 1097-1126.

Ramsey, J. B. (1969). "Tests for Specification Errors in Classical Linear Least Squares Regression Analysis," Journal of the Royal Statistical Society B 31: 350–371.

Rapach, D. E. and M. E. Wohar (2007). "Forecasting the Recent Behavior of US Business Fixed Investment Spending: An Analysis of Competing Models," Journal of Forecasting, 26(1): 33-51.

Roman, P. A. and D. M. Vasquez (2013). "Are Business Tendency Surveys Useful to Forecast Private Investment in Peru? A Non-Linear Approach," available at: http://www.bcrp.gob.pe/docs/Publicaciones/Documentos-de-Trabajo/2013/documento-de-trabajo-03-2013.pdf.

Tevlin, S. and K. Whelan (2003). "Explaining the Investment Boom of the 1990s," Journal of Money, Credit, and Banking 35: 1-22.

Chapter 4

Nonlinear Effects of Fiscal Stimulus Under Different Credit Supply Conditions: Insights from A TVAR Analysis[1]

4.1. Introduction

Expansionary fiscal policy may have played a crucial role in speeding up economic recovery in the U.S. after the recent credit crunch. In the fall of 2008, the bankruptcy of Lehman Brothers caused financial panic and triggered a credit crunch. The lack of credit soon had a negative impact on both aggregate supply and demand, and the U.S. economy began to contract at an alarming rate. Compared with fiscal policy, monetary policy can be relatively quick at injecting liquidity and thus stabilizing the financial system in a credit crisis. This is because unlike fiscal policy, monetary policy does not have to go through the arduous legislative process. However, early in the crisis, the Federal Reserve had cut the benchmark interest rate effectively to zero and resorted to quantitative easing. With monetary policy constrained by the zero lower bound, the need for fiscal stimulus to combat the recession was particularly acute. As a result, various fiscal stimulus measures were introduced. The most important stimulus package was the $787 billion American Recovery and Reinvestment Act (ARRA) enacted by Congress in early 2009. The ARRA was a combination of tax reductions, transfers, and additional government spending. The total cost of fiscal stimulus in the U.S. over the crisis is estimated to be $1 trillion, about 7% of U.S. GDP (Blinder and Zandi, 2010).

[1] I am grateful to Prof. Nathan Balke for kindly sharing his RATS codes, which I modified to conduct the nonlinearity tests, estimate the TVAR model, and generate the impulse responses in this chapter.

Given the limitations on monetary policy as a support to growth in the recent credit crisis, policymakers and academics have become interested in gaining a better understanding of the effectiveness of fiscal stimulus measures under different credit supply conditions. Tax cuts can be considered as a way for the government to increase credit lines to households and firms, and may be more effective in fostering output growth under tight credit conditions than under loose credit conditions. When households and firms face borrowing constraints, they may have a higher marginal propensity to consume (see for example, Roeger and in't Veld, 2009; Gali et al., 2007). As a result, a larger share of tax cuts may be consumed rather than saved when credit supply is low. On the other hand, government spending increases may be less successful at boosting output under tight credit conditions than under loose credit conditions because they could crowd out more private investment in times of low credit supply. When households and firms are credit-constrained, government expenditure increases financed by borrowing may raise interest rates to higher levels. This may further reduce the supply of credit available to the private sector and thus discourage private spending.

The objective of this chapter is to examine the potentially nonlinear impacts of fiscal stimulus on output under tight and loose credit supply conditions in the U.S.. We employ a Threshold Vector Autoregression (TVAR) model to capture the possible nonlinear output effects of fiscal policy. In our TVAR framework, we choose the excess bond premium, a newly available measure of credit supply conditions constructed in Gilchrist and Zakrajsek (2012), as the threshold variable. When the excess bond premium is higher than the estimated threshold value, the economy is in a tight credit regime. On the other hand, when the excess bond premium is below the estimated threshold value, the economy is in a loose credit regime. Each regime is itself a linear VAR model with different autoregressive matrices, and fiscal policy therefore has different effects in the two regimes. By applying a recursive identification scheme, we estimate the TVAR model and compute the generalized impulse response function proposed in Koop et al. (1996). Our results show that the output effects of tax cuts are either subject to high uncertainty in the tight credit regime or very mild in the loose credit regime. Therefore, spending increases seem to be more effective at stimulating output growth than tax cuts, especially in periods of loose credit.

The rest of the chapter is organized as follows. Section 4.2 reviews the related literature. Section 4.3 discusses the methodology. Section 4.4 describes the dataset. Section 4.5 presents the TVAR estimation results, and section 4.6 conducts various robustness checks. Finally, section 4.8 concludes.

4.2. Literature Review

4.2.1. VAR Analysis of Fiscal Policy

A large number of econometric studies have used Vector Autoregression (VAR) models to assess the effects of fiscal policy shocks. However, there is no consensus regarding the quantitative response of output to fiscal policy. The two main approaches used in the fiscal VAR literature are: the Structural VAR (SVAR) approach and the event-study approach. In this section, we will briefly review these two approaches.

4.2.1.1 SVAR Approach

A structural VAR model with k endogenous variables and p lags is defined as:

$$AX_t = \omega_0 + \omega_1 X_{t-1} + \cdots \omega_p X_{t-p} + Be_t \quad (4.1)$$

where X_t is a $(k\times1)$ vector of endogenous variables, A is a $(k\times k)$ matrix describing the contemporaneous relationship between the endogenous variables in X_t, ω_0 is a $(k\times1)$ vector of constants, $\omega_1, \ldots \omega_p$ are $(k\times k)$ coefficient matrices, e_t is a $(k\times1)$ vector of mutually uncorrelated structural innovations with zero mean and a variance-covariance matrix Ω_e, and B is a $(k\times k)$ matrix describing how the structural shocks affect the endogenous variables.[2] Because the explanatory variables are endogenous, the Ordinary Least Squares (OLS) estimates of the structural model are biased and inconsistent.

Multiplying equation (4.1) by A^{-1}, we can transform the structural form into the reduced form in which each variable is a function of its own past values and the past values of other variables:

$$X_t = A^{-1}\omega_0 + A^{-1}\omega_1 X_{t-1} + \cdots A^{-1}\omega_p X_{t-p} + u_t \quad (4.2)$$

The relationship between the reduced form shocks u_t and the structural innovations e_t is:

$$Au_t = Be_t \quad (4.3)$$

[2] This is known as the standard AB model of Lutkepohl (2005).

We can estimate the reduced form model (4.2) using OLS. Because the reduced form shocks are linear combinations of the structural shocks, they have no economic interpretation. In order to construct the impulse response function and conduct policy analysis, we need to recover the structural shocks which drive the dynamics of the economic variables in X_t. By rearranging equation (4.3), we have:

$$u_t = A^{-1}Be_t \quad (4.4)$$

Equation (4.4) implies that:

$$\Omega_u = A^{-1}B\Omega_e B'(A^{-1})' \quad (4.5)$$

In equation (4.5), there are $(k^2 + k)/2$ known elements in the variance-covariance matrix of the reduced form disturbances Ω_u, $(k^2 - k)$ unknown elements in A (diagonal elements of A are known to be one), k unknown elements in the variance-covariance matrix of the structural shocks Ω_e (the covariance terms of mutually uncorrelated structural shocks are zero), and k^2 unknown elements in B. In total, we can form $(k^2 + k)/2$ distinct equations with $2k^2$ unknowns from equation (4.5). In order to exactly identify all the structural shocks from the reduced form shocks, we need to impose $(3k^2 - k)/2$ additional constraints on the parameters of matrices A and B. According to Caldara and Kamps (2008), there are three main identification strategies in the SVAR literature: the recursive identification, the Blanchard-Perotti (BP) identification, and the sign restriction identification.

4.2.1.1.1. Recursive Identification

The recursive identification strategy is first proposed in Sims (1980). To just-identify the SVAR system, this strategy imposes the restrictions that A is a lower triangular matrix with unit diagonal ($(k^2 - k)/2$ restrictions) and B is a $(k \times k)$ identity matrix (k^2 restrictions). Identification is achieved by the Choleski decomposition of the reduced form variance covariance matrix, which is given by $\Omega_u = CC'$, where C is a lower triangular matrix. Equation (4.5) can then be solved by letting $A^{-1} = CD^{-1}$and $\Omega_e = DD'$, where D is a diagonal matrix with the same diagonal as C.

For the recursive identification method, the ordering of the variables determines the casual links among the variables. For example, consider $X_t = [r_t, g_t, y_t]'$, where g_t is government spending, y_t is output, and r_t is tax revenues. In this three-variable system, suppose we order government spending first, output second, and tax revenues last. In the matrices form, equation (4.3) can be expressed as:

$$\begin{bmatrix} 1 & a_{12} & a_{13} \\ a_{21} & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^r \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} e_t^g \\ e_t^y \\ e_t^r \end{bmatrix} \quad (4.6)$$

When we use the recursive identification method, equation (4.6) becomes:

$$\begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} u_t^g \\ u_t^y \\ u_t^r \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t^g \\ e_t^y \\ e_t^r \end{bmatrix} \quad (4.7)$$

This gives three distinct equations:

$$e_t^g = u_t^g \quad (4.8)$$

$$e_t^y = a_{21}u_t^g + u_t^y \quad (4.9)$$

$$e_t^r = a_{31}u_t^g + a_{32}u_t^y + u_t^r \quad (4.10)$$

Equations (4.8)-(4.10) imply the following assumptions on the contemporaneous relations among the three variables: (1) government spending only responds contemporaneously to government spending shocks, (2) output responds contemporaneously only to government spending and output shocks, and (3) taxes respond contemporaneously to tax, government spending, and output shocks. Different ordering of variables would imply different contemporaneous effects of shocks.

Fatas and Mihov (2001) apply the recursive approach to study the effects of fiscal policy on economics variables. They find a sustained increase in private output after a positive spending shock. Furthermore, their results show that the response of private output peaks after about two years. Ilzetzki et al. (2013) perform a cross-country analysis of fiscal multipliers using the recursive identification. Their findings indicate that the government spending multipliers are higher in high-income countries, countries with fixed exchange-rate regimes, and closed economies.

4.2.1.1.2. BP Identification

The BP identification is developed in Blanchard and Perotti (2002). It incorporates external information about transfers, tax, and spending programs to calculate the elasticities of fiscal variables to macroeconomic variables such as interest rates and output. Blanchard and Perotti (2002) consider three endogenous variables in X_t: government spending g_t, output y_t, and taxes r_t. They begin their analysis by assuming that the relationship between the reduced form shocks u_t and the structural shocks e_t takes the following form:

$$u_t^r = -a_{13}u_t^y + b_{12}e_t^g + e_t^r \quad (4.11)$$

$$u_t^g = -a_{23}u_t^y + b_{21}e_t^r + e_t^g \quad (4.12)$$

$$u_t^y = -a_{31}u_t^r - a_{32}u_t^g + e_t^y \quad (4.13)$$

Equation (4.11) implies that the unexpected change in taxes u_t^r can be attributed to the unexpected change in output u_t^y, the structural shock to government spending e_t^g, and the structural shock to taxes e_t^r. Similar interpretations can be made from equations (4.12) and (4.13). Based on equations (4.11)-(4.13), we can re-write equation (4.6) as:

$$\begin{bmatrix} 1 & 0 & a_{13} \\ 0 & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} u_t^r \\ u_t^g \\ u_t^y \end{bmatrix} = \begin{bmatrix} 1 & b_{12} & 0 \\ b_{21} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t^r \\ e_t^g \\ e_t^y \end{bmatrix} \quad (4.14)$$

Therefore, from the start, Blanchard and Perotti (2002) implicitly impose nine restrictions on matrices A and B: $a_{12} = a_{21} = b_{13} = b_{23} = b_{31} = b_{32} = 0$ and $b_{11} = b_{22} = b_{33} = 1$.

Subsequently, using the tax and output data for the U.S., Blanchard and Perotti (2002) calibrate the output elasticity of tax revenues $-a_{13} = 2.08$. Because they use quarterly data in their SVAR estimation and assume that government spending takes at least a quarter to respond to an output shock, they set $a_{23} = 0$. In addition, they assume that the government makes spending decisions before tax decisions and restrict $b_{21} = 0$. After imposing these three additional restrictions, equation (4.14) becomes:

$$\begin{bmatrix} 1 & 0 & -2.08 \\ 0 & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} u_t^r \\ u_t^g \\ u_t^y \end{bmatrix} = \begin{bmatrix} 1 & b_{12} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t^r \\ e_t^g \\ e_t^y \end{bmatrix} \quad (4.15)$$

In total, they impose 12 restrictions to achieve the exact identification of the structural shocks. Comparing (4.15) with (4.7), we can observe three main differences between the recursive identification and the BP identification: (1) the recursive identification restricts all the parameters of matrix A above the principal diagonal to be zero, whereas the BP identification uses the external tax and output data to obtain a nonzero estimate of the contemporaneous effect of output on taxes, a_{13}, (2) the recursive identification does not impose any restriction on the parameters of matrix A below the principal diagonal, while the BP identification imposes a zero restriction on the contemporaneous effect of taxes on output, a_{21}, and (3) the recursive identification restricts the matrix B to be an identify matrix, while the BP identification allows one parameter b_{12} to be freely varying.

Blanchard and Perotti (2002) find that public spending increases have positive output multipliers while tax rises have negative impact multipliers. However, the multipliers are small in magnitude, generally close to one. Perotti (2005) applies the BP approach to study the effects of fiscal policy in OECD countries. His estimated government spending multipliers are smaller than one in most cases. In addition, he finds that tax cuts do not appear to be faster at stimulating output than spending increases.

4.2.1.1.3 Sign Restriction Identification

Unlike the recursive and the BP identification schemes, the sign restriction identification does not impose restrictions on the parameters of matrices A and B to exactly identify the structural shocks. Instead, it restricts the impulse responses of the endogenous variables at particular horizons to be positive or negative based on economic theory and achieves only partial identification of the structural shocks. For instance, Mountford and Uhlig (2009) study three types of fiscal policy: deficit-financed tax cuts, deficit-financed spending increases, and balanced budget spending increases. They restrict the sign of the impulse response of government revenue to a government revenue shock to be positive for a year after the shock. Similarly, they restrict the sign of the impulse response of government spending to a government spending shock to be positive one year after the shock. The purpose of these sign restrictions is to include only persistent fiscal shocks in the analysis. Furthermore, they impose the restrictions that fiscal shocks are orthogonal to both monetary shocks and business cycle shocks. However, they leave the sign on the responses of output, consumption, investment, interest rate, monetary base, and prices to fiscal shocks unrestricted. Their estimation shows that both deficit-financed and balanced budget spending increases crowd out private investment. On the other hand, they find that deficit-financed tax cuts have large output multipliers of up to five after five years.

4.2.1.2. Event-study Approach

The event-study approach examines historical documents to identify fiscal shocks that are exogenous to the state of the economy and directly estimates the reduced form regressions of output on the current and past values of exogenous tax or spending changes to evaluate the output effects of fiscal policy. Thus, this approach avoids the structural shock identification problem associated with the SVAR approach. Romer and Romer (2010) study the narrative record of presidential speeches and statements, the *Economic Report of the President* written by the Council of Economic Advisers, Congressional reports and other executive and legislative documents for the U.S. to identify 54 tax changes that were not related to short-run business cycle fluctuations. They point out that these exogenous tax shocks were designed either to lower inherited government debt or to promote long-term economic growth. Their results show that the exogenous tax increases have strong negative effects on output with large multipliers of about three. Ramey (2011) argue that military buildups are triggered by geopolitical factors and thus independent of current economic conditions. As a result, she uses news about future military spending changes as exogenous spending shocks and relies on news sources such as *Business Week* to construct a measure of the present value of the anticipated defense spending changes. Her estimated spending multipliers fall between 0.6 and 1.2.

4.2.2. Fiscal Policy and Credit Supply Conditions: Theoretical Studies

The defining characteristic of the recent financial crisis was the sudden reduction in the general availability of credit in the economy. Many previous theoretical studies have provided compelling support for the important role played by credit market frictions in propagating economic shocks. The pioneering model constructed by Stiglitz and Weiss (1981) demonstrates that credit rationing occurs due to asymmetric information in the credit market. Bernanke et al. (1996) develop a financial accelerator framework. In their analysis, borrowers such as households and small firms have high agency costs and are thus much less likely to receive external finance from banks in a recession, which leads to the flight-to-quality phenomenon.

The recent credit crunch has aroused renewed interest among economists in investigating how credit market conditions can influence the transmission of fiscal policy using theoretical models. Gali et al. (2007) extend the standard New Keynesian (NK) model by adding liquidity-constrained households. Their analysis shows that expansionary fiscal policy can raise the income of liquidity-constrained households, which in turn can increase their consumption. Therefore, they claim that expansionary fiscal policy is more effective if the proportion of credit-constrained households is higher. Andres et al. (2012) study the government spending multiplier under varying household leverage conditions. They conclude that the spending multiplier is more likely to exceed one if the initial leverage is high. However, they also find that the size of fiscal multiplier is negatively associated with the severity of the credit crisis. Eggertsson and Krugman (2012) study fiscal policy during a deleveraging crisis. In such a crisis, they argue that indebted agents are forced to decrease spending, which further reduces aggregate demand. Their model simulation shows that fiscal stimulus can increase the consumption of liquidity-constrained debtors and thus halt the debt-induced slump. Timing is crucial for the success of fiscal policy in NK models with financial frictions. For instance, Kara and Sin (forthcoming) conclude that fiscal policy has a much larger positive impact on output in a credit crisis when monetary policy is constrained by the zero lower bound. Their model shows that fiscal policy can alleviate credit constraints in the economy. Carrillo and Poilly (2013) show that the size of government spending multiplier is higher if the economy is in a liquidity trap. They argue that spending increases allow debtors to improve their financial positions, which in turn can crowd in investment.

4.2.3. Fiscal Policy and Credit Supply Conditions: Empirical Studies

Empirical studies on the nonlinear relationship between fiscal policy and credit supply conditions are relatively scarce, and yield mixed results. The commonly adopted approaches to study the nonlinear effects of fiscal policy are cross-country panel data analysis, the Threshold Vector Autoregression (TVAR), the Smooth Transition Vector Autoregression (STVAR), and the Time-Varying Probability Markov-Switching (TVPMS) model.

Using panel data for 127 OECD and non-OECD countries over the period 1981-2007, Afonso et al. (2010) do not find evidence that the effects of fiscal policy during financial crises are different from those during normal times. Turrini et al. (2012) perform a panel data analysis on 56 emerging and advanced economies to study the effectiveness of fiscal policy in banking crises. For the U.S., they identify episodes of banking crisis in 1988, 1989, 1991, 1990, and 2007. They conclude that fiscal stimulus measures, especially tax cuts, have much stronger effects on output during banking crises. Bouthevillain and Dufrenot (2011) employ a TVPMS model to analyze the nonlinear relationship between the output effects of fiscal policy and economic conditions in France. They find that output responses to spending increases are higher during times of economic crisis. Afonso et al. (2011) use the TVAR to study the possible nonlinear effects of fiscal policy under different financial market conditions. They employ the Financial Stress Index developed by the International Monetary Fund to identify periods of high financial stress. For the U.S., they report a minor difference in the fiscal multipliers between the high stress and the low stress regimes. Ferraresi et al. (2013) employ the spread between 10-year Treasury note yield and BAA-rated corporate bond yield as a proxy for credit market conditions in their TVAR model and find that the government spending multiplier in the U.S. is larger when the interest rate spread is high. However, they do not consider tax cuts in their analysis. An important contribution of this chapter to the literature is that we compare the nonlinear output responses to spending increases and tax cuts under different credit conditions within a TVAR framework. In addition, we employ a newly available measure called the excess bond premium developed in Gilchrist and Zakrajsek (2012) as the threshold variable in our main specification to identify credit supply shocks. We also consider an alternative threshold variable, the National Financial Conditions Credit Subindex (NFCCS) produced by the Federal Reserve Bank of Chicago, as a robustness check.

4.3. Methodology

4.3.1. Model Specification

The TVAR model uses a threshold variable to capture nonlinearities present in many economic systems, and has been used in the literature to study a wide range of economic issues. For instance, Balke (2000) and Atanasova (2003) apply the TVAR to explore the links between credit conditions and monetary policy. In this chapter, we follow the methodology of Balke (2000) and Afonso et al. (2011) for our TVAR estimation. The model is defined as:

$$Y_t = \alpha_1 Y_t + \beta_1(L)Y_{t-1} + \gamma_1 + (\alpha_2 Y_t + \beta_2(L)Y_{t-1} + \gamma_2)I(z_{t-d} > z) + \varepsilon_t \quad (4.16)$$

where Y_t is a vector of endogenous variables which includes the threshold variable z_t; $\beta_1(L)$ and $\beta_2(L)$ are lag polynomial matrices; γ_1 and γ_2 are constant terms; ε_t is the vector of structural shocks with zero mean and a variance-covariance matrix Ω_ϵ; and $I(z_{t-d} > z)$ is an indicator function that equals one if the value of the d-th lag of z_t exceeds the threshold value z and zero otherwise. The delay parameter d is set to one. The model introduces nonlinearities by allowing the coefficient matrices α and $\beta(L)$ and the constant term γ to differ across the two credit regimes.

There are six endogenous variables in Y_t: government spending (excluding interest payments and transfers) g_t, net taxes (which is defined as total government tax receipts less interest payments and transfers) t_t, output y_t, the inflation rate π_t, the short-term interest rate i_t, and the credit supply threshold variable z_t. Because the threshold variable is included as an endogenous variable, the regime switch process is endogenized and can be triggered by a shock to any of the six variables in the TVAR model.

A recursive identification scheme similar to Caldara and Kamps (2008) is imposed, with government spending first, output second, inflation third, and net taxes fourth, followed by the interest rate and the credit supply variables. By ordering government spending before output, we assume that fiscal policy takes at least one quarter to react to output shocks (Blanchard and Perotti, 2002). According to Caldara and Kamps (2008), output and inflation are ordered before net taxes because government revenue is sensitive to business cycle fluctuations and shocks to output and inflation have an immediate effect on the tax base of our economy. As Caldara and Kamps (2008) also point out, interest rate is ordered after government spending, output, inflation, and tax revenue because (1) public spending and net taxes variables both exclude interest payments, and thus do not react quickly to interest rate shocks, and (2) the Federal Reserve sets monetary policy based on inflation and the output gap. Lastly, the credit supply threshold variable is allowed to react contemporaneously to all variables.

4.3.2. Threshold Value Estimation

To select the threshold value, we follow Balke (2000) and perform a grid search over the sample range of the threshold variable z_{t-d} (i.e. all potential threshold values). To ensure that each regime contains a sufficient number of observations, a certain number of observations at both the upper and the lower tails of the empirical distribution of z_{t-d} are excluded from the grid search. As in Balke (2000), this trimming number at each tail is set to be the sum of the number of coefficients in our model and 15% of the total number of observations. For every possible threshold value over the grid, we estimate the TVAR model. Following Balke (2000), we identify the threshold value as the one that minimizes the log determinant of the variance-covariance matrix of the residuals Ω_{ϵ}:

$$\hat{z} = \underset{z}{\operatorname{argmin}} \log |\Omega_{\epsilon}(z)| \quad (4.17)$$

4.3.3. Testing Nonlinearity

It is important to test whether our system indeed offers threshold behavior. In our TVAR model, the threshold value z is unknown *a priori* and is undefined under the null hypothesis of linearity (i.e., $\alpha_2 = \beta_2(L) = \gamma_2 = 0$). As a consequence, the conventional likelihood ratio, Lagrange multiplier, and Wald test statistics have nonstandard asymptotic distributions (see Davies, 1977, 1987; Hansen, 1996). Following the methodology used in Balke (2000), we employ the simulation-based nonlinearity tests proposed in Hansen (1996) to circumvent this problem of unidentified parameter z under the null hypothesis.

For each possible threshold value over the grid constructed in section 4.3.2, we calculate the Wald test statistic testing the null hypothesis of no threshold nonlinearity. Next, we follow Hansen (1996) and Balke (2000), and compute three different test statistics: the supremum of all Wald statistics (sup-Wald) over the grid of potential threshold values, the average of all Wald statistics (avg-Wald) over the grid of potential threshold values, and the sum of exponential Wald statistics (exp-Wald) over the grid of potential threshold values. By applying the simulation method developed in Hansen (1996), we generate 500 bootstrap replications to approximate the asymptotic distributions of sup-Wald, avg-Wald, and exp-Wald statistics under the null hypothesis of a linear model, and derive the asymptotic p-values.

4.3.4. Generalized Impulse Response Function

According to Gallant et al. (1993) and Koop et al. (1996), impulse responses produced by nonlinear models are much more complicated than those produced by linear models because they are conditional on the entire history of the system before the shock hits as well as the size and the sign of the shock. In our case, depending on the initial state of the economy, a large enough tax or spending shock could cause the threshold variable z_{t-d} to cross the threshold and therefore induce a credit regime shift during the propagation of the shock. As a result, the economy may switch between the two credit regimes over the horizon of the impulse response. The conventional linear impulse response function is not suitable for our purpose because it is insensitive to the initial conditions and assumes that the economy stays in the same credit regime prevailing at the time of the initial shock.[3] To overcome this problem, we apply the history-dependent generalized impulse response function (GIRF) introduced in Koop et al. (1996).

Formally, Koop et al. (1996) define the GIRF as a function of conditional expectations:

$$GIRF = E[Y_{t+k}|v_{it}, \psi_{t-1}] - E[Y_{t+k}|\psi_{t-1}] \quad (4.18)$$

where k is the forecast horizon, v_{it} is an exogenous shock to the i-th variable of Y at time t, ψ_{t-1} is the history of the data up to time $t-1$ before the shock hits (i.e. the initial conditions), and Y_{t+k} is the response of the variables k periods after the shock. Because the shock v_{it} may trigger a regime switch, the GIRF depends on the size and direction of the shock and on the initial conditions before the shock occurs. Hence, shocks of different magnitudes may result in disproportionate impulse responses and shocks of different directions may lead to asymmetric responses.[4] Appendix 4.1 provides a detailed explanation of how the GIRF is computed.

4.4. Data

4.4.1. Variable Definitions

[3] For a detailed discussion on the limitations of using the conventional linear impulse response function to analyze nonlinear models, please see Koop et al. (1996).

[4] Please refer to Gallant et al. (1993), Koop (1996), and Koop et al. (1996) for a detailed discussion on the asymmetry and disproportionality of the GIRF.

Our benchmark model is estimated using quarterly U.S. data over the sample period 1973Q1- 2012Q4. Following the definitions in Blanchard and Perotti (2002), we construct the government spending and net taxes variables. Government spending is the sum of government consumption and government investment, which by definition does not include interest payments and transfers. Net taxes are derived as government tax receipts minus interest payments and transfers. We use GDP to measure output. For inflation, we take the first difference of the natural logarithm of the Consumer Product Index (CPI). To describe monetary policy, we use the effective federal funds rate. To proxy for credit supply conditions, we employ the excess bond premium constructed in Gilchrist and Zakrajsek (2012).

An overview of data sources is shown in Appendix 4.2. All data are seasonally adjusted. The nominal terms series are deflated with the implicit GDP price deflator to produce real terms series. When necessary, we produce quarterly series by taking the arithmetic average of monthly figures. All the variables are made stationary prior to our TVAR estimation. Hence, GDP, government spending, and net taxes are expressed in first differences of the natural logarithm while the inflation rate, the federal funds rate, and the excess bond premium are in levels.

The data series are shown in Figure 4.1. Panel A shows the government spending variable. It is calculated as the first difference of natural logarithm of government consumption and investment multiplied by 100, which is an approximation of the percentage growth rate of government spending. As one can observe from Panel A, government spending growth was in positive territory most of the time, indicating that government spending was steadily increasing over the sample period. Panel B illustrates the output variable. It is constructed as the first difference of the natural logarithm of GDP multiplied by 100, which is an approximation of the percentage growth rate of output. There were large falls in output in the early 1970s recession and the early 1980s recession. The growth rate of output stayed positive most of the time from the mid-1980s to 2008. During the recent financial crisis in 2008-2009, output experienced a sharp fall. Panel C depicts the net taxes variable. It is computed as the first difference of the natural logarithm of net taxes multiplied by 100, which is an approximation for the percentage growth rate of taxes. There were large declines in taxes during the early 1970s downturn and the recent credit crunch. Panel D shows the quarter-on-quarter inflation rate. The 1970s was a period of high inflation. In the early 1980s, the Federal Reserve, under Paul Volcker's leadership, applied tight monetary policy to combat high inflation and successfully brought inflation down. Since then, the inflation rate has stayed low at a low level. There was a short period of deflation in 2008Q4 and 2009Q1 at the height of the recent credit crisis. Panel E depicts the federal funds rate series. During the Volcker disinflation in the early 1980s, the Federal Reserve raised the federal funds rate to high levels in order to reduce inflation. The federal funds rate came down in the early 1980s and has remained low since then. Starting from 2008Q4, the Federal Reserve has maintained the federal funds rate at close to zero in an effort to stimulate the economy. Panel F shows the excess bond premium series.[5]

The descriptive statistics of these series are presented in Table 4.1. The government spending, output, and net taxes variables represent growth rates. All three variables have positive means, suggesting government spending, output, and net taxes

[5] Please refer to section 4.4.2 for a detailed discussion of the excess bond premium.

were increasing on average during the sample period. The output variable has a higher standard deviation than the government spending and output variables, implying that the quarterly growth rate of taxes is more volatile than those of government spending and output. The average inflation rate is 1.061% and the average federal funds rate is 5.896% over the sample period.

4.4.2. Excess Bond Premium

We consider periods of tight credit as times when there is a large reduction in credit supply. Previous empirical studies have used variables such as the volume of credit (Claessens et al., 2009) or the yield spread between corporate bonds and Treasury bonds (Balke, 2000; Ferraresi et al., 2013) to identify credit supply shocks. However, credit volumes and interest rate spreads may not be accurate credit supply measures because they can also be affected by shifts in credit demand. Instead, we use a newly available measure called the excess bond premium developed in Gilchrist and Zakrajsek (2012) (GZ). The excess bond premium is specifically constructed as a timely indicator of credit supply conditions in the economy. We will briefly explain the methodology that GZ use to derive the excess bond premium below.

First, GZ use a large sample of U.S. non-financial corporate bonds to compute the average credit spread of corporate bonds over risk-free Treasury bonds in month t, S_t^{GZ}.

Next, GZ decompose S_t^{GZ} into two components:

$$S_t^{GZ} = \widehat{S_t^{GZ}} + EBP_t \quad (4.19)$$

where $\widehat{S_t^{GZ}}$ is the predicted component of S_t^{GZ} and EBP_t is the residual component called the excess bond premium. $\widehat{S_t^{GZ}}$ is estimated primarily based on the expected default risk, which is calculated using the distance-to-default model introduced in the seminal work of Merton (1974). According to GZ, the linear decomposition of the credit spread is partly motivated by the credit spread puzzle, which refers to the phenomenon that the expected default losses can only explain less than half of the credit spread. They claim that the unexplained part seems to be mostly related to the risk premium beyond the perceived default losses demanded by lenders for their exposure to default risks.

The excess bond premium represents the part of the corporate bond yield that is unrelated to the movements in the risk-free interest rate and the risk characteristics of corporations. GZ argue that the excess bond premium measures the risk attitude of corporate bond investors, and thus the credit supply conditions in the economy. As GZ point out, when investors become more risk-averse, the excess bond premium increases and credit supply falls. In addition, GZ plot the excess bond premium against the return on assets for the U.S. financial corporate sector and show that there is a strong negative correlation between these two series. They believe that this co-movement provides evidence that the excess bond premium is negatively related to the risk-bearing capacity of financial intermediaries. Panel F of Figure 4.1 shows that the excess bond premium rises in periods of tight credit and reached high levels in the early 1970s recession, the early 1980s recession, the savings and loan crisis of the 1980s and early 1990s, the burst of the dot-com bubble of the early 2000s, and the more recent 2007-2009 global financial crisis. As reported in Table 4.1, the mean of the excess bond premium variable is close to zero, which implies that on average, lenders were not charging a risk premium on corporate bonds beyond the expected default losses over the sample period.

Furthermore, following GZ, we compare the excess bond premium with survey-based measures of credit availability. The Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending Practices asks U.S. commercial banks whether they have changed their credit standards on commercial and industrial (C&I) loans over the past three months. The SLOOS survey data are available starting in 1990. Figure 4.2 plots the excess bond premium against the net percentage of banks that reported tightening their credit standards on C&I loans to large and middle-market firms. The correlation between these two series is 0.80. We also plot the excess bond premium against the net percentage of banks that reported tightening their credit standards on C&I loans to small firms in Figure 4.3. The correlation is 0.79. This suggests that the excess bond premium is also a valid measure of credit availability to small firms despite the fact that it is constructed using corporate bonds issued mostly by large companies. The strong positive associations between the excess bond premium and the SLOOS survey results suggest that the excess bond premium is a reliable indicator of credit availability to the corporate sector. By assuming that the household and the corporate credit supply conditions are positively correlated, we use the excess bond premium to proxy for the availability of credit in the whole economy.

4.5. Results

4.5.1. Preliminary Analysis

To determine the optimal lag length of the endogenous variables in the TVAR, we use the usual information criteria. While both the Schwarz Information Criterion (SIC) and the Hannan-Quinn (HQ) Criterion suggest one lag, the Akaike Information Criterion (AIC) suggests three lags. The estimation power of a nonlinear model decreases substantially with the addition of parameters (Hansen, 1996; Baum and Koester, 2011). In addition, because the number of observations in the tight credit regime is relatively small, there is a danger of over-fitting if we include too many lags (Baum and Koester, 2011). Consequently, we use only one lag in our estimation.

The stationarity of the threshold variable is required for the TVAR estimation. Hence, we carry out the Augmented Dickey-Fuller (ADF) test to check the unit root hypothesis for the excess bond premium variable. We use the AIC to choose the number of lags in the ADF regression. Table 4.2 presents the test results. The *p*-value indicates that the unit root hypothesis is rejected at the 5% level.

In addition, we conduct the nonlinearity tests for the TVAR system. Table 4.3 reports the sup-Wald, avg-Wald, and exp-Wald test results. All three tests reject the null hypothesis of no threshold effects at the 5% level, which indicates the presence of two significantly different credit regimes.

4.5.2. Threshold Value

The estimated threshold value for the excess bond premium is 0.27. Figure 4.4 plots the excess bond premium and the estimated threshold value. The threshold value splits the sample into an upper (tight credit) regime with 36 observations and a lower (loose credit) regime with 123 observations. It accurately identifies periods of tight credit such as the dot-com bubble in the early 2000s and the Great Recession in 2008-2009.

4.5.3. Impulse Response Analysis

To provide insight into the dynamic properties of the TVAR model, we follow Koop et al. (1996) and estimate the GIRFs for a negative tax shock of 1% of GDP and a positive government spending shock of 1% of GDP. Because government spending, net taxes, and output are specified in first differences of the natural logarithm in the TVAR, the impulse response function of the output variable represents the change in output growth. To captures a shock's effect on the level of output, we also compute the cumulative impulse response function of the output variable.

Figure 4.5 and Figure 4.6 report, respectively, the impulse response functions and the cumulative impulse response functions of output growth to negative tax shocks. The 95% confidence intervals are computed using bootstrap.[6] Figure 4.7 and Figure 4.8 show, respectively, the impulse responses and the cumulative impulse responses of output growth to positive government spending shocks. The 95% confidence intervals of impulse responses are narrower in the loose credit regime than in the tight credit regime. This is likely because there are a lot fewer observations under tight credit conditions, which leads to larger parameter uncertainty. In the model, net taxes are ordered after output. Therefore, output responds to tax shocks with a time lag of one quarter. On the other hand, government spending is ordered before output. As a result, output reacts to spending shocks in the same quarter. Table 4.4 reports the cumulative impulse responses of output growth over different forecast horizons.

[6] Please refer to Appendix 4.1 for a detailed discussion of the bootstrap method used to construct the confidence intervals.

4.5.3.1. Negative Tax Shocks of 1% GDP

In the tight credit regime, a negative tax shock of 1% of GDP increases output by 0.633% on impact (Figure 4.6). Compared with pre-existing linear VAR studies which assume that the output effects of tax cuts are independent of credit supply conditions, this estimate controlling for tight credit conditions is similar to the estimate obtained by Blanchard and Perotti (2002) (0.7%), but higher than the ones reported in Perotti (2005) (0.3%) and Mountford and Uhlig (2002) (0.2%). As the 95% confidence interval is above zero on impact, this impact output effect is statistically significant. For the rest of the forecast horizon, output growth is not statistically distinguishable from zero. This is in line with the results reported in Caldara and Kamps (2008), which does not find tax cuts to have sustained significant effects on output. In the loose credit regime, output growth is only 0.407% on impact and is statistically significant. This is higher than the estimated values in Perotti (2005) and Mountford and Uhlig (2002), but below the results of Blanchard and Perotti (2002). For the rest of the forecast period, we cannot reject the null hypothesis that output growth is zero.

The findings suggest that tax reductions seem to have stronger output effects under tight credit conditions than under loose credit conditions. When firms lack access to reasonably priced credit, they may have a higher marginal propensity to invest (see for example, Roeger and in't Veld, 2009; Gali et al., 2007). Therefore, when credit supply is low, firms may be more likely to spend tax cuts on investment projects, which could lead to higher output.

4.5.3.2. Positive Spending Shocks of 1% GDP

In Figure 4.8, in the tight credit regime, the impact output growth after a positive government spending shock of 1% of GDP is 0.418% and is statistically significant. Compared with previous linear VAR studies which assume that the output effects of spending increases do not vary under different credit supply conditions, this estimate allowing for tight credit conditions is close to the estimate reported in Perotti (2005) (0.4%), below the results of Blanchard and Perotti (2002) (0.9%), Gali et al. (2007) (0.8%), and Caldara and Kamps (2008) (1.0%), and above the estimates obtained in Fatas and Mihov (2001) (0.1%) and Moutford and Uhlig (2002) (0.2%). The increase in output remains significantly different from zero for two quarters after the shock. In the loose credit regime, output growth is 1.085% on impact. This is close to the estimated values in Blanchard and Perotti (2002), Gali et al. (2007), and Caldara and Kamps (2008), and above the findings of Perotti (2005), Fatas and Mihov (2001), and Moutford and Uhlig (2002). Output growth remains positive and significantly different from zero for five quarters after the shock.

Based on the results, spending increases appear to have smaller effects on output under the tight credit regime than under the loose credit regime. One possible explanation could be that the crowding out effect of government spending on private investment is stronger when credit conditions are tight. When the financial sector is eliminating credit lines, many firms face borrowing constraints. Under this circumstance, spending increases financed by borrowing may lead to higher interest rates. Therefore, firms' financial constraints may worsen and private investment may fall even more. This could result in a smaller spending multiplier effect under tight credit conditions.

4.5.3.3. Policy Implications

The findings in sections 4.5.3.1 and 4.5.3.2 have important implications.[7] In the tight credit regime, the output response to spending increases remains positive and significant for two quarters after impact while the output response to tax cuts is not significantly different from zero after impact. Furthermore, the output responses to spending increases have considerably narrower 95% confidence bands than those to tax cuts. Therefore, compared with spending increases, tax cuts have less certain effects on output when credit is tight.

In the loose credit regime, the output response to spending increases is much higher than that to tax cuts on impact. In addition, the output response stays positive and statistically significant for five quarters after spending increases while the output response to tax cuts is insignificantly different from zero for the rest of the forecast horizons. Hence, tax cuts appear to generate lower output growth than expenditure increases when credit conditions are loose. This could be explained by the classical Keynesian theory: when the government increases its expenditure, the full amount of the spending increase is injected into the economy to stimulate aggregate demand; however, when the government reduces tax rates, households and firms may not spend all of the tax cut. Our results are in line with other studies in the fiscal VAR literature which find expenditure-based fiscal expansions to have higher output effects than tax-based fiscal expansions (see for example, Blanchard and Perotti, 2002; Mountford and Uhlig, 2002; Perotti, 2002; Baum et al. 2012).

[7] I would like to thank Prof. Guido Ascari for his comments on policy implications.

The findings suggest that tax cuts may not be a very effective countercyclical fiscal tool because they either have very uncertain output effects when credit conditions are tight or have very mild effects on output when credit conditions are loose. Therefore, the government may want to focus on expenditure increases rather than tax cuts when designing a fiscal stimulus package, especially in periods of loose credit.

4.5.3.4. Increasing the Shock Size

As we have discussed in section 4.3.4, the GIRF may be disproportional to the size of the shock. Figure 4.6 also plots the cumulative impulse response function of output growth to a negative tax shock of 2% of GDP. Table 4.4 shows that, the impact output response to a negative tax shock of 2% GDP is more than twice the impact output response to a negative tax shock of 1% GDP in the tight regime, but less in the loose regime. At longer forecast horizons after impact, the output responses to negative tax shocks of 1% and 2% GDP are insignificantly different from zero in both regimes. Therefore, we find evidence that larger tax shocks have disproportionately larger impact output effects in the tight credit regime and disproportionately smaller impact output effects in the loose credit regime. These findings suggest that large tax cuts seem to be less effective at fostering output growth under loose credit conditions than under tight credit conditions.

In Figure 4.8, we also plot the cumulative impulse response function of output growth to a positive government spending shock of 2% of GDP. Table 4.4 shows that, in both regimes, the output response to a positive government spending shock of 2% GDP is about twice as large as that to a positive government spending shock of 1%

GDP. Therefore, we do not find evidence that spending shocks of differing magnitudes have disproportionate output effects.

4.5.4. Diagnostic Test

To check the validity of the estimation results of our specification with one lag in the TVAR model, we employ the multivariate Lagrange Multiplier test to detect autocorrelation in the residuals. With a *p*-value of 0.63, the test does not reject the null hypothesis of no first order serial correlation.

4.6. Robustness Checks

4.6.1. Alternative Threshold Value

The results of TVAR estimation may be sensitive to the threshold value chosen. Based on equation (4.17), we choose the excess bond premium value in our sample period that minimizes the log determinant of the variance-covariance matrix of the residuals as the threshold value. In this section, we use zero as our threshold value and re-estimate the model. According to equation (4.19), a positive excess bond premium value implies that credit supply conditions are tight because lenders are demanding a risk premium beyond the expected default losses. Conversely, a negative excess bond premium value implies that credit supply conditions are loose. With a threshold value of zero, the number of observations in the tight credit regime increases to 69 while the number of observations in the loose credit regime falls to 90. Figure 4.9 illustrates the cumulative impulse responses of output growth to negative tax shocks. Figure 4.10 presents the cumulative impulse responses of output growth to positive government spending shocks. Table 4.5 reports the cumulative impulse responses at different horizons.

As shown in Figure 4.9, in the tight credit regime, the impact output growth after a negative tax shock of 1% of GDP is 0.785%. The output response becomes statistically insignificant shortly after two quarters. In the loose credit regime, after a negative tax shock of 1% of GDP, output grows by 0.407% in the loose credit regime on impact. The output effect is not significantly different from zero for the rest of the forecast horizon.

In Figure 4.10, for a positive government spending shock of 1% of GDP, the output response is stronger in the loose credit regime. In the tight credit regime, there is an initial rise of 0.519% in output on impact. Output growth increases to 1.196% after eight quarters. In the loose credit regime, the impact output growth is 1.245%. After eight quarters, output growth increases to 1.527%.

Subsequently, we compare the output effects of tax cuts and spending increases in each regime. In the tight credit regime, the output response to spending increases stays positive and significant for eight quarters after the shock while the output response to tax cuts is only statistically distinguishable from zero on impact. In addition, output responses to spending increases have much narrower error bands than those to tax cuts. Therefore, tax cuts appear to have less certain output effects spending increases in the tight credit regime, consistent with the findings in section 4.5. In the loose credit regime, the output response to spending increases is much higher than that to tax cuts on impact. In addition, the increase in output after the positive spending shock is statistically significant for ten quarters but the rise in output after tax cuts is statistically significant only on impact. Hence, tax cuts have lower output effects than spending increases in the loose credit regime, which is also consistent with the results in section 4.5. Therefore, spending increases appear to be more effective at stimulating output than tax cuts, especially in the loose credit regime.

4.6.2. National Financial Conditions Credit Subindex

In this section, we employ the National Financial Conditions Credit Subindex (NFCCS) as an alternative threshold variable to check the robustness of our results in section 4.5. The index is constructed by the Federal Reserve Bank of Chicago using various credit condition indicators.[8] Figure 4.11 plots the NFCCS. The ADF test rejects the null hypothesis of a unit root for the NFCCS variable over the sample period 1973Q-2014Q4 (see Table 4.2). The Hansen (1996) nonlinearity tests show that the TVAR system displays threshold effects (see Table 4.3). Because the NFCCS is normalized so that it has a mean of zero and a standard deviation of one, a positive NFCCS value indicates that credit conditions are tighter than average while a negative NFCCS value indicates the opposite. Hence, we choose zero as our threshold value. This gives us 59 observations in the tight credit regimes and 100 observations in the loose credit regime. Figure 4.12 plots the cumulative impulse responses of output growth to negative tax shocks. Figure 4.13 presents the cumulative impulse responses of output growth to positive government spending shocks. Table 4.6 reports the cumulative impulse responses over different forecast horizons.

As one can observe from Figure 4.12, in the tight credit regime, the output effect after a tax cut of 1% of GDP is never significantly different from zero throughout the

[8] For more information about the NFCCS, please see Brave and Butters (2012).

forecast horizon. In the loose credit regime, the impact output growth is only 0.115%. After one quarter, we cannot reject the null hypothesis that the output response is zero.

In Figure 4.13, in the tight credit regime, the impact output growth is 0.218% after a positive spending shock of 1% of GDP. The output effect cannot be considered as significantly different from zero after one quarter. In the loose credit regime, the impact output growth is 1.040%. The output response remains positive and significant for three quarters.

Next, we compare the output responses to spending increases with those to tax cuts under different credit conditions. In the tight credit regime, the output response to tax cuts is statistically insignificant over the forecast horizon while the output response to spending increases is statistically significant on impact. Furthermore, the output responses to tax cuts also have notably wider confidence bands than those to spending increases. Therefore, we again find that tax cuts have less certain effects on output than spending increases when credit is tight. In the loose credit regime, the output responses to tax cuts are consistently lower than those to spending increases. Hence, these findings also suggest that spending increases are a more preferable stimulus measure than tax cuts, especially in the loose credit regime.

4.6.3. Excluding 2007Q1-2012Q4

After the start of the Great Recession, the U.S. government has implemented large-scale fiscal stimulus packages to sustain growth and employment. In addition, the Federal Reserve has maintained the interest rate close to zero. To check whether the use of these extraordinary monetary and fiscal policies in the recent financial crisis affects our results in section 4.5, we follow Baum and Koester (2011) and Ferraresi et al. (2013) and re-estimate our model excluding the post-crisis period 2007Q1-2012Q4. For the threshold variable, the ADF test rejects the null hypothesis of a unit root over this shorter sample period 1973Q1-2006Q4 (see Table 4.2). The Hansen (1996) tests reject the null hypothesis that the model is linear (see Table 4.3). The estimated threshold value is 0.32. Figure 4.14 plots the cumulative impulse responses of output growth to negative tax shocks. Figure 4.15 presents the cumulative impulse responses of output growth to positive government spending shocks. Table 4.7 reports the cumulative impulse responses over different forecast horizons.

As depicted in Figure 4.14, in the tight credit regime, the impact output response to a tax shock of 1% GDP is -1.853%. After one quarter, the output response becomes statistically indistinguishable from zero. In the loose credit regime, the output response is statistically insignificant throughout the forecast horizon.

Figure 4.15 shows that, in the tight credit regime, output growth on impact after a positive government spending shock of 1% of GDP is 0.656%. It becomes insignificant after two quarters. In the loose credit regime, the impact output growth is 1.317%. After eight quarters, it rises to 1.422%.

In addition, we compare the effects of tax cuts and spending. In the tight credit regime, the output responses to tax cuts have much wider confidence intervals than those to spending increases. Therefore, the output effects of tax cuts are subject to higher uncertainty than those of spending increases under tight credit conditions. In the loose credit regime, tax cuts generate consistently lower output growth than spending increases over the forecast horizon. Therefore, the results show that that fiscal stimuli based on spending are more effective at spurring output growth than fiscal stimuli based on taxes, especially in the loose credit regime.

4.7. Conclusions

The aim of this chapter is to study the nonlinear effects of tax cuts and government expenditure increases on output under different credit conditions. We employ a TVAR model to capture the nonlinear relationship between the output effects of fiscal policy shocks and credit availability in the economy. In this model, we use the excess bond premium as the threshold variable to proxy for credit supply conditions. The threshold variable is included in the TVAR model to endogenize the regime-switching process. As the Hansen (1996) nonlinearity tests indicate the presence of two different credit regimes, we proceed to estimate our TVAR model and compute the generalized impulse response functions of output to negative tax shocks and positive government spending shocks. The estimation results show that compared with spending increases, tax cuts have either less certain output effects when credit is tight or smaller output effects when credit is loose. Therefore, spending increases appear to be the more preferable fiscal stimulus measure, especially under loose credit conditions.

Table 4.1. Descriptive statistics

Variable	Mean	25% Percentile	Median	75% Percentile	Std. Dev.
Government Spending	0.455	-0.074	0.465	0.934	0.871
Output	0.679	0.322	0.756	1.102	0.825
Net Taxes	0.274	-1.139	0.458	2.907	5.678
Inflation	1.061	0.591	0.878	1.414	0.826
Interest Rate	5.896	3.203	5.515	8.115	3.855
Excess Bond Premium	0.0408	-0.265	-0.031	0.215	0.488

Notes: Government spending, output, and net taxes are expressed in first differences of the natural logarithm while the inflation rate, the federal funds rate, and the excess bond premium are in levels.

Table 4.2. Augmented Dickey-Fuller test

Variable	Sample Period	Specification	*t*-statistic
Excess Bond Premium	1973Q1-2012Q4	2 lags with constant	-4.693 (0.0001)
NFCCS	1973Q1-2012Q4	4 lags with constant	-3.102 (0.0264)
Excess Bond Premium	1973Q1-2006Q4	9 lags with constant	-3.645 (0.0050)

Notes:
The null hypothesis is that the variable has a unit root.
P-values are in parentheses.

Table 4.3. Nonlinearity tests

Variable	Sample Period	Sup-Wald	Avg-Wald	Exp-Wald
Excess Bond Premium	1973Q1-2012Q4	221.63 (0.000)	111.40 (0.000)	106.80 (0.000)
NFCCS	1973Q1-2014Q4	181.32 (0.000)	98.51 (0.000)	86.45 (0.000)
Excess Bond Premium	1973Q1-2006Q4	233.67 (0.000)	130.93 (0.000)	112.87 (0.000)

Notes:
The null hypothesis is that the model is linear.
P-values are in parentheses.

Table 4.4. Cumulative impulse responses of output growth

		Impact	4 Quarters	8 Quarters	12 Quarters	Peak (Quarter)
Tax Shock of -1% GDP	Tight	0.633	0.934	1.313	1.455	1.489(15)
	Loose	0.407	0.231	0.229	0.212	0.407(1)
Tax Shock of -2% GDP	Tight	1.620	1.534	2.032	2.274	2.329(15)
	Loose	0.806	0.439	0.421	0.372	0.806(1)
Spending Shock of +1% GDP	Tight	0.418	1.020	1.199	1.331	1.406(15)
	Loose	1.085	1.185	1.319	1.445	1.531(15)
Spending Shock of +2% GDP	Tight	0.836	2.082	2.560	2.891	3.085(15)
	Loose	2.170	2.311	2.559	2.800	2.969(15)

Table 4.5. Cumulative impulse responses of output growth (threshold value = 0)

		Impact	4 Quarters	8 Quarters	12 Quarters	Peak (Quarter)
Tax Shock of -1% GDP	Tight	0.785	1.188	1.579	1.659	1.659(12)
	Loose	0.407	0.231	0.229	0.212	0.247(5)
Tax Shock of -2% GDP	Tight	1.636	1.828	2.288	2.412	2.412(12)
	Loose	0.806	0.439	0.421	0.372	0.468(5)
Spending Shock of +1% GDP	Tight	0.519	1.026	1.196	1.315	1.394(15)
	Loose	1.245	1.424	1.527	1.629	1.706(15)
Spending Shock of +2% GDP	Tight	1.038	2.041	2.368	2.593	2.746(15)
	Loose	2.490	2.828	3.006	3.185	3.325(15)

Table 4.6. Cumulative impulse responses of output growth (threshold variable: NFCCS)

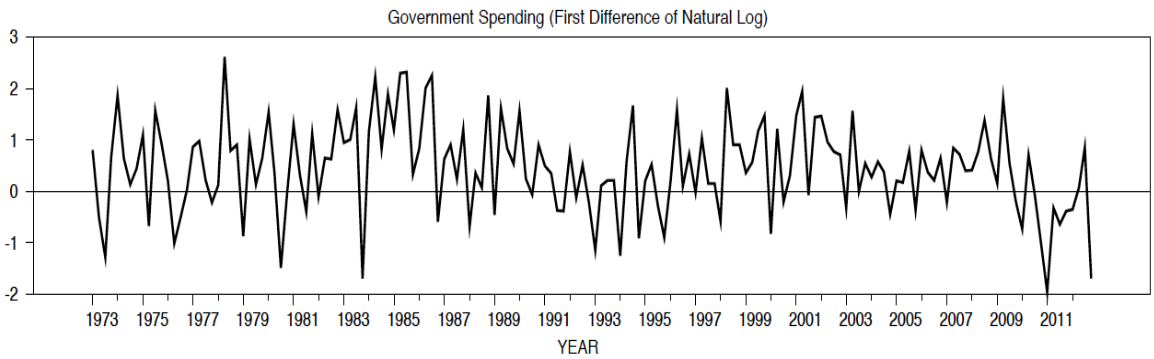
		Impact	4 Quarters	8 Quarters	12 Quarters	Peak (Quarter)
Tax Shock of -1% GDP	Tight	0.632	1.209	1.794	2.175	2.366(15)
	Loose	0.115	0.110	0.100	0.106	0.120(15)
Tax Shock of -2% GDP	Tight	1.054	2.469	3.555	4.266	4.627(15)
	Loose	0.301	0.418	0.430	0.438	0.455(15)
Spending Shock of +1% GDP	Tight	0.218	-0.183	0.354	0.791	1.064(15)
	Loose	1.040	1.306	1.581	1.809	1.936(15)
Spending Shock of +2% GDP	Tight	0.436	-0.492	0.526	1.420	2.003(15)
	Loose	2.079	2.623	3.163	3.607	3.859(15)

Table 4.7. Cumulative impulse responses of output growth (sample period: 1973Q1-2006Q4)

		Impact	4 Quarters	8 Quarters	12 Quarters	Peak (Quarter)
Tax Shock of -1% GDP	Tight	-1.853	-0.186	2.129	3.282	3.685(15)
	Loose	0.166	0.091	-0.012	-0.122	0.166(1)
Tax Shock of -2% GDP	Tight	-3.911	-1.427	3.002	5.209	5.870(15)
	Loose	0.378	0.154	-0.110	-0.369	0.378(1)
Spending Shock of +1% GDP	Tight	0.656	0.995	1.145	1.256	1.317(15)
	Loose	1.000	1.183	1.422	1.586	1.678(15)
Spending Shock of +2% GDP	Tight	1.317	2.144	2.658	2.961	3.108(15)
	Loose	2.000	2.370	2.853	3.184	3.369(15)

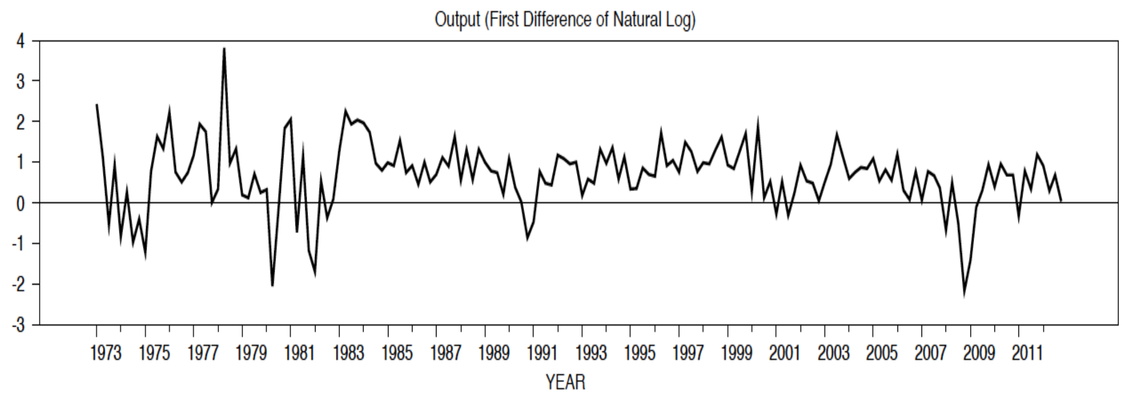
Figure 4.1. Data series

Panel A



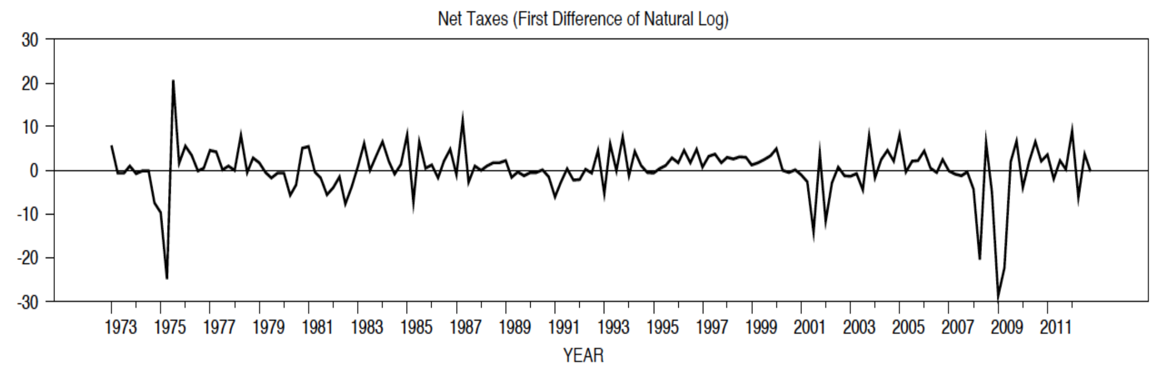
Source: Bureau of Economic Analysis

Panel B



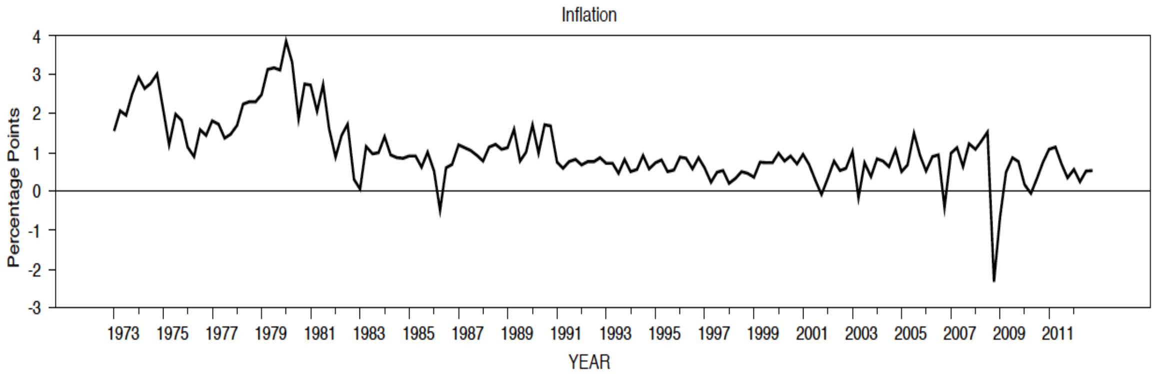
Source: Bureau of Economic Analysis

Panel C



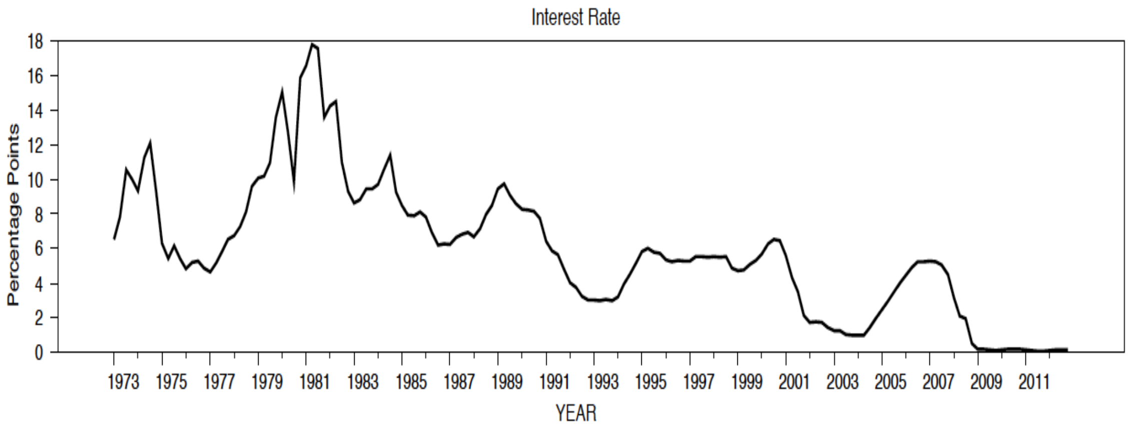
Source: Bureau of Economic Analysis

Panel D



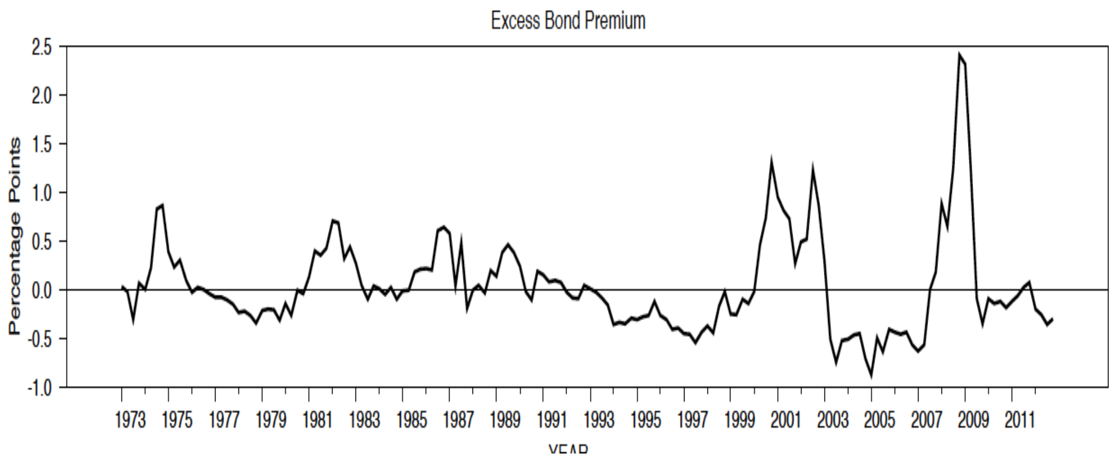
Source: Federal Reserve

Panel E



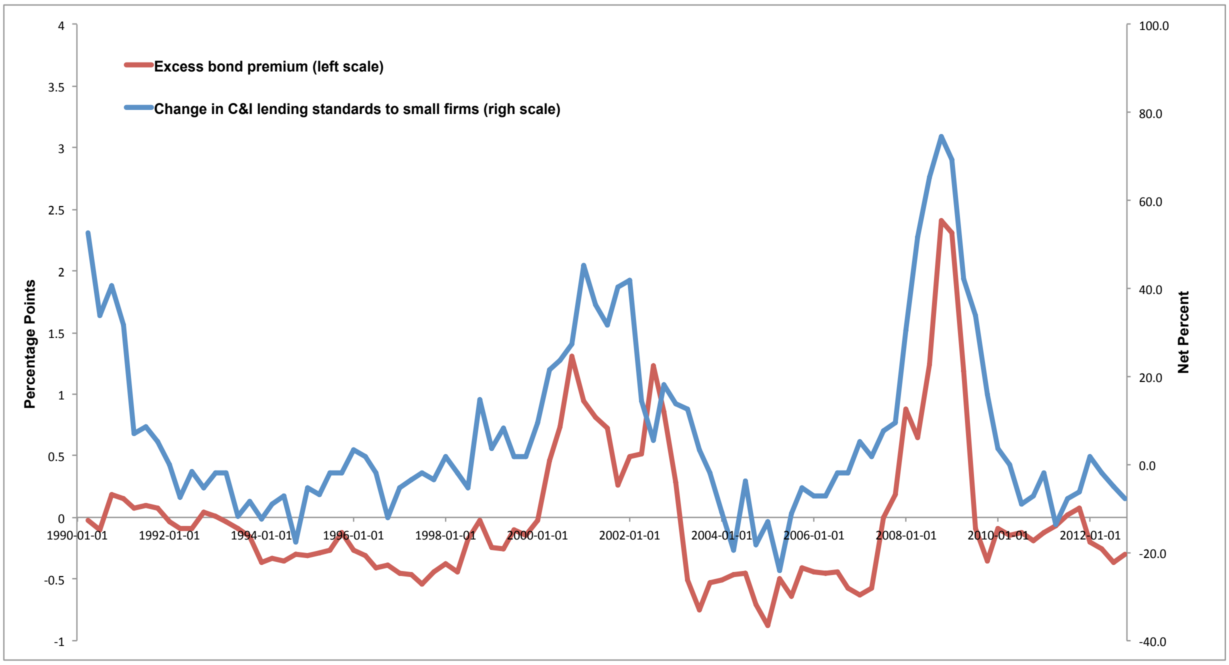
Source: Federal Reserve

Panel F



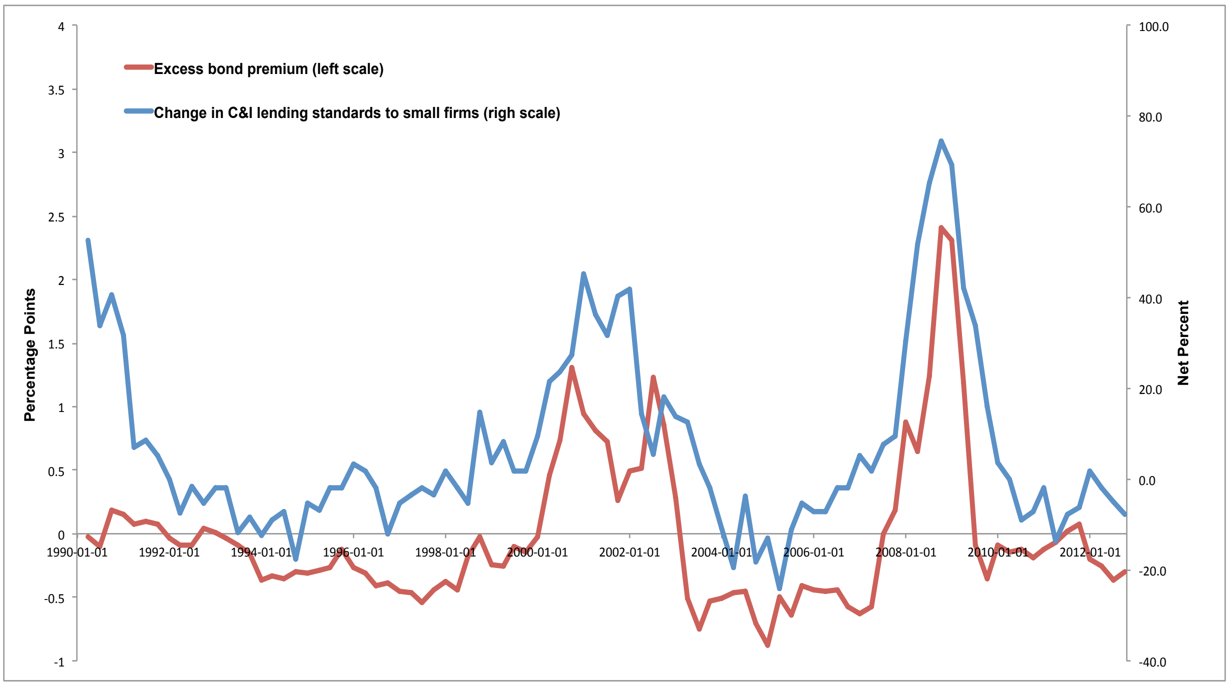
Source: Gilchrist and Zakrajsek (2012)

Figure 4.2. Excess bond premium and changes in lending standards to large and middle-market firms



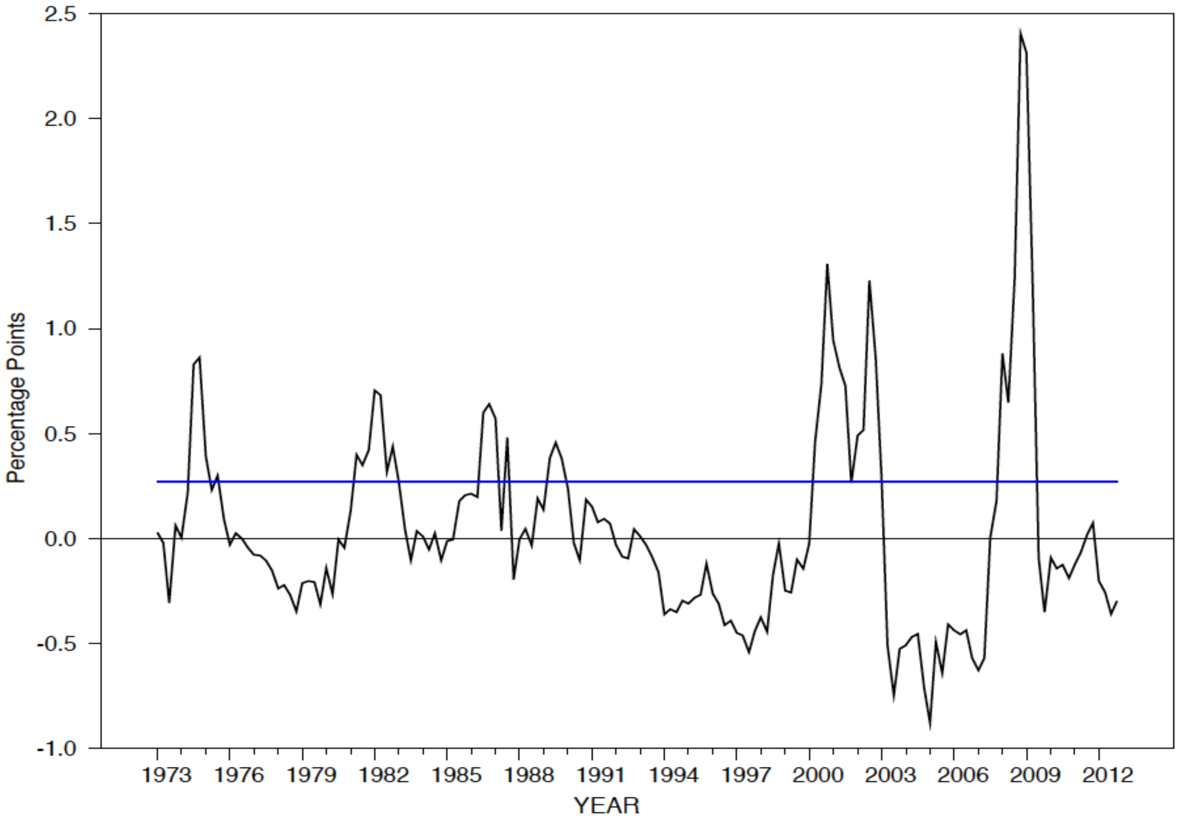
Sources: Gilchrist and Zakrajsek (2012) and Senior Loan Officer Opinion Survey on Bank Lending Practices.

Figure 4.3. Excess bond premium and changes in lending standards to small firms



Sources: Gilchrist and Zakrajsek (2012) and Senior Loan Officer Opinion Survey on Bank Lending Practices.

Figure 4.4. Excess bond premium and estimated threshold value

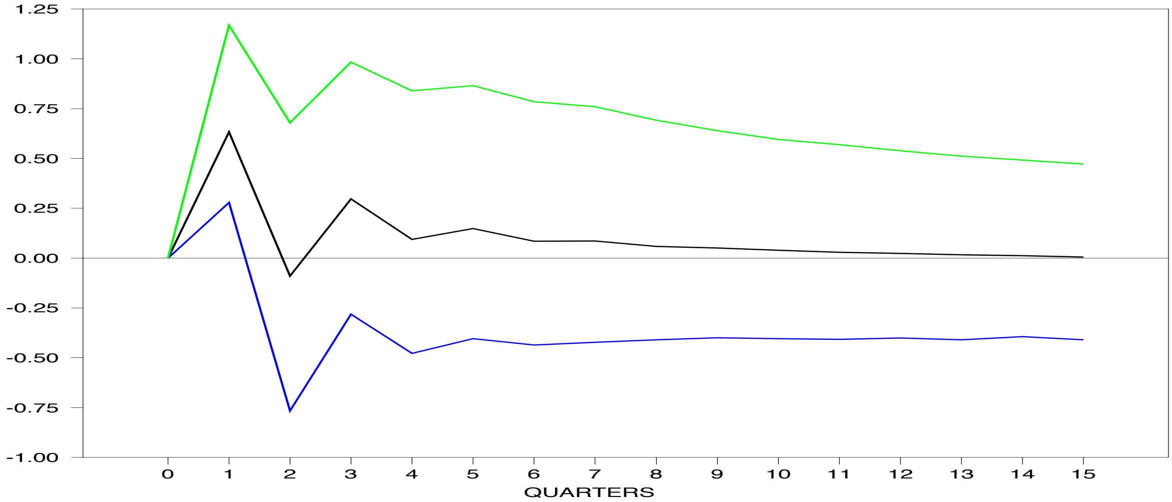


Note: The blue line is the estimated threshold value
Source: Gilchrist and Zakrajsek (2012) and author's calculations.

Figure 4.5. Impulse responses of output growth to tax shocks

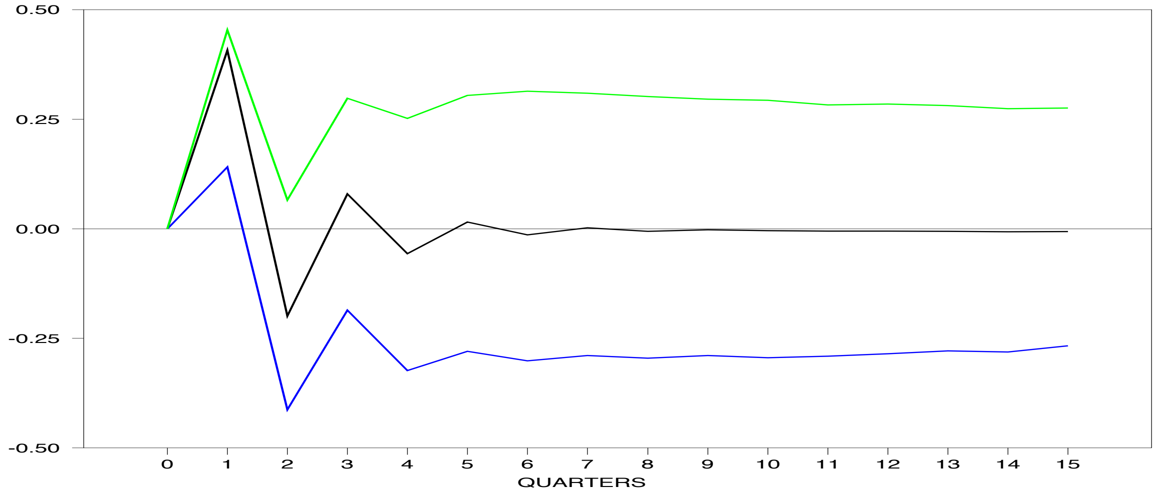
-1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

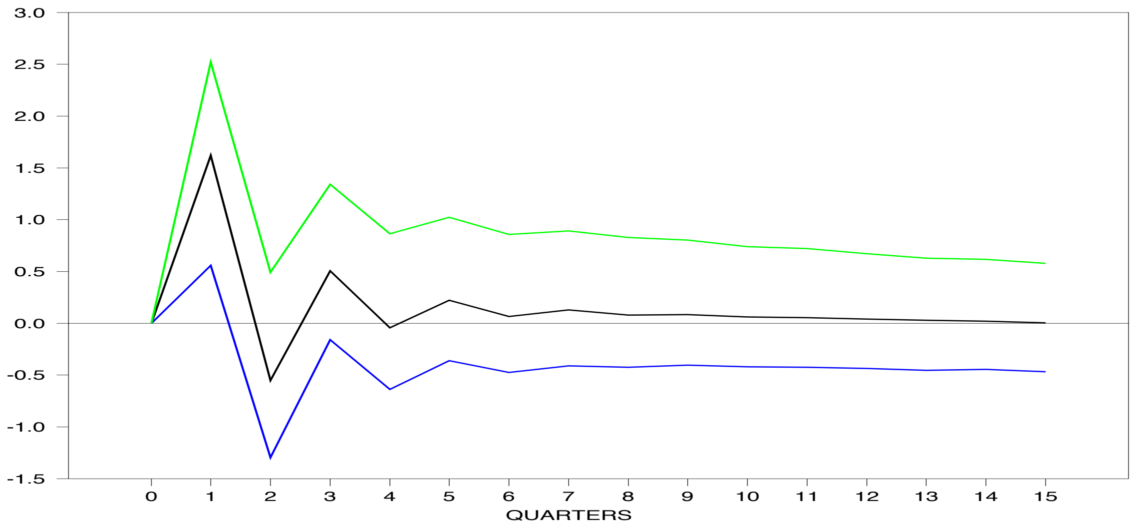
Loose Credit



Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

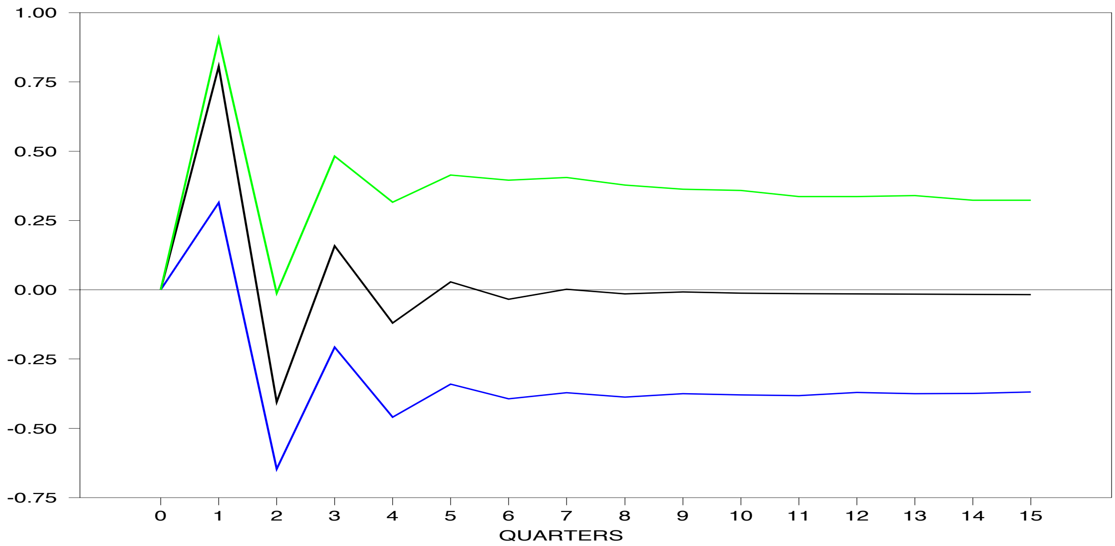
-2% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

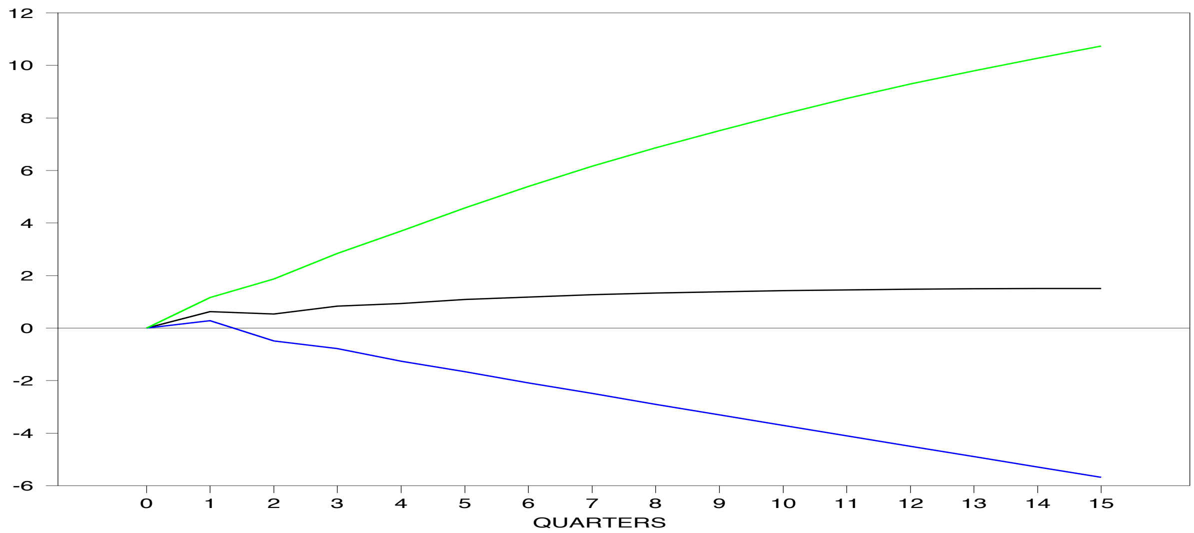


Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.6. Cumulative impulse responses of output growth to tax shocks

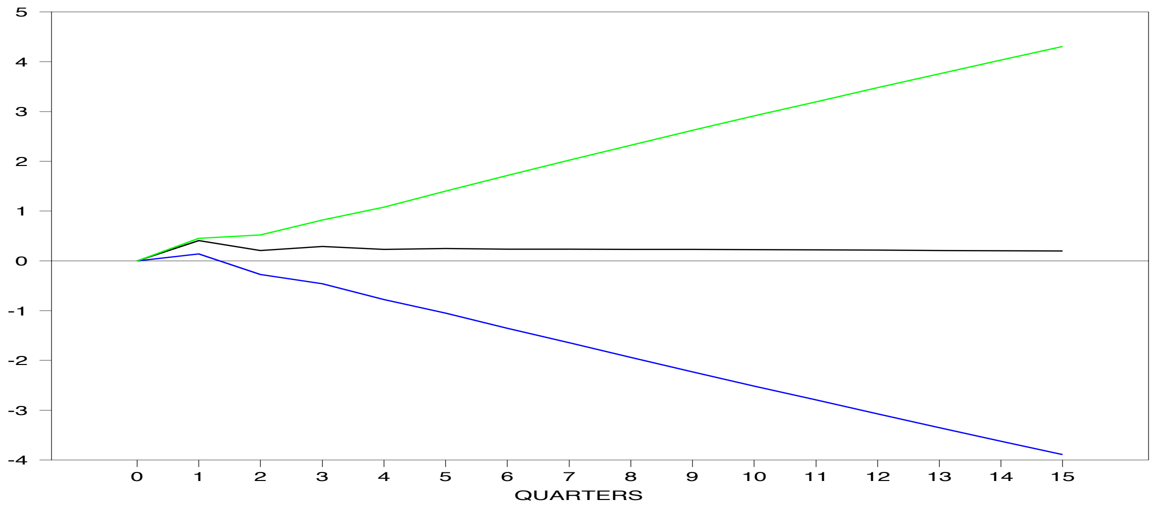
-1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

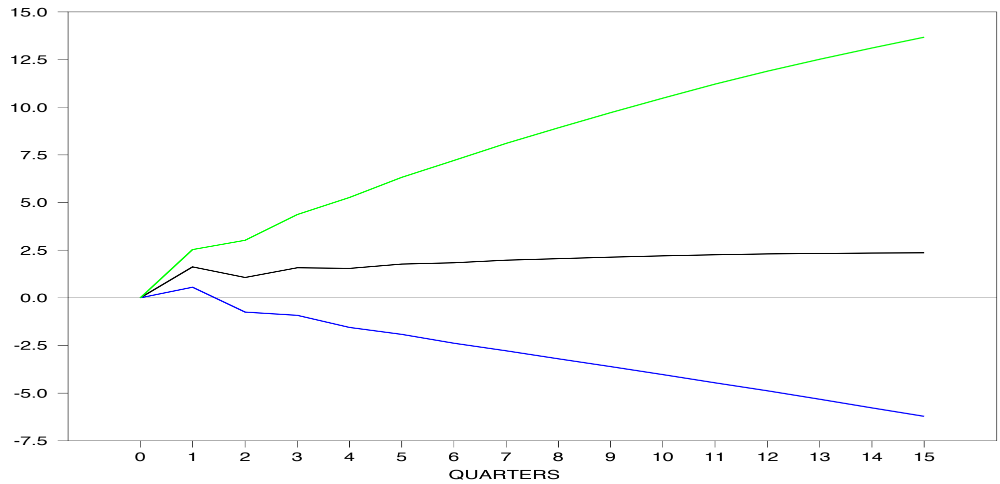
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

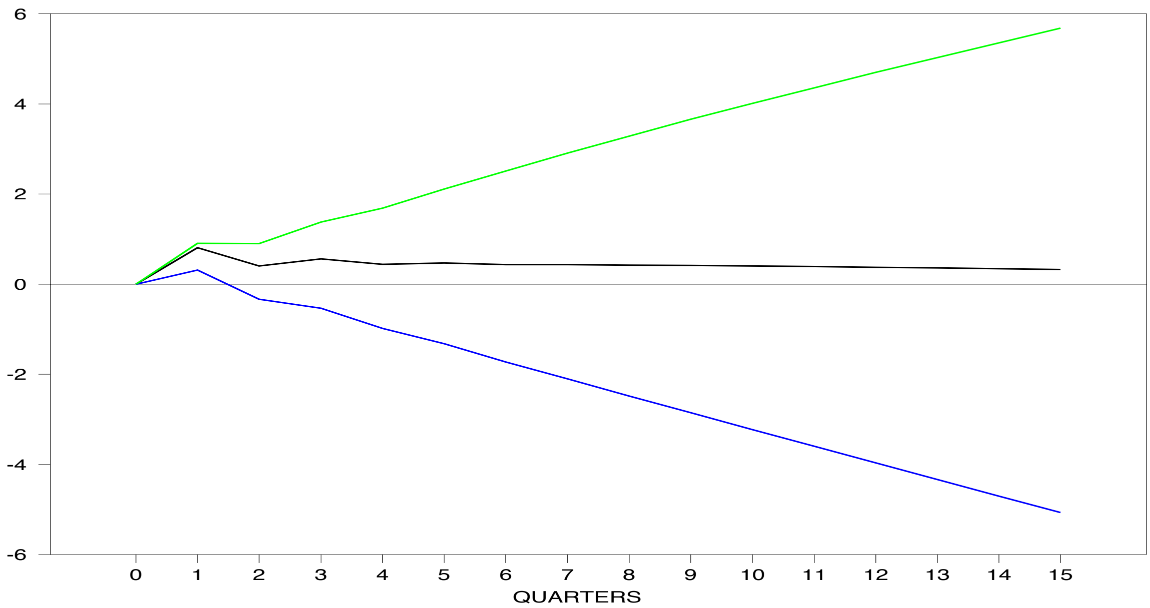
-2% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

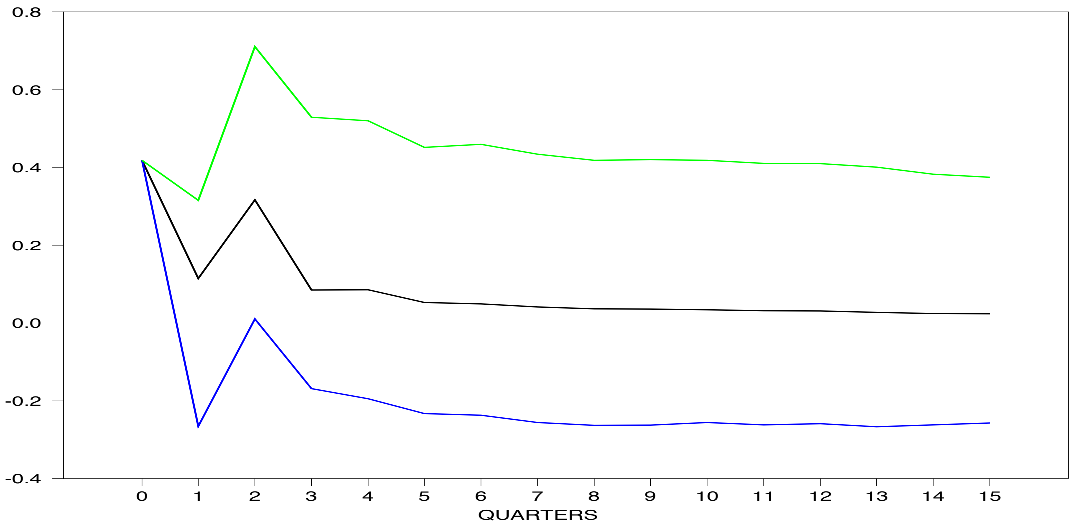


Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.7. Impulse responses of output growth to spending shocks

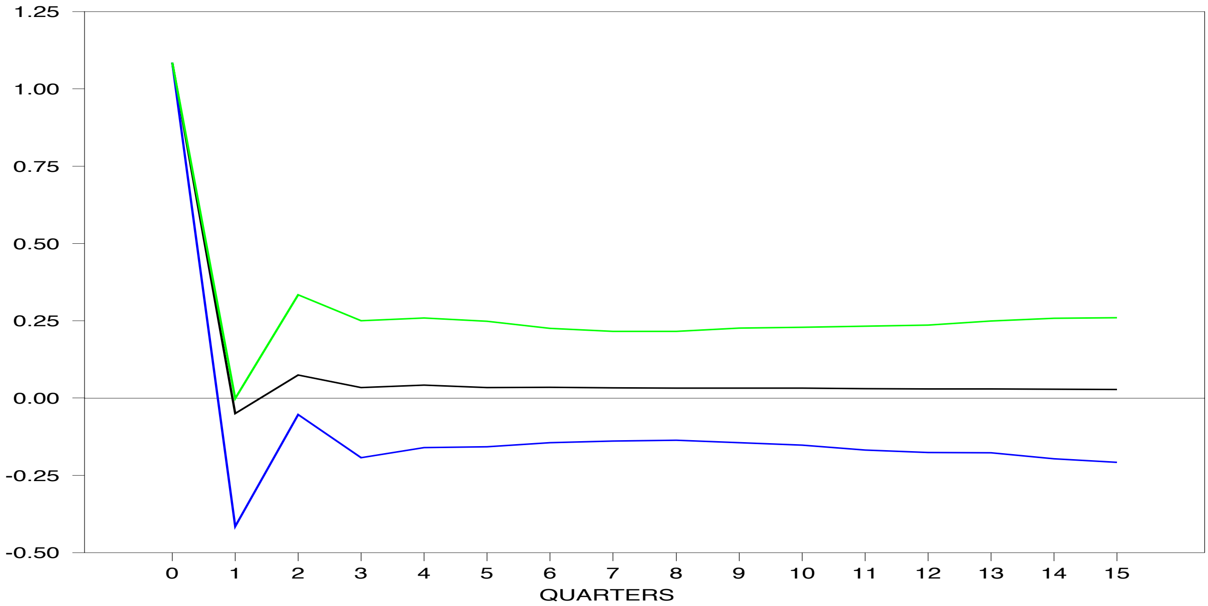
+1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

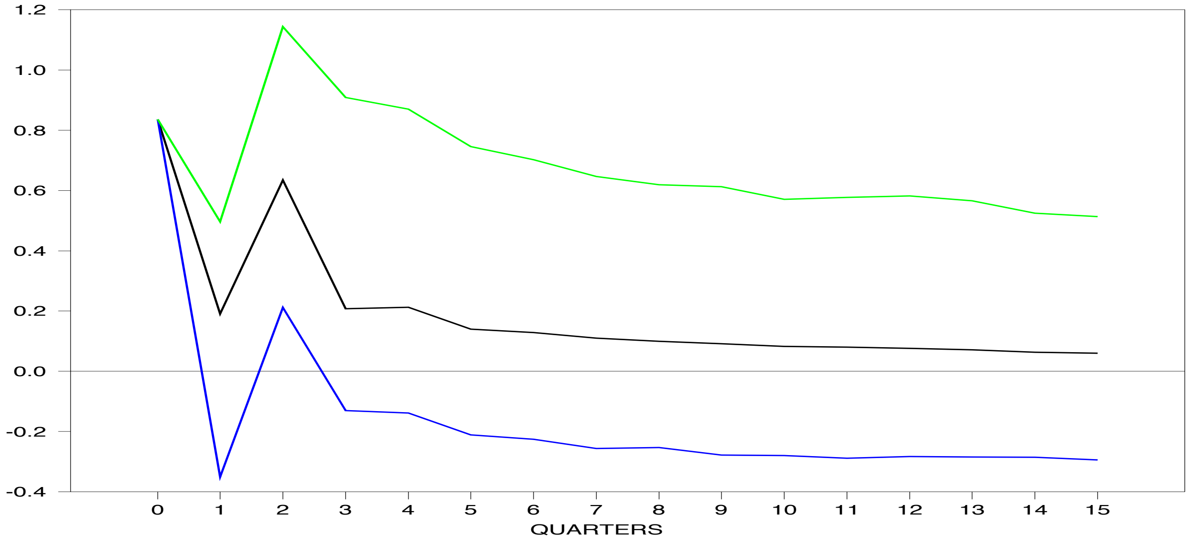
Loose Credit



Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

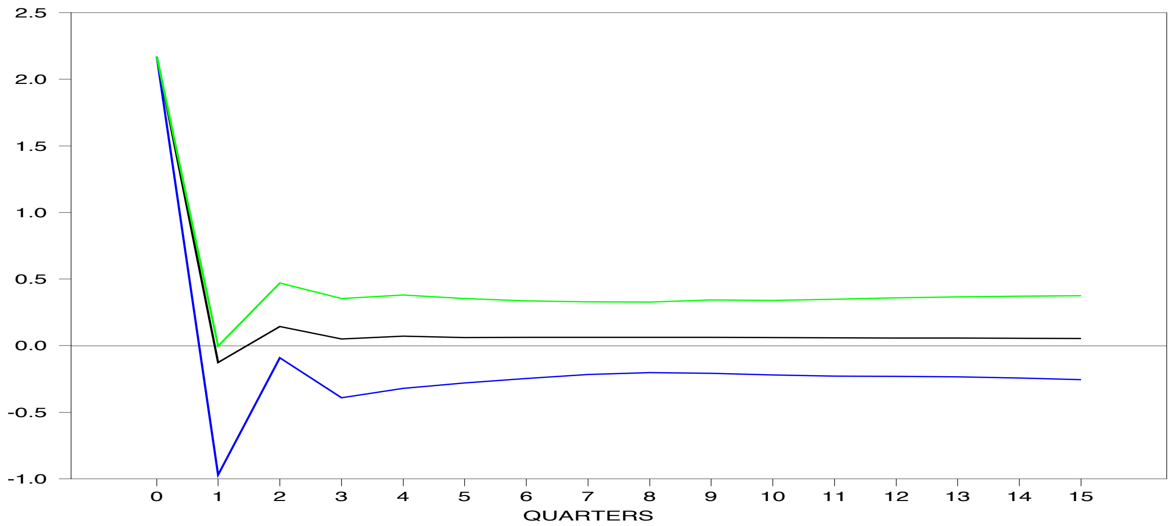
+2% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

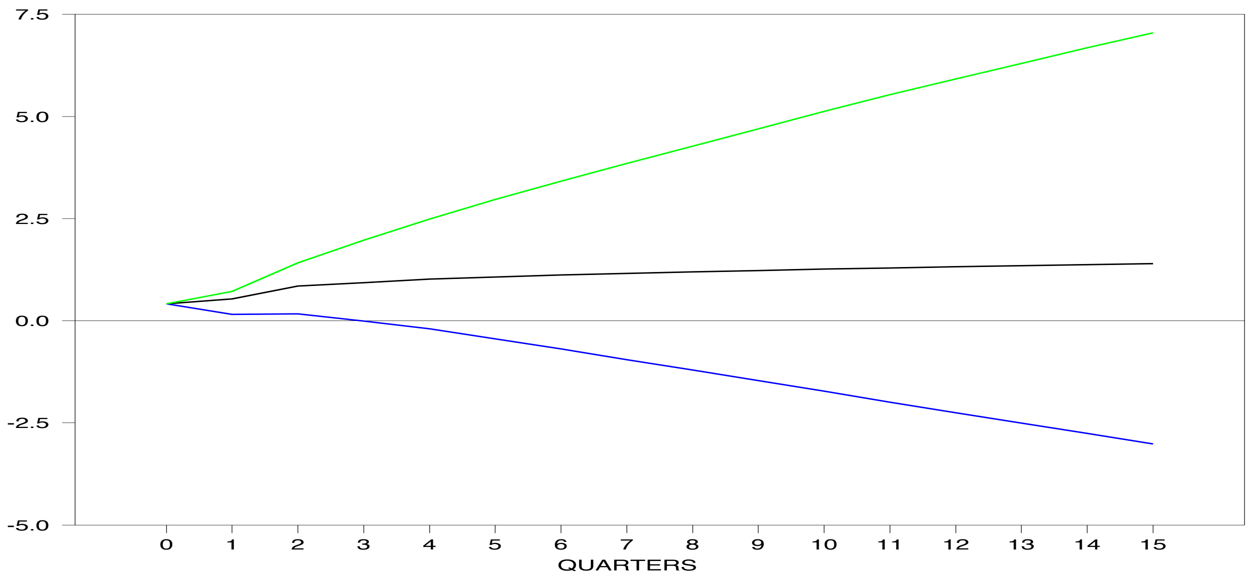


Source: Author's calculations.
Notes: The black line represents the impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.8. Cumulative impulse responses of output growth to spending shocks

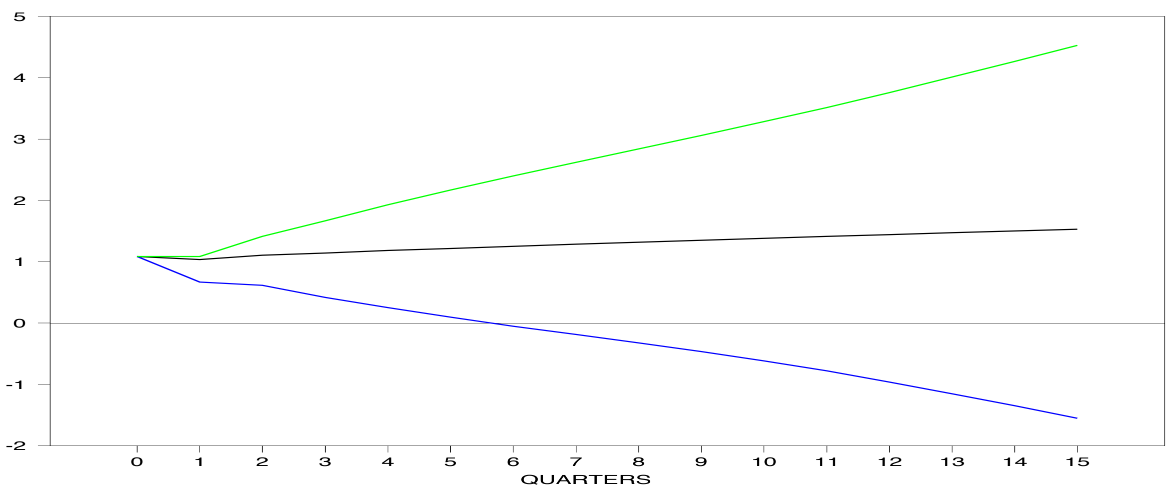
+1% GDP

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

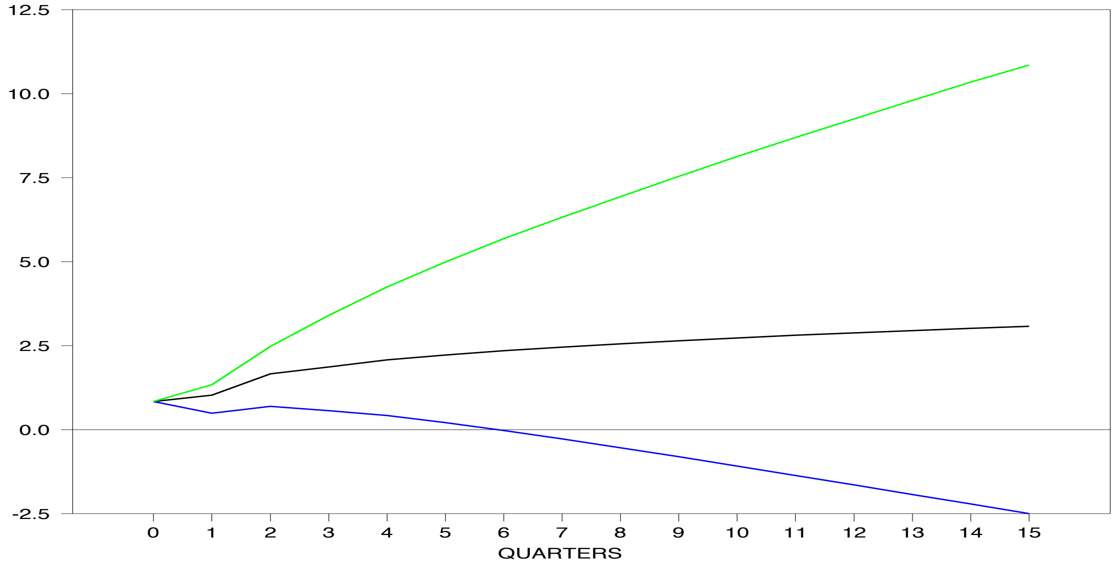
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

+2% GDP

Tight Credit



Source: Author's calculations.
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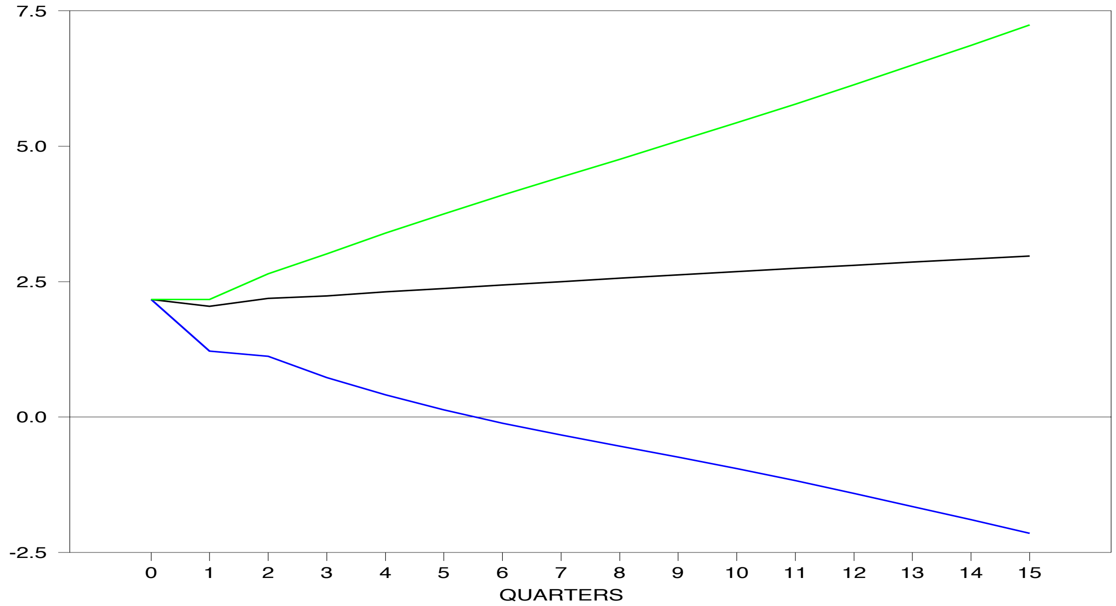
Loose Credit

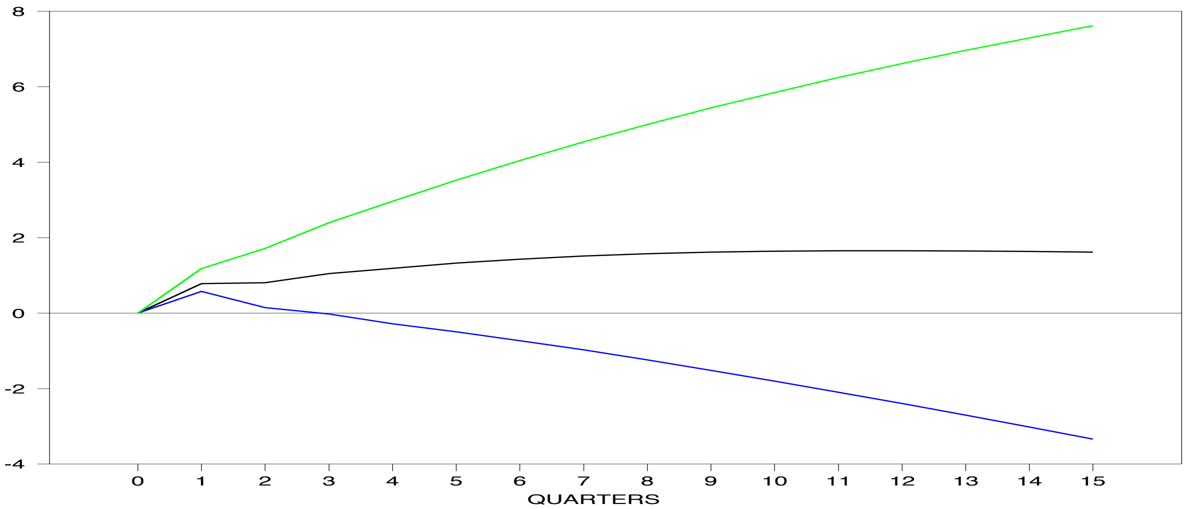


Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.9. Cumulative impulse responses of output growth to tax shocks (threshold value=0)

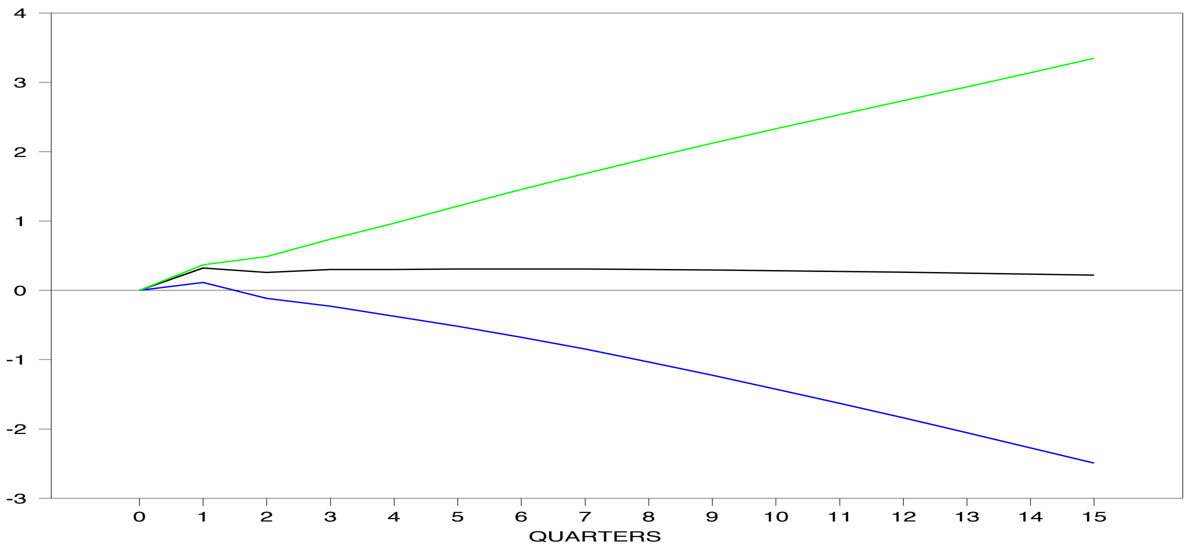
-1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

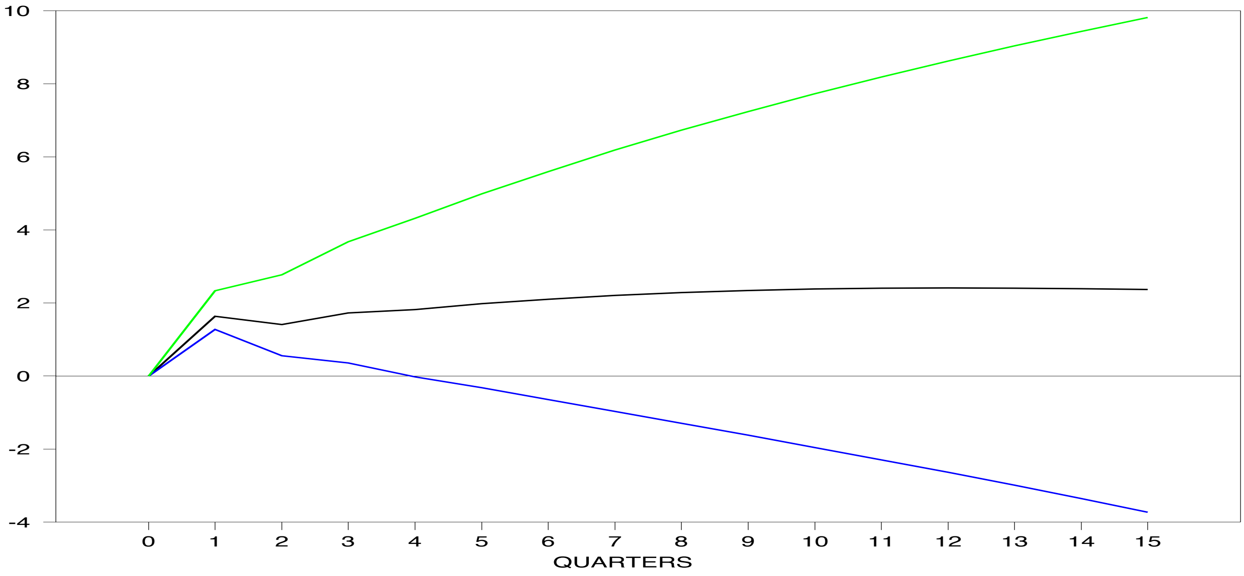
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

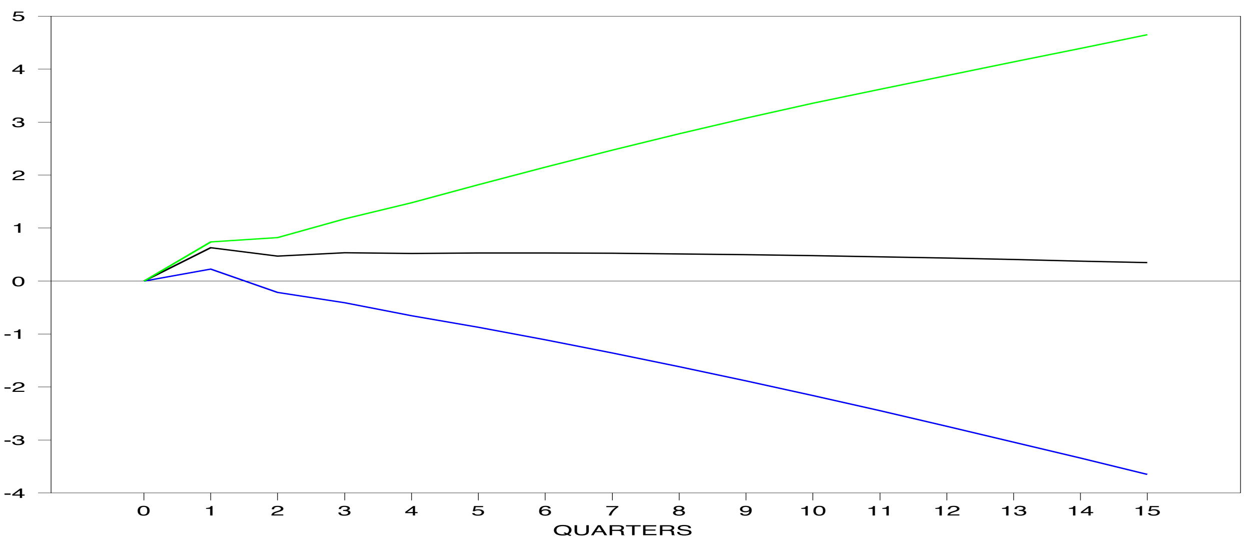
-2% GDP Shock

Tight Credit



Source: Author’s calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

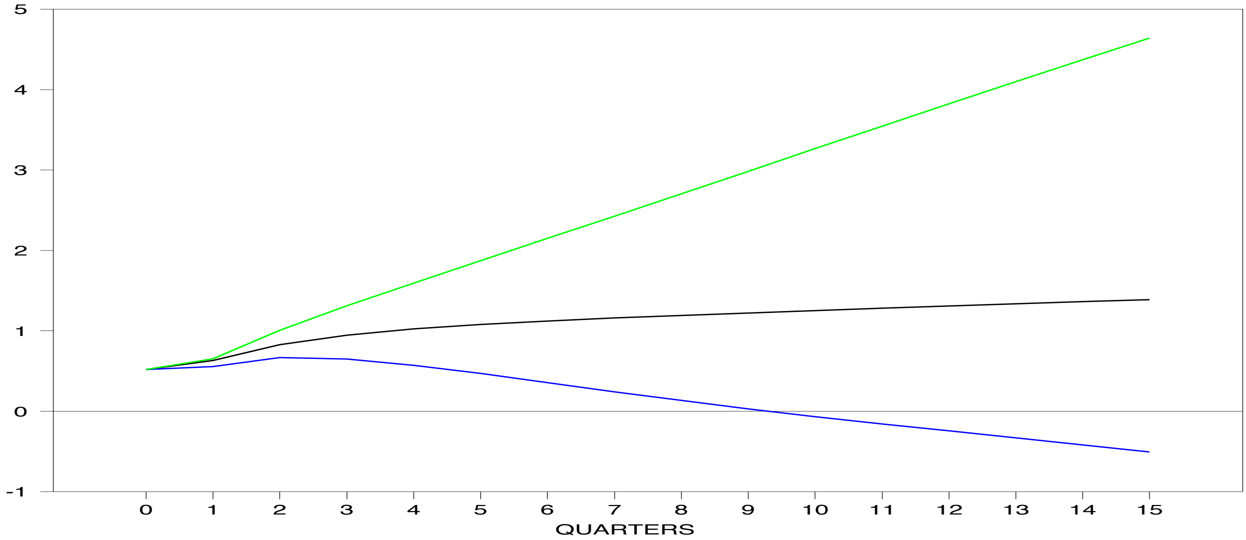


Source: Author’s calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.10. Cumulative impulse responses of output growth to spending shocks (threshold value=0)

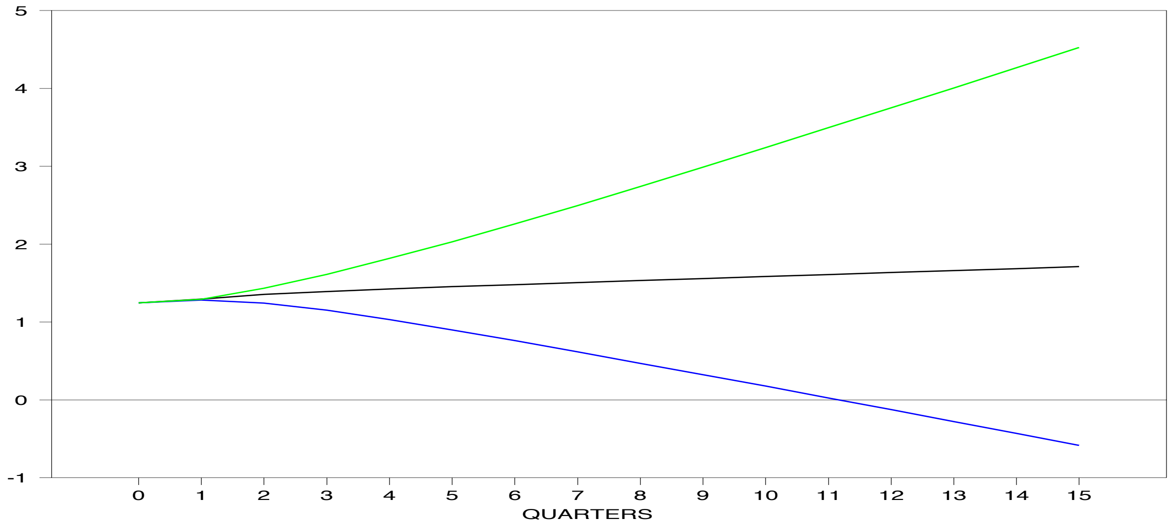
+1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

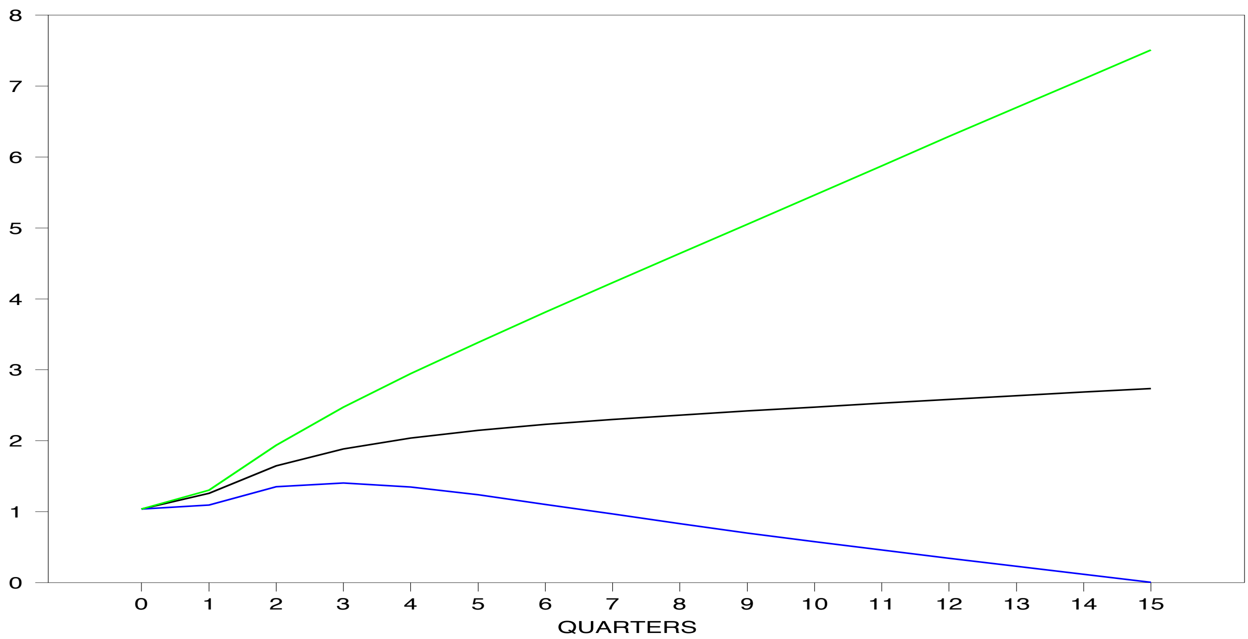
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

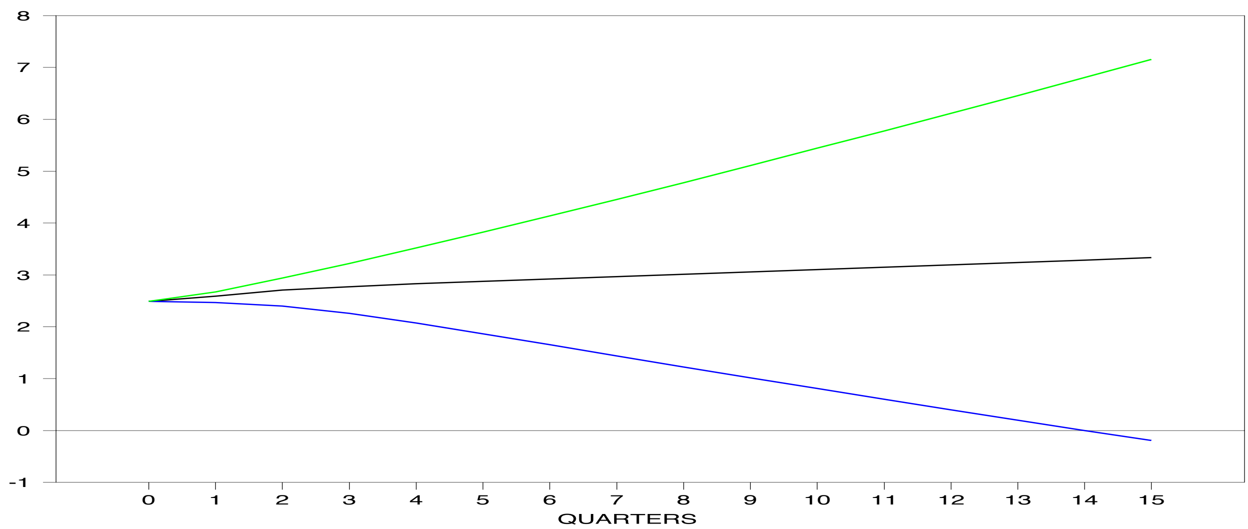
+2% GDP Shock

Tight Credit



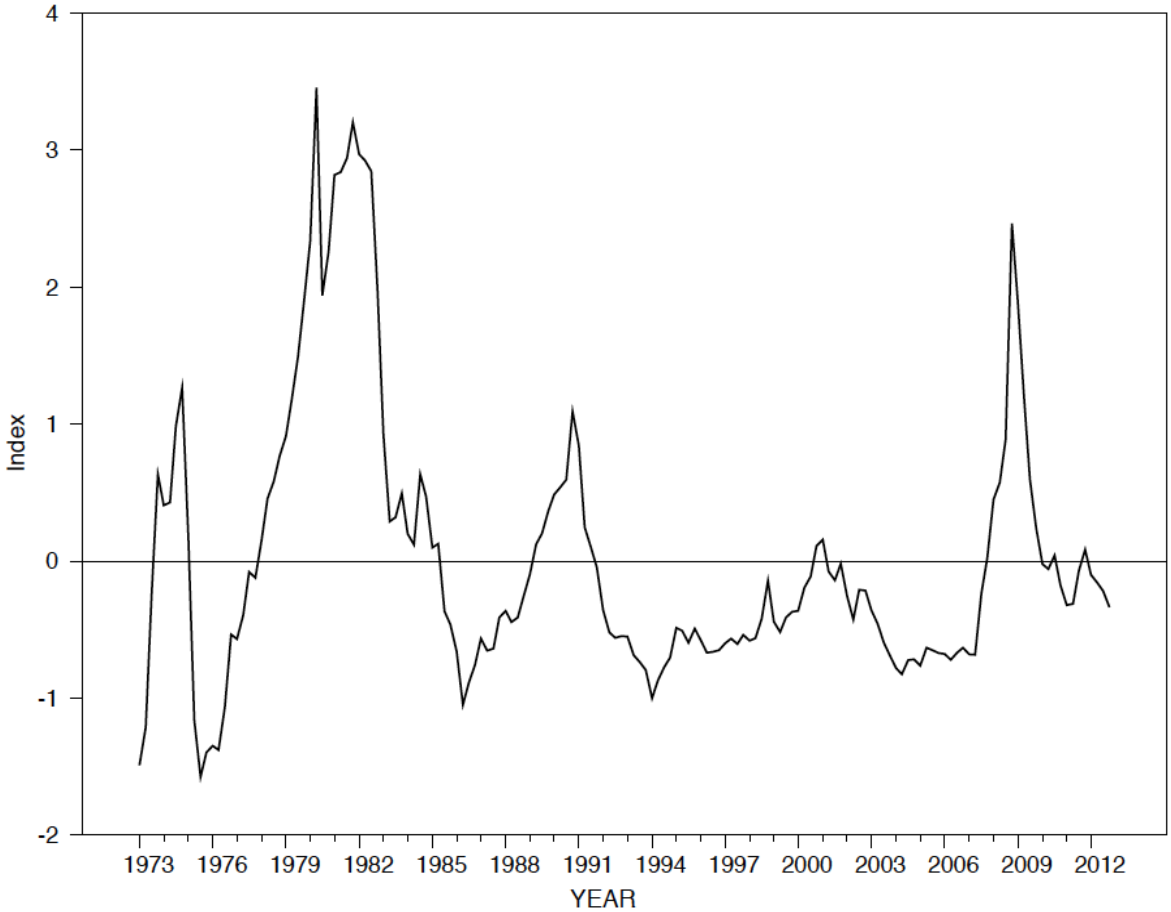
Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response, and the green line and the blue line represent the 95% confidence interval.

Figure 4.11. National Financial Conditions Credit Subindex

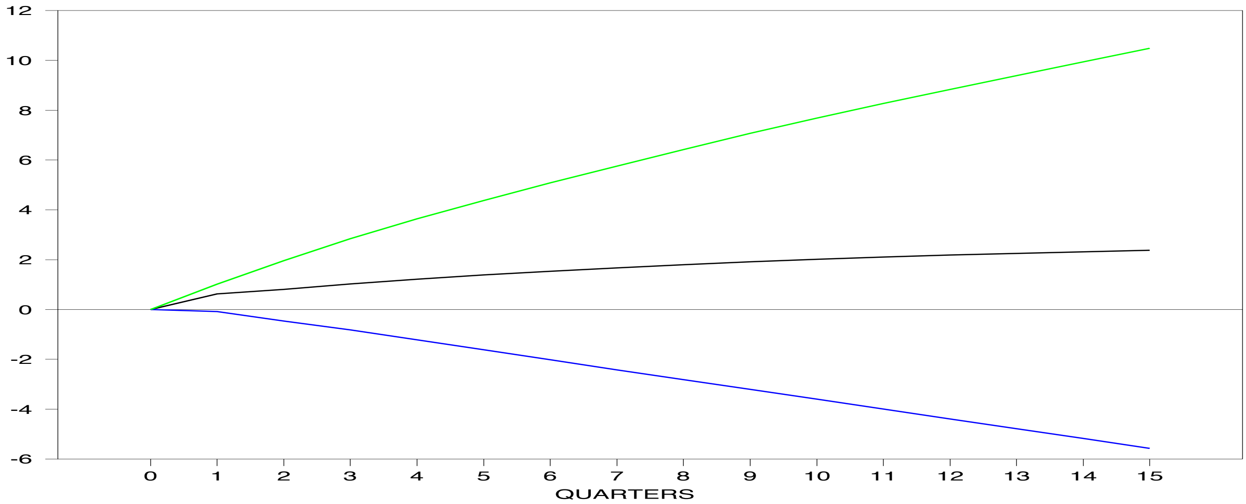


Source: The Federal Reserve Bank of Chicago

Figure 4.12. Cumulative impulse responses of output growth to tax shocks (threshold variable: NFCCS)

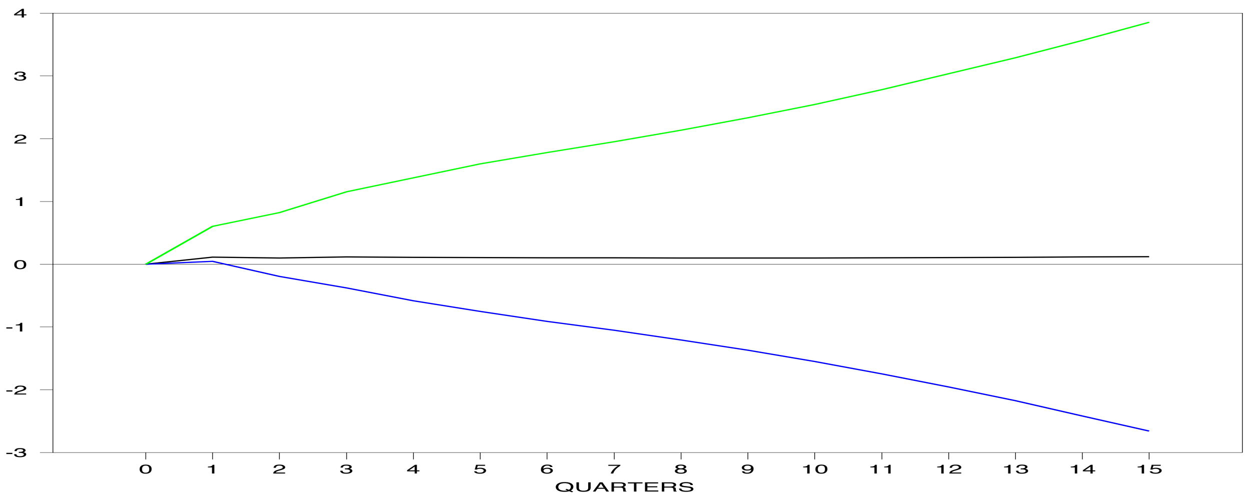
-1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

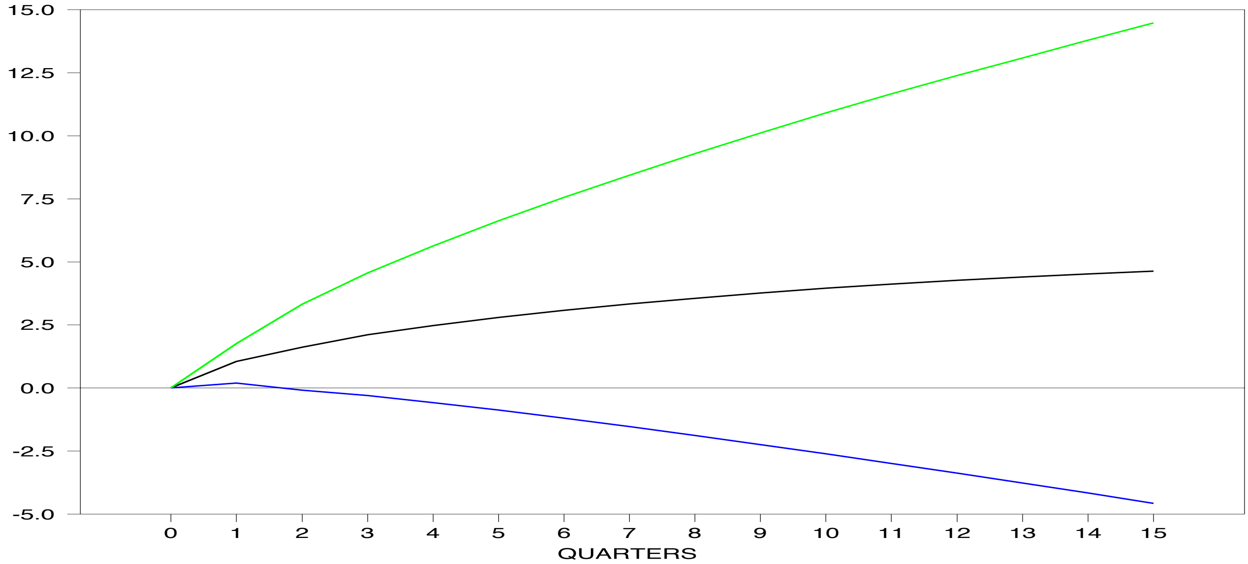
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

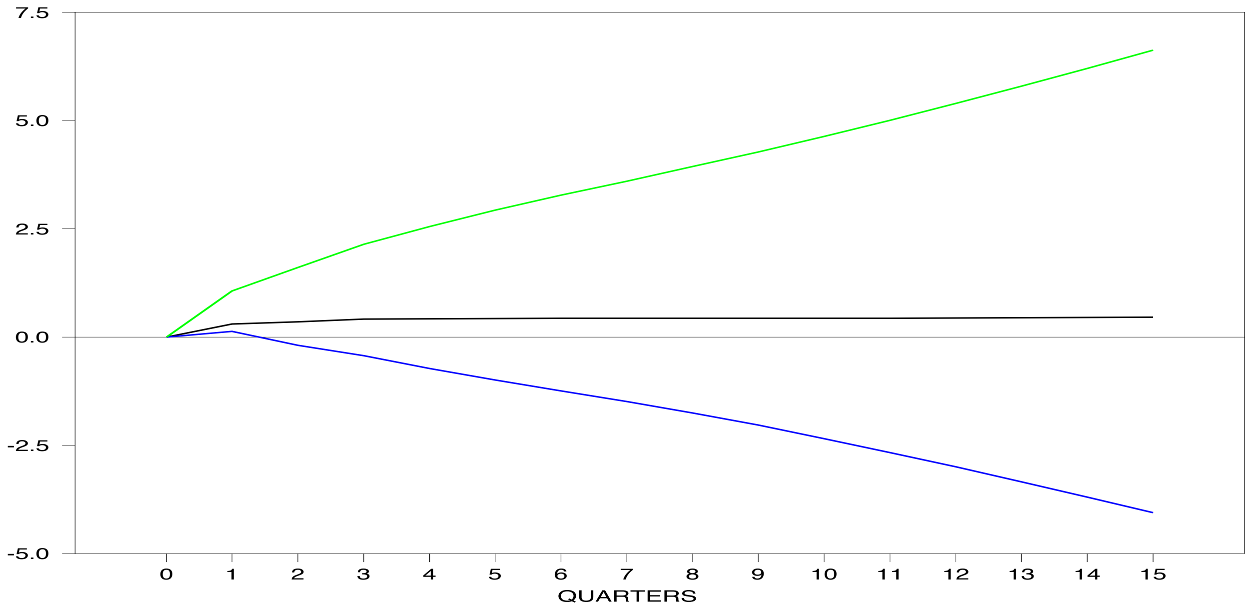
-2% GDP Shock

Tight Credit



Source: Author’s calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

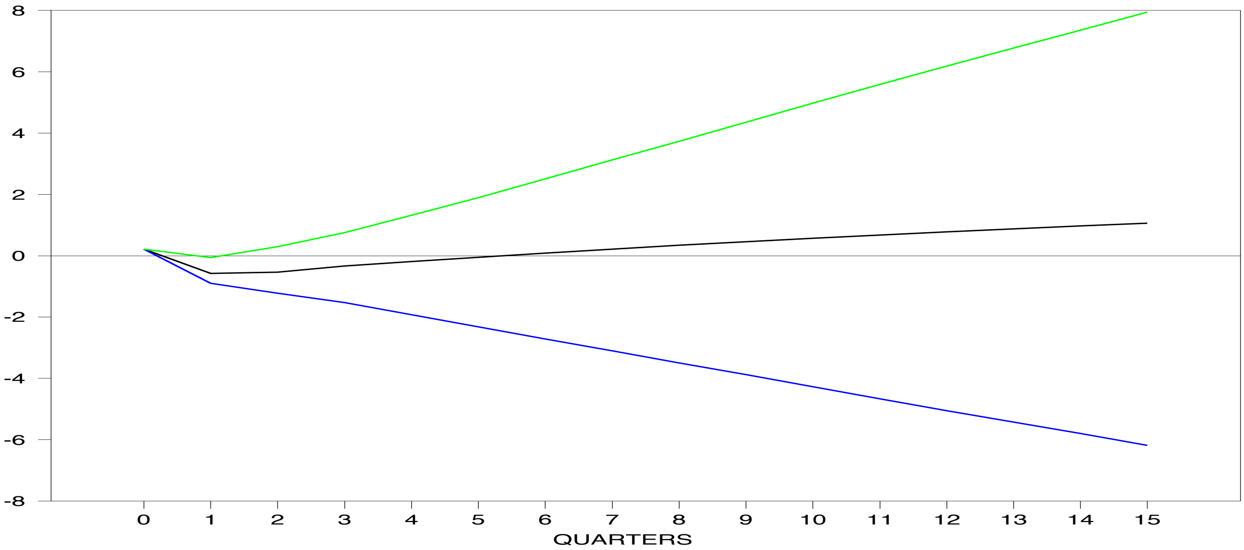


Source: Author’s calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.13. Cumulative impulse responses of output growth to spending shocks (threshold variable: NFCCS)

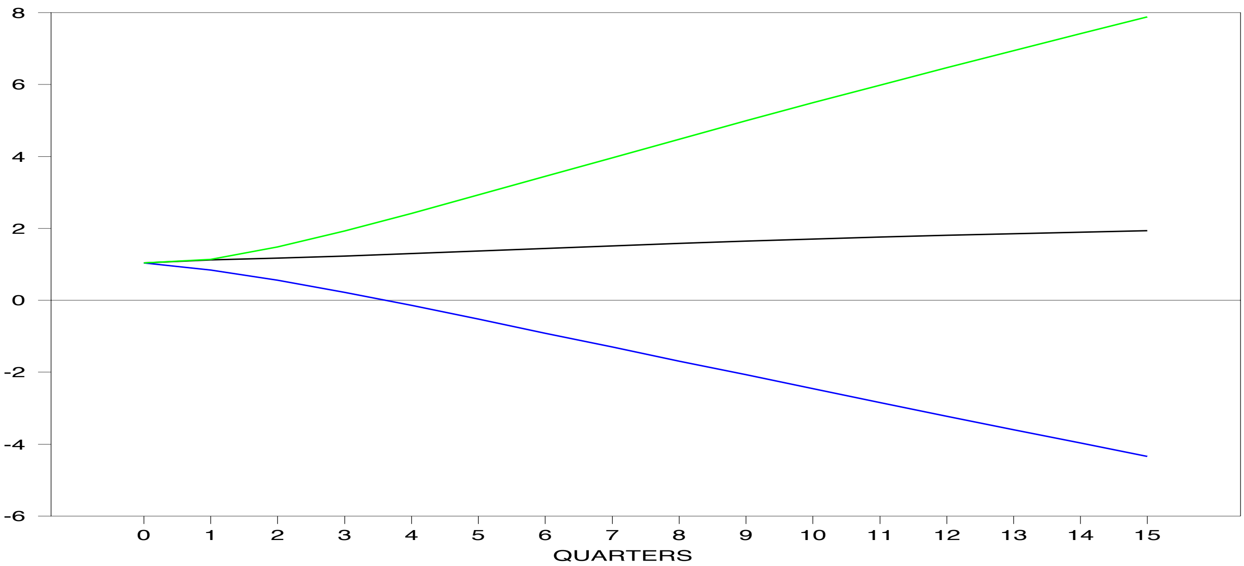
+1% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

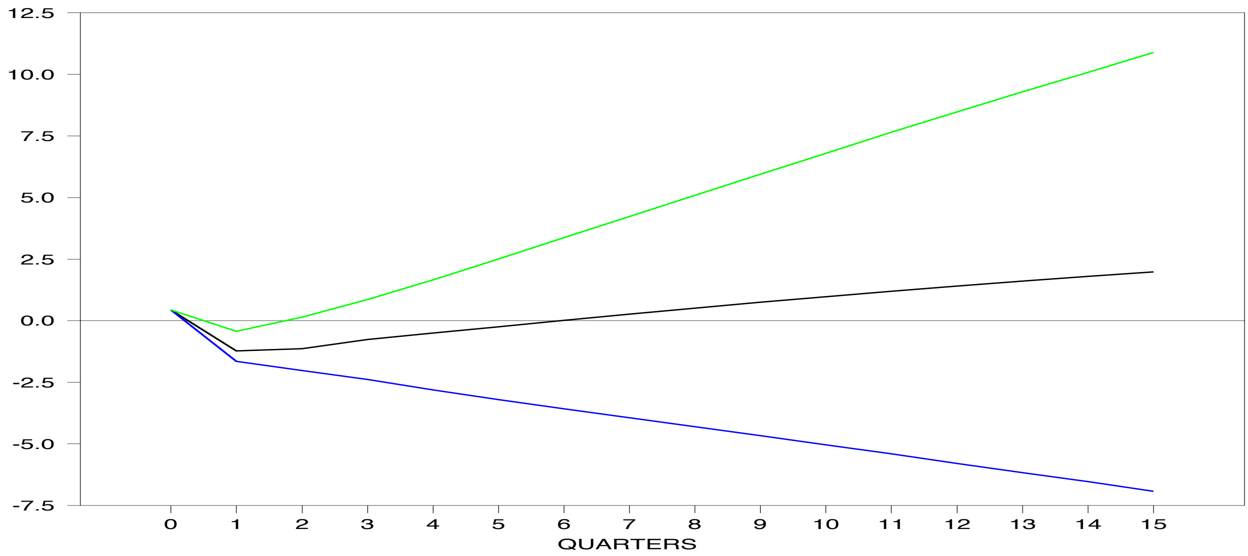
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

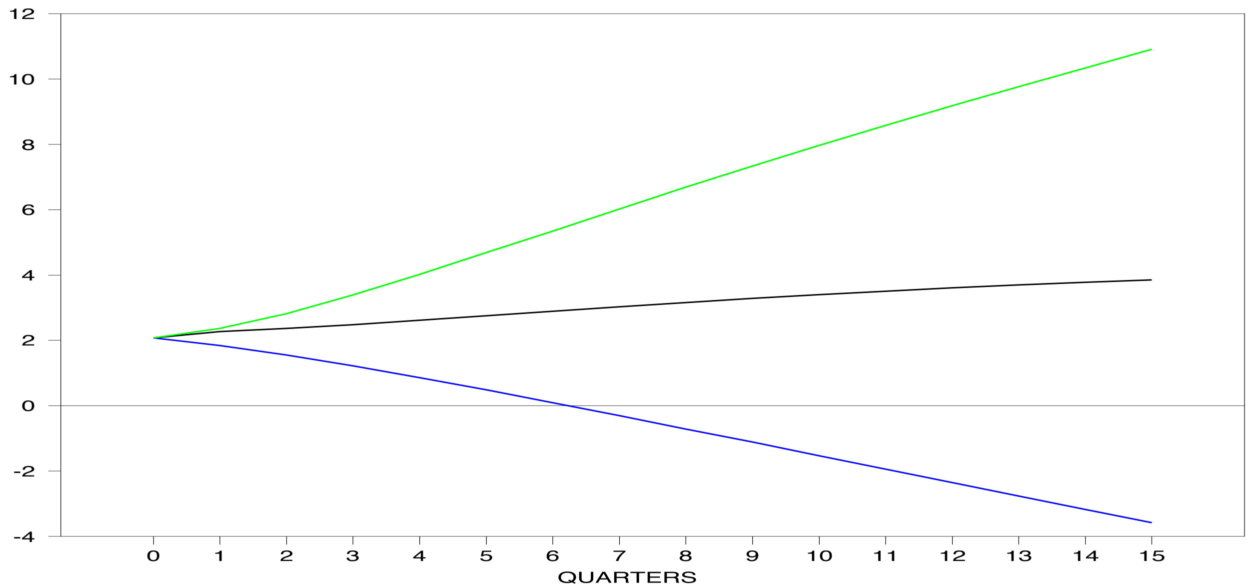
+2% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

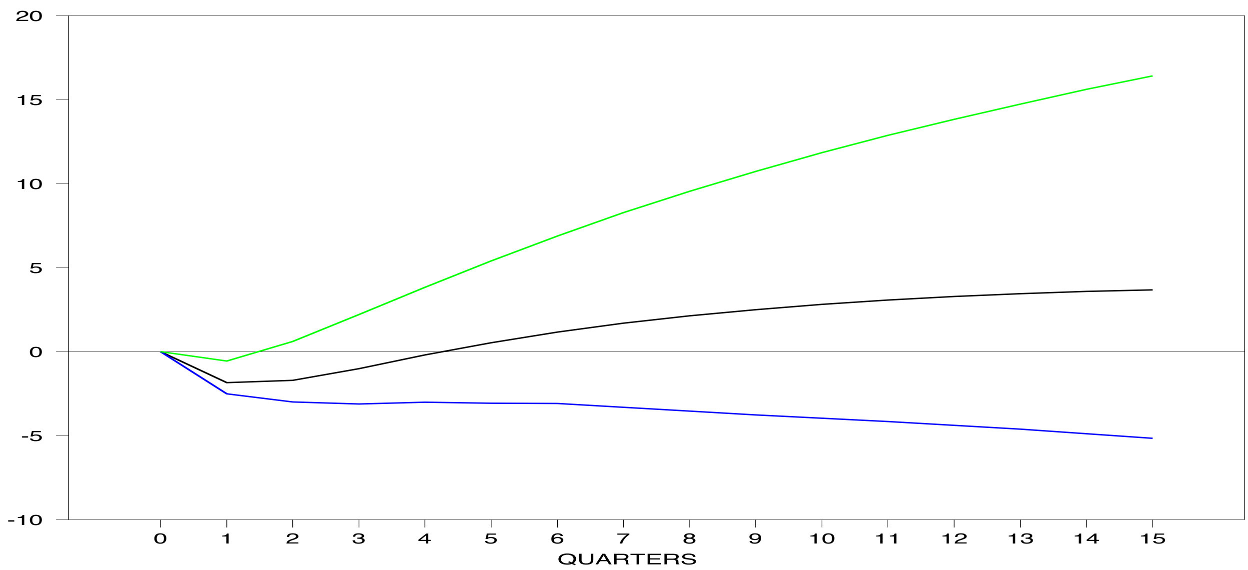


Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.14. Cumulative impulse responses of output growth to tax shocks (1973Q1-2006Q4)

-1% GDP Shock

Tight Credit



Source: Author's calculations.
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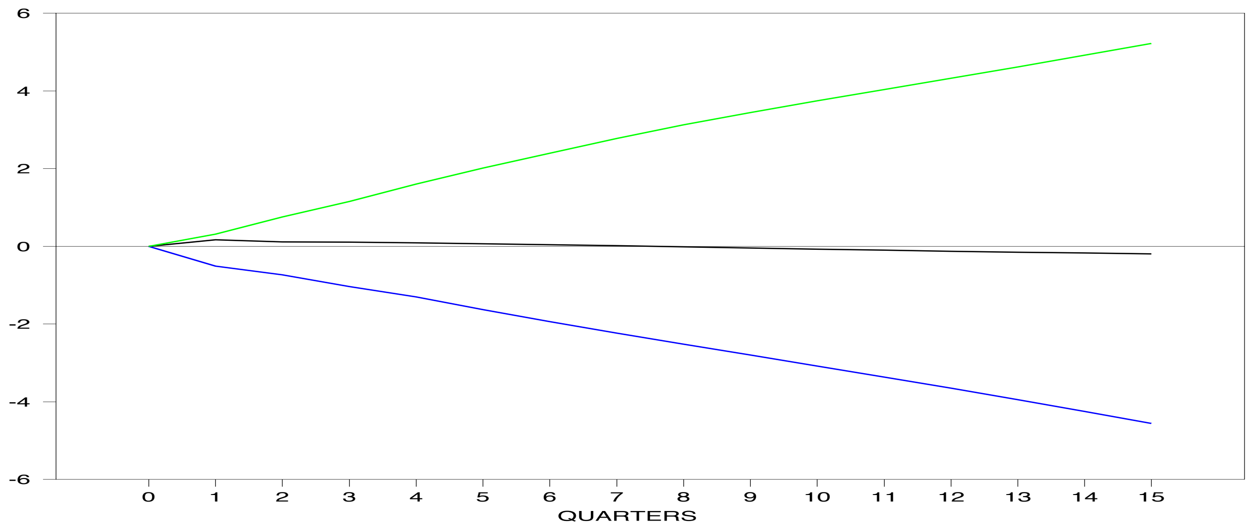
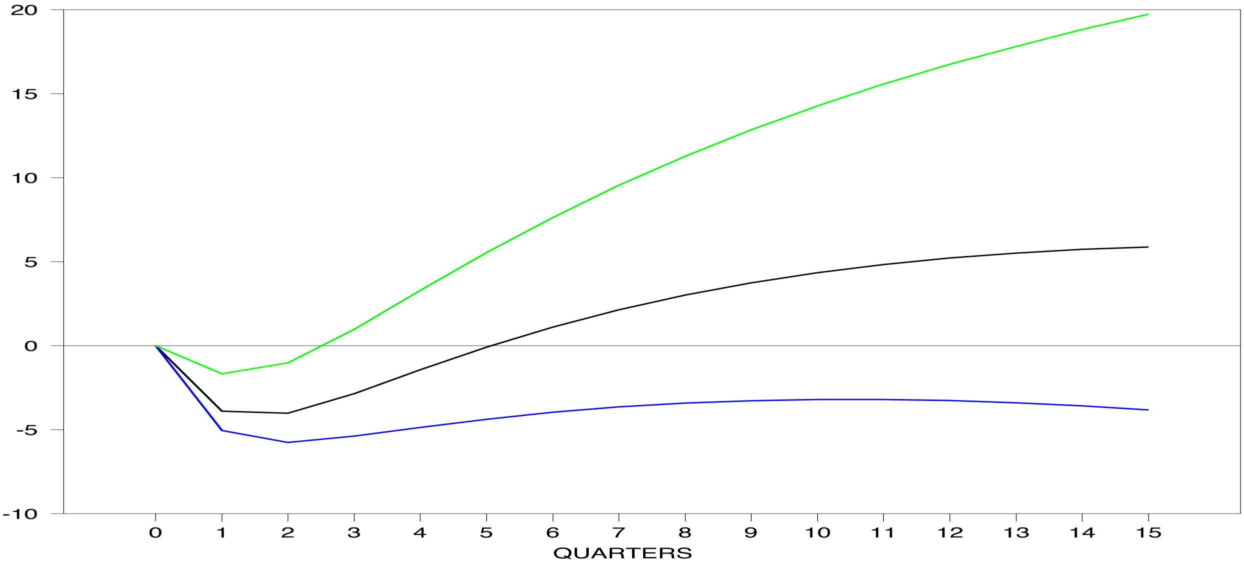
Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

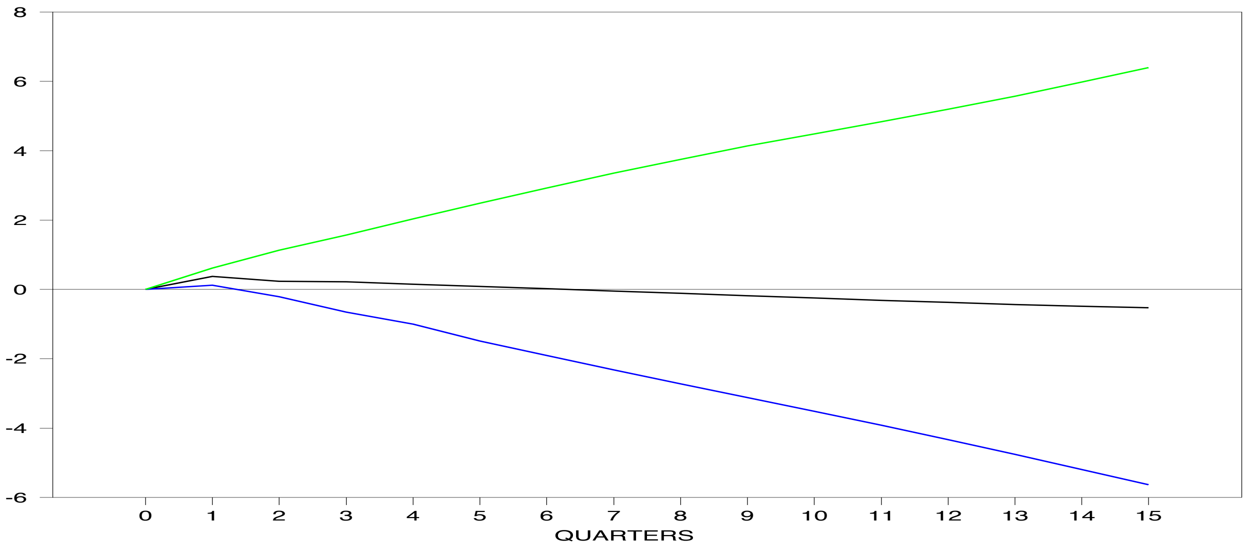
-2% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit

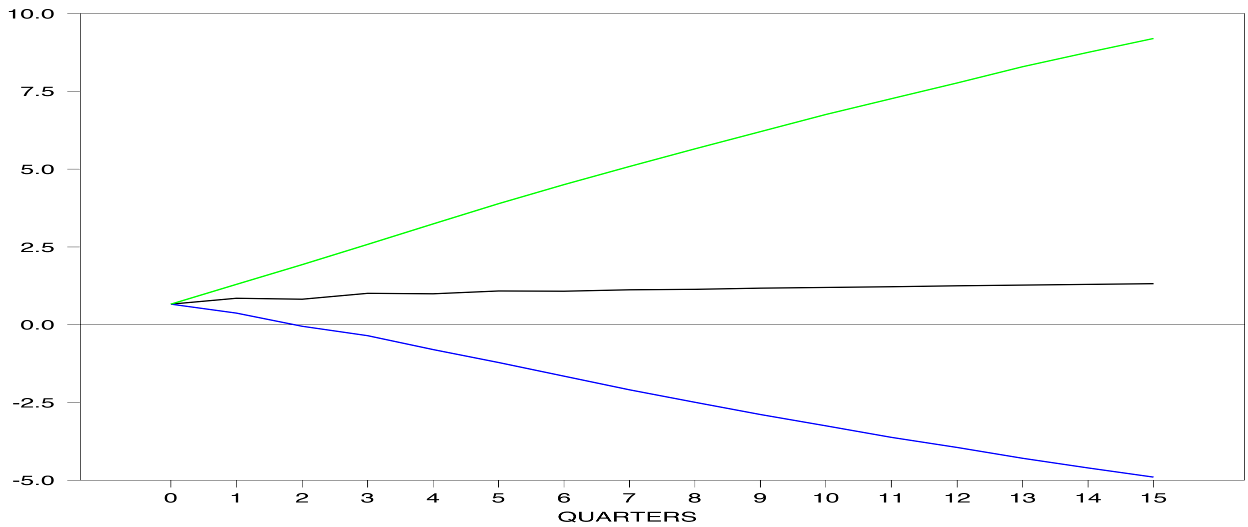


Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Figure 4.15. Cumulative impulse responses of output growth to spending shocks (1973Q1-2006Q4)

+1% GDP Shock

Tight Credit



Source: Author's calculations.
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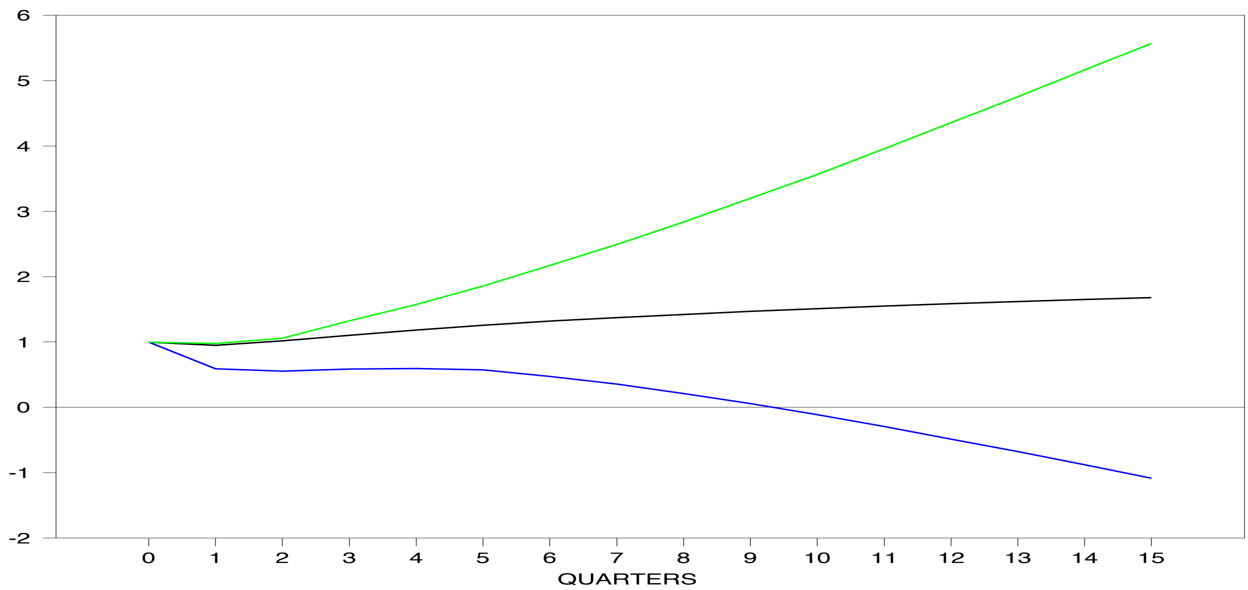
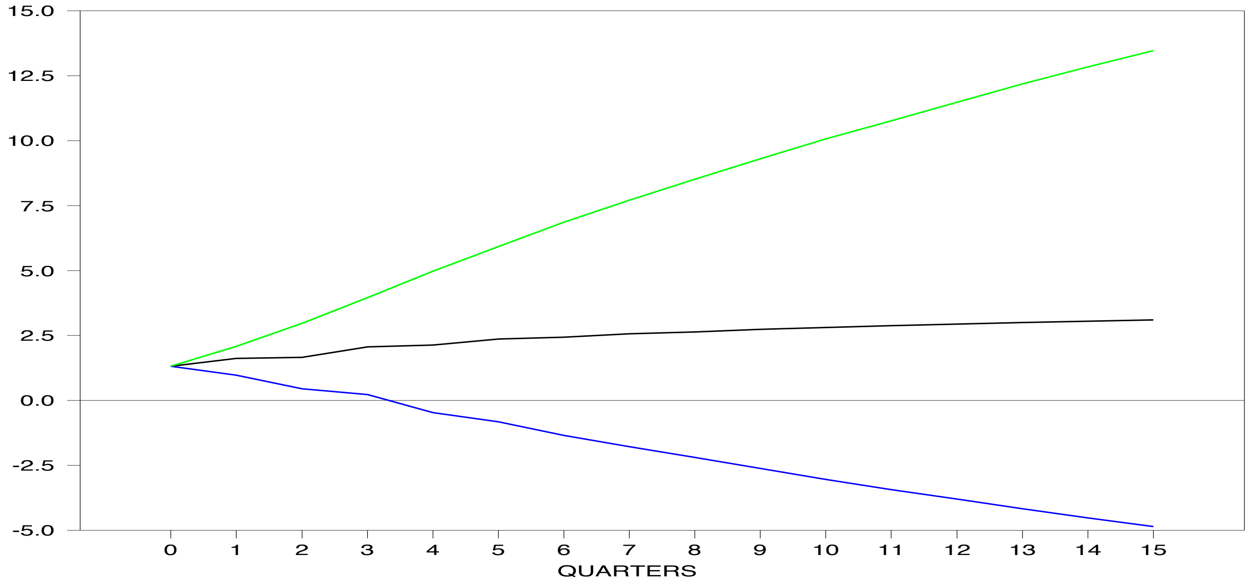


Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

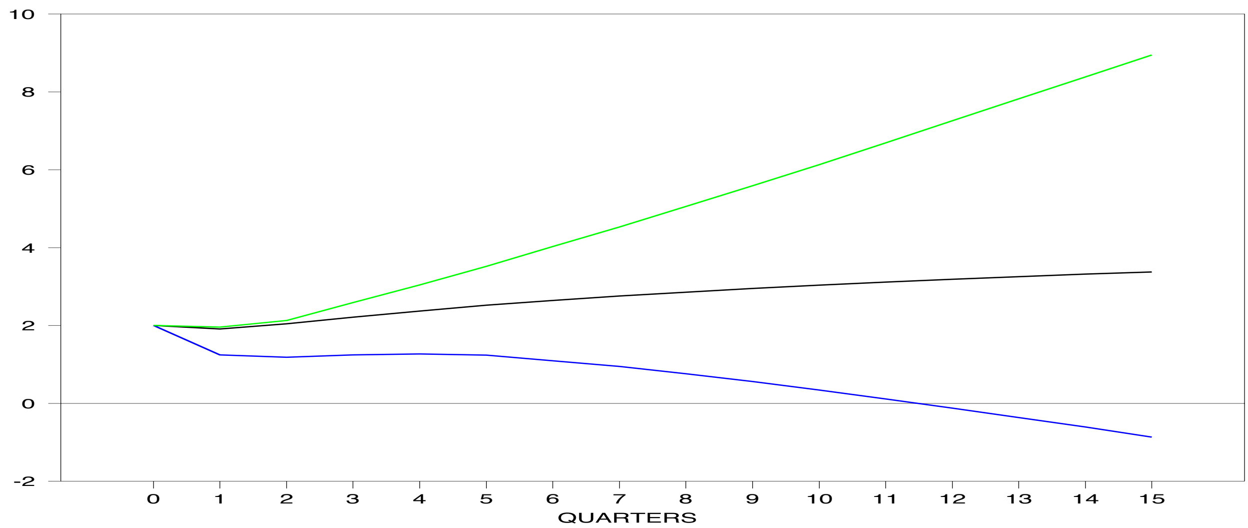
+2% GDP Shock

Tight Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Loose Credit



Source: Author's calculations.
Notes: The black line represents the cumulative impulse response. The green line and the blue line represent the 95% confidence interval.

Appendix

Appendix 4.1. Generalized impulse response function algorithm

Following Koop et al. (1996), we use the algorithm outlined below to compute the GIRF:

1. Let b =1, 2, … , B be the dates of observations in the regime that the GIRF is conditional on. Therefore, B is equal to the number of observations in the chosen regime. Pick a history ψ_{t-1}^{b} from this chosen regime. The history is the actual value of all the lagged endogenous variables at the chosen date b.

2. A sequence of six-dimensional shocks u_{t+n}, n = 0, 1,…, k is randomly drawn with replacement from the estimated residuals of the TVAR model.

3. For the history ψ_{t-1}^{b}, this sequence of shocks u_{t+n} is fed through the TVAR model to produce a baseline forecast $Y_{t+k}(\psi_{t-1}^{b})$.

4. Let v_{it} be a shock to the i-th variable of Y at time t. Substitute the i-th element of u_t (i.e. the initial shock to the i-th variable in Y) with v_{it}. Repeat step 3 and denote the resulting forecast as $Y_{t+k}(v_{it}, \psi_{t-1}^{b})$.

5. Repeat steps 2-4 R times for this particular history ψ_{t-1}^{b}. Following Balke (2000), we set the number of simulations R to be 500.

6. Repeat steps 1-5 B times for all possible ψ_{t-1}^{b}. In total, we obtain $R\times B$ bootstrap estimates of $[Y_{t+k}(v_{it}, \psi_{t-1}^{b}) - Y_{t+k}(\psi_{t-1}^{b})]$. The GIRF is computed by averaging over all bootstrap estimates:

$$\frac{1}{RB}[Y_{t+k}(v_{it}, \psi_{t-1}^{b}) - Y_{t+k}(\psi_{t-1}^{b})]$$

The 95% confidence interval of the GIRF is computed as:

$$[s_{2.5}, s_{97.5}]$$

where $s_{2.5}$ and $s_{97.5}$ are the 2.5th percentile and the 97.5th percentile, respectively, of the bootstrap distribution of $[Y_{t+k}(v_{it}, \psi_{t-1}^{b}) - Y_{t+k}(\psi_{t-1}^{b})]$.

Appendix 4.2. Data

Output: Gross Domestic Product (Bureau of Economic Analysis National Income and Product Accounts (NIPA) Table 1.1.3 Line 1)

Government spending: Government consumption expenditures and gross investment (NIPA Table 1.1.6 Line 22)

Net taxes: Federal government current receipts (NIPA Table 3.2 Line 1) + State and local government current receipts (NIPA Table 3.3 Line 1) - Federal grand-in-aid to state and local governments (NIPA Table 3.3 Line 17) - Federal government social benefits to persons (NIPA Table 3.2 Line 24) - Federal government interest payments (NIPA Table 3.2 Line 29) - State and local government social benefits to persons (NIPA Table 3.3 Line 23) - State and local government interest payments (NIPA Table 3.3 Line 24)

Inflation: Log difference of the Consumer Price Index for All Urban Consumers (All Items) (Federal Reserve Economic Data (FRED) Database, CPIAUCSL)

Interest rate: Effective Federal Funds Rate (FRED Database, FEDFUNDS)

Price deflator: Price index for Gross Domestic Product (NIPA Table 1.1.4 Line 1)

References

Afonso, A., H. P. Grüner, and C. Kolerus (2010). "Fiscal Policy and Growth: Do Financial Crises Make a Difference?" ECB Working Paper Series 1217, European Central Bank.

Afonso, A., J. Baxa, and M. Slavik (2011). "Fiscal Developments and Financial Stress: A Threshold VAR Analysis," ECB Working Paper Series 1319, European Central Bank.

Andres, J., J. Bosca, and J. Ferri (2012). "Household Leverage and Fiscal Multipliers," Banco de Espana Working Paper 1215.

Atanasova, C. (2003). "Credit Market Imperfections and Business Cycle Dynamics: A Nonlinear Approach," Studies in Nonlinear Dynamics and Econometrics, Berkeley Electronic Press 7(4): 78-97.

Balke, N. (2000). "Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks," Review of Economics and Statistics, 82(2): 344-349.

Baum, A. and G. B. Koester (2011). "The Impact of Fiscal Policy on Economic Activity over the Business Cycle - Evidence from a Threshold VAR Analysis," Discussion Paper Series 1: Economic Studies No.03/2011, Deutsche Bundesbank.

Baum, A., C. Checherita-Westphal, and P. Rother (2012). "Debt and Growth: New Evidence for the Euro Area," ECB Working Paper Series 1450, European Central Bank.

Baum, A., M. Poplawski-Ribeiro, and A. Weber (2012). "Fiscal Multipliers and the State of the Economy," International Monetary Fund Working Paper, No. 12–286.

Bernanke, B., M. Gertler, and S. Gilchrist (1996). "The Financial Accelerator and the Flight to Quality," Review of Economics and Statistics 78: 1–15.

Blanchard, O. J. and R. Perotti (2002). "An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output," Quarterly Journal of Economics 117: 1329–1368.

Blinder, A. S. and M. Zandi (2010). "How the Great Recession Was Brought to an End," available at: http://www.economy.com/mark-zandi/documents/End-of-Great-Recession.pdf.

Bouthevillain, C. and G. Dufrenot (2011). "Are the Effects of Fiscal Changes Different in Times of Crisis and Non Crisis? The French Case," Revue D'économie Politique 121(3): 371-407.

Brave, S. and S. A. Butters (2012)."Diagnosing The Financial System: Financial Conditions and Financial Stress," International Journal of Central Banking 8(2): 191-239.

Caldara, D. and C. Kamps (2008). "What are the Effects of Fiscal Policy Shocks? A VAR-based Comparative Analysis," ECB Working Paper No. 877, European Central Bank.

Carrillo, J. A. and C. Poilly (2013). "How Do Financial Frictions Affect the Spending Multiplier During a Liquidity Trap?" Review of Economic Dynamics 16(2): 296-311.

Claessens, S, M. A. Kose and M. Terrones (2009). "What Happens During Recessions, Crunches, and Busts?" Economic Policy 60: 653–700.

Davies, R. B. (1977). "Hypothesis Testing When a Nuisance Parameter Is Present Only under the Alternative," Biometrika 64: 247-254.

Davies, R. B. (1987). "Hypothesis Testing When a Nuisance Parameter Is Present Only under the Alternative," Biometrika 74: 33-43.

Eggertsson, G. B. and P. Krugman (2012). "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach," Quarterly Journal of Economics 127: 1469–1513.

Fatas, A. and I. Mihov (2001). "The Effects of Fiscal Policy on Consumption and Employment: Theory and Evidence," CEPR Discussion Paper 2760.

Ferraresi, T., A. Roventini, and G. Fagiolo (2013). "Fiscal Policies and Credit Regimes: A TVAR Approach," University of Verona Department of Economics Working Paper Series 03/2013.

Galí, J., J. D. López-Salido, and J. Vallés (2007). "Understanding the Effects of Government Spending on Consumption," Journal of the European Economic Association 5: 227–270.

Gallant, A. R., P. E. Rossi, and G. Tauchen (1993). "Nonlinear Dynamic Structures," Econometrica 61, No.4: 871-908.

Gilchrist, S. and E. Zakrajšek (2012). "Credit Spreads and Business Cycle Fluctuations," American Economic Review 102(4): 1692-1720.

Hansen, B. (1996). "Inference When A Nuisance Parameter is Not Identified Under the Null Hypothesis," Econometrica 64(2): 413-430.

Ilzetzki, E., E. G. Mendoza, and C. A. Végh (2013). "How Big (Small?) Are Fiscal Multipliers?" Journal of Monetary Economics 60: 239–254.

Kara, E. and J. Sin. Forthcoming. "Fiscal Policy in a Liquidity-Constrained New Keynesian Economy," Scandinavian Journal of Economics, available at: https://sites.google.com/site/enginkaraweb/SJEfiscalshort.pdf.

Koop, G. (1996). "Parameter Uncertainty and Impulse Response Analysis," Journal of Econometrics 72(1): 135-149.

Koop, G., M. Pesaran, and S. Potter (1996). "Impulse Response Analysis in Nonlinear Multivariate Models," Journal of Econometrics 74: 119-148.

Lutkepohl, H. (2005). "New Introduction to Multiple Time Series Analysis." Berlin; Heidelberg; New York: Springer.

Merton, R. C. (1974). "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." Journal of Finance 29(2): 449–70.

Mountford, A., and H. Uhlig (2009). "What Are the Effects of Fiscal Policy Shocks?" Journal of Applied Econometrics 24(6): 960-992.

Perotti, R. (2005). "Estimating the Effects of Fiscal Policy in OECD Countries," CEPR Discussion Paper 168.

Ramey, V. A. (2011). "Identifying Government Spending Shocks: It's All in the Timing," Quarterly Journal of Economics 126(1): 1-50.

Roeger, W. and J. In't Veld (2009). "Fiscal Policy with Credit Constrained Households," European Economy Economic Papers, N 357

Romer, C. D. and D. H. Romer (2010). "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," American Economic Review 100(3): 763-801.

Sims, C. A. (1980). "Macroeconomics and Reality," Econometrica 48(1): 1-48.

Stiglitz, J. E. and A. Weiss (1981), "Credit Rationing in Markets with Imperfect Information," American Economic Review 71: 393–410.

Turrini, A., W. Roger, and I. P. Szekely (2012). "Banking Crises, Output Loss, and Fiscal Policy," CESifo Economic Studies (2012) 58 (1): 181-219

Chapter 5
Conclusions

5.1. Summary of the Results

This dissertation consists of three essays on applied econometrics. In Chapter 2, we use the establishment (reporting unit)-level ARD data and the sector-level CBI survey data to investigate the factors influencing U.K. manufacturing investment. First, we follow Bean (1981) and Bond et al. (2003) to construct a baseline error correction investment model. Subsequently, we introduce CBI survey variables to the baseline model and find that the survey variables pertaining to demand uncertainty and financing constraints have negative effects on manufacturing investment, while the survey variable related to the volume of new orders has a positive impact on manufacturing investment.

In Chapter 3, we aim to construct forecasting models for aggregate U.K. manufacturing investment with the help of the CBI survey data. We start our analysis by deriving an error correction forecasting model for aggregate manufacturing investment which only conditions on lagged explanatory variables. However, the baseline model has poor out-of-sample forecast properties over the recent financial crisis period (2007-2012). Next, we introduce additional CBI survey variables to the baseline model and find survey measures of business optimism and expected future demand to be especially useful in improving the forecast performance.

In Chapter 4, we study the nonlinear effects of fiscal stimulus on output under different credit regimes in the U.S.. In the analysis, we employ a TVAR model and we choose the excess bond premium constructed in Gilchrist and Zakrajsek (2012) as the threshold variable. The TVAR system is in a tight credit regime if the excess bond premium is higher than the estimated threshold value, and vice versa. The results reveal that tax cuts either have very uncertain effects on output in the tight credit regime, or have very small output effects in the loose credit regime. Therefore, government spending increases seem to be more effective at increasing output than tax cuts, especially when credit conditions are loose.

5.2. Limitations of the Study

Our study has unavoidable limitations. In Chapter 2, the ARD microdata is over-represented by large reporting units and may not be representative of the whole manufacturing industry. Therefore, the resulting estimates may be biased. Furthermore, we use the CBI survey data to provide information on factors such as financing constraints and demand uncertainty. However, because the CBI does not publish the survey results for individual respondents but only at the sector-level, the CBI survey variables used in the analysis are sector average values and therefore measure the true conditions facing individual reporting units with error. This may be the reason why we find the effects of these CBI survey variables on manufacturing investment to be quantitatively small.

In Chapter 3, our preferred econometric forecasting model uses survey variables for the manufacturing sector as a whole related to business confidence and expected future demand. Out-of-sample forecasts from this model outperform the forecasts that were published in real time by the CBI. However, we select this preferred forecasting model after observing the outturns for manufacturing investment growth over the period 2007-2012. In real time, it may not have been clear which survey variables have high predictive power for manufacturing investment and should be used to construct the forecasting model.

In Chapter 4, as is common in the existing TVAR literature, we allow for the presence of two regimes in our TVAR model: the tight credit regime and the loose credit regime. However, in reality, the credit supply conditions may be more complicated and may have more than two distinct states. Therefore, a two-regime TVAR system may be too restrictive to accurately model the nonlinearity in the relationship between the output effects of fiscal policy and credit supply conditions.

5.3. Future Research

There are several possible extensions to the work presented in this thesis. For the investment research using the microdata in Chapter 2, we can extend our analysis to establishments in non-manufacturing industries in the U.K., such as distribution, construction, and services. Furthermore, the U.K. manufacturing industry has been declining since the 1970s, and it will be interesting to compare the investment behavior of manufacturing firms in the U.K. with that of manufacturing firms in emerging countries such as China, where manufacturing activity has been growing over the same period.

For the investment forecasting exercise in Chapter 3, rather than using the single-equation error correction model, we could explore constructing a multi-equation vector error correction model (VECM) for forecasting investment and output jointly. Furthermore, by using business survey data for the other sectors of the economy, we could employ a similar methodology to that used in this chapter to forecast total business investment, which is an important component of GDP.

In Chapter 4, we can extend the work on the nonlinear effects of fiscal stimulus by conducting similar TVAR analysis on more countries and comparing the results. Different identification strategies such as the Blanchard-Perotti identification method may also be applied to the TVAR estimation. In addition, we could investigate the possibility of allowing for more than two regimes in the TVAR model. For instance, we could have three credit regimes to represent periods of tight credit, normal credit, and loose credit.

References

Bean, C. R. (1981). “An Econometric Model of Manufacturing Investment in the UK,” Economic Journal 91:106–121.

Bond, S. R., J. Elston, J. Mairesse, and B. Mulkay (2003). “Financial Factors and Investment in Belgium, France, Germany and the UK: A Comparison Using Company Panel Data,” Review of Economics and Statistics 85 (1): 153–165.

Gilchrist, S. and E. Zakrajsek (2012). “Credit Spreads and Business Cycle Fluctuations,” American Economic Review, 102 (4): 1692-1720.