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TESIS DOCTORAL

Sobre el origen de las fluctuaciones cíclicas en la economía española

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

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SOBRE EL ORIGEN DE LAS FLUCTUACIONES CICLICAS EN LA ECONOMÍA ESPAÑOLA

Tesis para la obtención del título de Doctor en Economía
realizada por

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Departamento de Análisis Económico y Economía Cuantitativa
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Enero 2019

A la memoria de mis padres, Georgeta y Marin,

y

a tí, Eugen

Every great and deep difficulty bears in itself its own solution.
It forces us to change our thinking in order to find it.
Niels Bohr

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Resumen

Nuestros resultados empíricos sugieren que una fracción importante de las fluctuaciones del ciclo económico puede estar impulsada por cambios en las expectativas.

Beaudry and Portier (2004)

La presente tesis doctoral está estructurada en una introducción, tres "essays" independientes de análisis macro-econométrico y una parte final que recoge las conclusiones. Se puede ver como parte de la literatura macroeconómica que investiga los shocks de noticias, "news shocks", donde se utilizan los modelos de identificación del tipo vector autorregresivo estructural (SVAR) y los modelos de equilibrio general dinámico estocástico (DSGE) para explicar las causas de los ciclos económicos.

El propósito de esta disertación es entender más profundamente la naturaleza de los shocks de noticias analizando los canales a través de los cuales se propaga en el ciclo económico. Por lo tanto, utilizo datos españoles para investigar esta contribución de los "news shocks" a las fluctuaciones cíclicas.

La literatura sobre los "news shocks" se basa sobre la idea de que los agentes reciban nueva información sobre el desarrollo futuro de la tecnología, tomando medidas para ajustarse en consecuencia. Esas medidas desencadenan dinámicas sustanciales, a pesar de que no van acompañadas de ningún cambio fundamental en la economía. El cambio en las expectativas debido a la nueva información podría causar fluctuaciones en los ciclos económicos y parece ser sensato para explicar los altibajos de las actividades económicas.

En el primer ”essay”, titulado ”Is there any news shock in the Spanish business cycle?”, identifico los "news shocks" utilizando un modelo estructural de identificación del tipo vector autorregresivo (SVAR). Utilizo observaciones del índice IBEX 35 para identificar cambios permanentes anticipados en la productividad total de los factores (TFP) en la economía española en el período 1970-2015. La razón principal para usar los índices bursátiles es que generalmente se las consideran variables que incorporan nueva información antes que otras variables nominales y reales. Como tal, se cree que los índices de precios bursátiles son informativos sobre los cambios anticipados en las variables fundamentales. En concreto, para identificar los shocks de noticias estimo las funciones de impulso-respuesta imponiendo restricciones a modo secuencial a corto y largo plazo en un modelo SVAR.

El segundo ”essay” titulado ”An evaluation of the news shock identification methodologies” consiste en el análisis de dos de los enfoques de identificación de los "news shocks" más utilizados en la literatura macroeconómica: el primer método consta en maximizar la varianza del error de predicción (MFEV), mientras que el segundo método impone restricciones de corto y largo plazo en un modelo SVAR. Centrándome en la diferencia entre ambos enfoques, los aplico utilizando datos de la economía española y comparo los resultados midiendo los efectos en las variables macroeconómicas.

En el tercer ”essay”, titulado ”News-driven housing booms? Spain vs Germany”, motivado por el housing-boom en España en la década de los principios del 2000, investigo la contribución de los "news shocks" en los ciclos económicos español y alemán. Considero el cambio en el progreso técnico incorporado en los bienes de inversión (ISTC) como medida de productividad para explicar la inversión residencial en la economía española y la inversión en estructuras y bienes de equipos en la economía alemana. Identifico los "news shocks" como el impacto que maximiza la proporción de varianza del error de predicción del ISTC en un horizonte finito de 10 años. Al mismo tiempo, utilizo un modelo teórico DSGE para interpretar los "news shocks"

identificados. Encuentro evidencia de la importancia de los "news shocks" y del mecanismo de propagación que estimula la inversión residencial, siendo consistente con el boom inmobiliario en España.

Abstract

Our empirical results suggest that an important fraction of business cycle fluctuations may be driven by changes in expectations.

Beaudry and Portier (2004)

This dissertation consists of an introduction, three independent essays on macroeconometric analysis and a final part of conclusions. It can be seen as part of the news shocks literature that has sought to use Structural Vector Autoregression identification (SVAR) methods and Dynamic Stochastic General Equilibrium (DSGE) models to understand the causes of business cycles.

The purpose of this dissertation is to gain deeper understanding about the nature of the news shocks by looking at the channels through which it propagate the business cycle. Hence, I use Spanish data to investigate this shocks contribution to cyclical fluctuations.

The news shocks literature develops the idea that agents receive new information about future development of technology taking measures to adjust accordingly. Those measures trigger substantial dynamics, even though they are not accompanied by any fundamental change in the economy. The change in expectations due to new information could cause business cycle fluctuations and seems to be sensible to explain the ups and downs of economic activities.

In the first essay, titled ”Is there any news shock in the Spanish busi-

ness cycle?", I identify news shocks using structural vector autoregression (SVAR). I use observations on IBEX 35 index to identify anticipated permanent changes in total factor productivity (TFP) for the Spanish economy in the period 1970 - 2015. The main reason for using stock prices is that they are typically considered forward looking variables that incorporate new information before other nominal and real aggregate variables. As such, the stock prices are believed to be informative about anticipated changes in fundamentals. I estimate structural impulse response functions with Spanish data by imposing sequentially short-run and long-run restrictions on the SVAR model to identify the news shocks.

The second essay titled "An evaluation of the news shock identification methodologies" considers the methodological analysis of two of the most commonly used news shocks identification approaches in macroeconomics: the maximum forecast error variance method, (MFEV), and the method of imposing short-run and long-run restrictions on the SVAR model. I apply the two approaches to Spanish data and compare the results measuring the effects on the macroeconomic variables.

In the third essay, titled "News-driven housing booms? Spain vs Germany", motivated by the Spanish residential investment boom episode of the 2000s, I investigate the contribution of the news shocks to the Spanish and German business cycles. I consider the investment-specific technical change (ISTC) as a measure of productivity to explain the residential investment for the Spanish economy and business structures and equipment for the German economy. I identify the news shock as the shock that maximizes the forecast error variance share of investment-specific technology at 10 years finite horizon. In the same time, I used the theoretical way of isolating these news shocks by encoding them within an explicit business cycle model and use full information methods. I find evidence that the news shocks propagation mechanism stimulate investment in residential structures, being consistent with the housing boom in Spain.

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Part I

THESIS INTRODUCTION

This dissertation is a collection of essays written in preparation for the degree of Doctor of Philosophy in Economics. It consists of a general introduction, three main essays on macroeconometric analysis, and a final part that presents the dissertation's conclusions. The essays investigate the impacts of news shocks in the Spanish business cycle. It tries to find an answer to one of the most difficult questions in macroeconomic theory, a theme of an endless debate: *What are the causes and the nature of economic fluctuations?*

In general, the macroeconomic literature offers many possible answers to that question, although until now the researchers have still not reached a consensus on this issue. At the beginning of the 1980s Kydland and Prescott (1982) and Long and Plosser (1983) introduced the real business cycle (RBC) model showing that shocks to technology are the main driving force of the business cycles fluctuations.

Nevertheless, scholars found also evidence in favor of others shocks like the preference shock, oil price shock, or credit, fiscal and monetary shocks. However, there is another view that argues that the macroeconomic fluctuations are not only driven by current developments in the economy but are often influenced by perceptions of future developments.

Pigou (1927) introduced the idea that the business cycle may be driven by changes in expectations: "The varying expectations of businessmen ... constitute the immediate cause and direct causes or antecedents of industrial fluctuations". The fluctuations are the "wave-like swings in the mind of the business world between errors of optimism and errors of pessimism".

Pigou (1927) shows that economic booms arise when agents are receiving informations about the future and decide to increase their investment in expectation of future demand. In the case where their expectations are not met, there will be a period of decrease in the investment, which is likely to cause a recession.

Based on that idea, Beaudry and Portier (2004) introduced the concept of news shocks and since then, a large body of recent literature has focused on news shocks as the main driver of business cycles. A non-exhaustive list of recent papers that document the importance of news shocks includes Beaudry and Portier (2004, 2006, 2014), Schmitt-Grohé and Uribe (2012), Jaimovich and Rebelo (2009), Christiano et al. (2008), Fujiwara et al. (2011), Barsky and Sims (2011, 2012), Kurmann and Otrok (2013), Forni et al. (2014a).

The news shocks hypothesis is based on the idea that agents receive new information today about development of new technology tomorrow and take measures to adjust accordingly. Those measures trigger substantial dynamics on the macroeconomic variables, even though they are not accompanied by any fundamental change in the economy. Practically, the news shocks could be defined as the set of signals that agents receive some periods in advance about futures developments on fundamentals that it should be reflected contemporaneously in the forward-looking variables, without affecting current fundamentals.

In this dissertation, I am looking at the potential role of news shocks and the channels through which it propagates the Spanish business cycle. In particular, my aim is to gain deeper understanding about this important source of macroeconomic fluctuations, concentrating my attention on the nature of those shocks. In the first place, I identify the news shocks and assess if the changes in expectations about future fundamentals are a major source of fluctuations in the Spanish business cycle. Then, I try to match the empirical evidence of news shocks with theoretical models that incorporate them. Those two methodologies provide complementary readings on the quantitative importance and dynamics of the news shocks.

In much of the empirical news literature the fundamental that is predicted is total factor productivity (TFP), although in general, the fundamentals of interest could come from any exogenous driving force. For example, Beaudry and Portier (2006) present evidence that news of productivity shocks anticipate actual changes to productivity, arguing that innovations in the growth rate of total factor productivity are to a large extent anticipated. They explicitly take into account that news about future technology may have effects today in the macroeconomic variables, even though it does not show up in current productivity. As such, they found for the US economy that the news shocks explain about half of the forecast error variance of consumption, output, and hours. Theirs results have fueled a new debate because raise fundamental questions about the empirical relevance of the news driven real business cycle hypothesis.

However, modeling and evaluating news driven business cycles raise a series of issues. Although empirically the news shocks appear to be relevant under the rational expectations hypothesis, from an econometric point of view, identifying news about future economic fundamentals pose substantial challenges. In order to recover the structural shocks, the evaluation depends on the identification assumptions as the agents' perceptions it is difficult to measure in practice.

In the theoretical framework as well, one needs to depart at least from some standard modeling assumption in order to be able to simulate the news driven business cycles. A simple macroeconomic model that represents in a robust way the idea that changes in agents' perceptions about the economy's future expectations can cause business cycle type fluctuations it has its difficulties to be build: incorporated in the most general setting of the neo-classical business cycle model, the expectations generate counterfactual predictions.

In particular, when introduced in the real business cycle models, news about future total factor productivity (TFP) it fails to generate business cycle fluctuations as it determines a negative correlation between consumption, hours worked and investment. As such, the news shocks to anticipated future changes in the exogenous source can generate the business cycle fluctuations as long as the expectations-driven business cycles models reflect to a situation in which output, consumption, investment, and hours worked simultaneously increase in response to good news.

The three main essays of my dissertation explore the strategies for isolating news shocks and illustrates the empirical problems of identifying them. To identify news shocks, I rely on reduced form time series techniques using two of the most popular methodologies used in the literature: Beaudry and Portier (2006) and Barsky and Sims (2011). Beaudry and Portier (2006) methodology uses structural vector autoregressions (SVAR) imposing a combination of short and long run restrictions. In this setting, they uncover anticipated shocks with the innovation in stock prices orthogonalized with respect to total factor productivity innovations. Barsky and Sims (2011) identify a TFP news shock directly as the innovation that accounts for most of the maximum forecast error variance (MFEV) of TFP over the same 10-year (40 quarters) horizon but has no contemporaneous effect on TFP. As such, the Barsky and Sims (2011) methodology is an extension of the FEV maximization approach of Uhlig (2004b). It uses TFP as the target variable and imposing the extra restriction that identified news shock is orthogonal to contemporaneous movements in TFP.

My first objective is to try to assess if those types of shocks drove the economic fluctuations by encouraging the creation of new investment opportunities, i.e. increasing investment in residential structures. In order to identify them, I estimate SVARs with different specifications and identification schemes. As a second objective, I am interested in the extent to which the SVARs results are robust to the two alternative SVAR methodologies.

As such the second part discusses strengths and weaknesses of this class of identification methodologies.

To choose my main observable variables on which I will base my primary analysis, I follow how identifying and modeling news shocks is done in the literature: the total factor productivity (TFP), the IBEX 35 stock market index, the investment-specific technical change (ISTC), the relative price of investment goods, and other macroeconomic variables. The source of data for this dissertation is the EU KLEMS data base, the 2017 release. Data are annual covering the period 1970 to 2015.

The reasons I choose these variables are that: (i) the TFP should help identify neutral technological innovations; (ii) the value of the stock market is considered as a forward-looking variable that incorporates instantaneously any changes in agents expectations about future economic conditions, helping to isolate news about future economical developments, being in general considered as an important measure of economic activity; (iii) the relative price of investment goods as an indicator of the exogenous source of productivity growth, the investment-specific technical change (ISTC), which therefore is likely to be helpful in identifying investment specific technical shocks.

The first essay, titled "Is there any news shock in the Spanish business cycle?" includes five chapters. It is motivated by the empirical observation of decreasing total factor productivity (TFP) starting from the 1985. I argue that IBEX 35 index contains information about future productivity developments. To this end, I look at a vector autoregressive (VAR) model that includes the measure of TFP and annual IBEX 35 data.

In particular, I use a bivariate VAR imposing sequentially two identifying restrictions following Beaudry and Portier (2006): the first restriction is that one shock has no long-run effects on TFP and label the orthogonal shock as the news shock; the second restriction is that one shock has zero short-run effect and label that shock as the news shock. The outcome is that the two restrictions lead to similar results. According to Beaudry and Portier (2006) hypothesis, the shock identified is a news shock. In Beaudry and

Portier (2004, 2006), this procedure is actually shown to identify correctly the structural shocks in that the empirical correlation is found to be positive and close to one, suggesting that positive news shocks in productivity are preceded by stock market booms.

Then, in a tri-variate VAR I look at the effect of the news shock on standard macroeconomic aggregates, including consumption, investment, and hours worked. I find that the identified news shock leads to positive conditional comovement among macroeconomic aggregates.

The conclusion from the empirical identification is that forward-looking variables strongly anticipate the fall in the total factor productivity, and that news shock account for a large fraction of the variance of aggregate variables at business cycle frequencies.

From a theoretical point of view, I will examine the news shocks from the perspective of a non-standard three-sector real-business-cycle model. As shown by Beaudry and Portier (2004, 2006), the standard one-sector growth model is unable to generate boom-bust cycles in response to news shocks. The wealth effect generated by expectations of improved future macroeconomic conditions, makes consumption to increase and hours worked to fall. Since the total output decreases as the technology has not improved yet, investment has to fall in order for consumption to increase despite the reduction in hours worked. In this setting, positive expectations about the future, create a boom in consumption and a decline in output, investment, and hours worked.

Since a two-sector model with consumption and capital goods is also unable to generate a boom in macroeconomic variables, I consider a three-sector model following Beaudry and Portier (2004, 2006). They show that "expectations-driven cycles can arise provided firms exhibit economy of scope or, in other words, internal cost complementarities between the production of different goods". In the last sections of this part, I present the model comparing its implications against the data. Once calibrated to match certain specific moments for the Spanish economy, the theoretical model with three sectors performs quite well to simulate the variation of medium to long term data.

This essay's results provide qualitative and quantitative empirical evidence that supports the business cycle hypothesis driven by news shock for the Spanish economy.

The second essay, titled "An evaluation of the news shock identification methodologies" includes seven chapters. In this essay, my first goal is to investigate a different question: are the results obtained in the first essay using the with Beaudry and Portier (2006) approach robust with respect to the methodology used? For that reason, I consider the methodological analysis of two of the most commonly used news shocks identification approaches in macroeconomics. To this end, I measure the effects on the Spanish macroeconomic variables from the method of imposing short- and long-run restrictions on the SVAR model on which in based Beaudry and Portier (2006) methodology, and the maximum forecast error variance method, (MFEV) on which is based Barsky and Sims (2011). On the other hand, my second goal is to analyze and contrast Beaudry and Portier (2006) and Barsky and Sims (2011) methodologies also because motivated by the debate that exists in the literature about the two identification methodologies of the news shock.

Besides the objectives stated above, in this part I introduce an exogenous source of productivity growth, the investment-specific technical change, ISTC. Specifically, I empirically investigate with Spanish data the possibility to identify a news shock in a SVAR where the first variable is the ISTC. The objective is to observe if forward-looking variables like the IBEX 35, investment, consumption or residential investment reflect expectations about future ISTC.

This essay's results are that in a 2 or 3 variable SVAR configuration the news shock is identified independently of the methodology used. The ISTC increases gradually with a significant delay, while the forward looking variables increase in the impact. In a 4-VAR, the identification strategy of Barsky and Sims (2011) on the ISTC news shock generates strong impact responses in IBEX 35 and variable macroeconomic, representing a large part of the fluctuations in the variables added to the medium and long term. The conclusions are that the Barsky and Sims (2011) approach, the maximum forecast error variance methods to identify news shocks can be easily implemented on VARs of higher dimension than 4 variables. In contrast, the zero-restriction based approach in Beaudry and Portier (2006) is difficult to implement beyond a tri-variate system.

Additionally, although the results are consistent with the interpretation of news shock, while Beaudry and Portier (2006) identify a shock with permanent effects on the variables, Barsky and Sims (2011) identifies a news shock that has only temporary effects.

The third essay is titled ”Why do countries experience housing booms? Spain vs Germany” and includes six chapters. In this essay that is motivated by the Spanish residential investment boom episode of the 2000s, I argue that agents' advance knowledge of future productivity growth in the investment sectors may be important not only in understanding macroeconomic fluctuations, but also the residential investment boom in Spain. This essay analyzes empirically the role of news shocks in the Spanish business cycle fluctuation and compare it with the German economy. To that end, I consider the investment-specific technical change (ISTC) as a measure of productivity to explain the residential investment for the Spanish economy and business structures and equipment for the German economy. Based on the second essay results, I follow Barsky and Sims (2011) methodology estimating the VAR in levels. As stated by Hamilton (1994), this is the ”conservative approach” that applies, in particular when there is uncertainty about common trends in the data. The news shock is identified as the shock that maximizes the forecast error variance share of investment-specific technology at 10 years finite horizon.

First, I quantify the effects of news shocks on relative prices of investment over the two economies and found robust evidence that the news shocks constitute a significant force behind Spanish and German economic business cycles. Positive news shocks does lead to comovement in macroeconomic aggregates as typically associated with business cycles. I argue that the news shocks on ISTC could entail the housing boom over the Spanish economy in the period 1970 - 2015. An important founding is that the percentage of the variance of output, investment, hours and categories investment explained by investment-specific shocks is larger in the Spanish case than the German one. The findings provide strong support to ISTC news shocks when investigating the fluctuations of the Spanish and German business cycles. The news shock in Spain has an effect of complementarity of increasing investment on one hand on residential and on other hand on its complements, structures and equipment. In Germany there is an effect of substitution, residential investment for business structures and especially equipment.

Then, I use the theoretical way of isolating these news shocks by encoding them within an explicit business cycle model and use full information methods. I find evidence that the news shocks propagation mechanism stimulate investment in residential structures, being consistent with the housing boom in Spain.

This dissertation is placed in a literature that characterize the dynamic consequences of news shocks. It can be seen as part of the news shocks literature that has sought to use Structural Vector Autoregression identification (SVAR) methods and Dynamic Stochastic General Equilibrium (DSGE) models to understand the causes of business cycles that includes Beaudry and Portier (2004, 2006, 2014), Schmitt-Grohé and Uribe (2012), Jaimovich and Rebelo (2009), Christiano et al. (2008), Fujiwara et al. (2011), Barsky and Sims (2011, 2012), Ben Zeev and Khan (2015) and Kurmann and Otrok (2013).

At the same time, this work has connections with other research agendas. First, is related to the housing literature. In this sense is related to Bernanke and Gertler (1995), Iacoviello (2005), Davis and Heathcote (2005), Fisher and Quayyum (2006), Iacoviello and Neri (2010), Huo and Rios-Rull (2015), Ríos-Rull and Sánchez-Marcos (2008), Mian et al. (2013), Aruoba et al. (2016), Davis and Van Nieuwerburgh (2015).

Second, there are links with another strand of the literature that focuses on the investment-specific technical change (ISTC) (see, in particular, Justiniano et al. (2011), Greenwood et al. (2000), Greenwood et al. (1997).

Finally, I also follow the tradition that studies the Spanish economy in the line of Puch and Licandro (1997), Díaz-Giménez and Puch (1998), Fernández-Villaverde and Ohanian (2010), Martín-Moreno et al. (2016), Díaz and Franjo (2016), and Casares and Vázquez (2016).

Part II

ARE THERE ANY NEWS SHOCKS IN THE SPANISH BUSINESS CYCLE?

This part investigates the effects of aggregate news shocks over the Spanish business cycle in the period 1974 - 2015. In a structural vector autoregressive (SVAR) approach, I identify the effects of news shocks on total factor productivity (TFP) and the IBEX 35. I find that news shocks are associated with large increase in the stock prices while the TFP is decreasing. The analysis suggests that the IBEX 35 contains information about the future development of TFP. In a simple three-sector model calibrated for the Spanish economy, I show how news shocks can help explain important features of the data. The results are consistent with the pattern implied by the news view of fluctuations, capturing the empirical evidence that the Spanish TFP is decreasing over the two last decades.

Chapter 1

Introduction

This part investigates the empirical relevance of the news driven business cycle hypothesis in the Spanish economy in the period 1974 - 2015. As news, I consider all the information received by the households and economic agents when Spain becomes a member of European Union first, and then member of the monetary union. In particular, I am referring to the expectation of lower interest rates in short and long-run enforced by the adoption of the euro in 1998 and the nearly total elimination of the risk premium of Spanish loans in comparison with Germany's. Additionally, the expectations triggered by those events were also due to facilitated access to credit and to European capital markets, decreasing inflation, and fall in the unemployment rates. Spanish firms and households found themselves facing new investment opportunities, able to borrow at attractive real rates and, more important, to assume that those rates would stay low and stable into the middle run. Blanchard and Giavazzi (2002) show that investment increases because financial integration lowers the cost of borrowing and economic integration makes it easier to repay the debt. Under those circumstances, a boom in investment in structures was a likely event.

The expectations role in generating the macro fluctuations it was recognized already by early economists like Pigou (1927). Beaudry and Portier (2004, 2006) were the first authors to reassess the importance of news shocks as drivers of business cycles. The news shocks literature develops the idea that agents receive new information today about development of new technology tomorrow. Even though there are not accompanied by any fundamental change in the economy, the change in expectations due to new information could lead to business cycle fluctuations. Although it starts from the the total factor productivity (TFP) improvement, the news shock can have many interpretations: it can be thought of as news about future government investment that enhances private productivity and results in increases in aggregate demand during the preliminary bidding phase; it can be thought of as a shock to expected demand from tourism due to political instability in other destinations; or as a structural reform that could increase the openness of the economy.

The purpose of this paper is to identify the importance of the news shocks in the Spanish business cycle from an empirical and a theoretical point of view. First, I follow the empirical strategy of Beaudry and Portier (2006) for the identification of news shocks relying on structural vector autoregression (SVAR). For the US economy, Beaudry and Portier (2006) use a bivariate system of total factor productivity (TFP) and stock prices (SP). They start from the idea that the volatility of stock prices provides important information for the future process of the economy. In their studies, they develop a new empirical strategy that "performs two different orthogonalization schemes as a means of identifying properties of the data that can then be used to evaluate theories of business cycle". Two disturbances are identified in this system: one represents the stock prices innovations that are contemporaneously orthogonal to innovations in TFP; and the second drives long run movements in TFP. The empirical results show that the correlation between these two shocks is positive and almost equal to one, that is, "the permanent changes in productivity growth are preceded by stock market booms".

I employ a structural bivariate SVAR that includes the Spanish total factor productivity (TFP) and a forward looking variable, the IBEX 35 stock prices index. For this purpose, by imposing different identifications, I find that news shocks about future technological developments are the important driving force in the macroeconomic fluctuations.

The SVAR strategy I follow consists in two steps. In the first step, I apply sequentially short-run and long-run restrictions as for example used in Blanchard and Quah (1989)[1] or Galí (1999) on the VAR model to identify the news shocks. Then, I compute the correlation between the two news shocks recovered from the two identification strategies. Like Beaudry and Portier (2006) for the US, for Spain I find a very high correlation between the news TFP shock series identified by these two alternative schemes and that impulse responses to variables are quite similar. Therefore, following Beaudry and Portier (2006), my conclusion is that the common component of these two shocks represents an anticipated TFP shock, suggesting that stock market booms are possibly good leading indicators of positive news shocks in productivity.

The impulse response analysis suggests that a part of the total TFP response is delayed rather than immediate, although is gradually decreasing. The shock on stock prices is affecting current TFP growth, and is highly correlated to the future changes of TFP. The two shocks correlation is very close to one suggesting that the dynamics of stock market booms are simultaneous related to negative news shocks in productivity. This feature of the identified shocks is preserved when a third variable, such as output, consumption, aggregate investment, or hours is added to the system.

From the theoretical point of view, I then evaluate a three-sector model economy presented in Beaudry and Portier (2004). In expectations-driven business cycles models, the news shock play an important role in generating the macro fluctuations when output, consumption, investment, and hours

[1] Blanchard and Quah (1989) assume that there are two shocks (demand and supply) affecting unemployment and output. The demand shock has no long-run effect on unemployment or output. The supply shock has no long-run effect on unemployment but may have a long-run effect on output. These differences in their long-run impacts allow Blanchard and Quah (1989) to identify the shocks and trace their impulse response function.

worked increase simultaneously in response to good news. However, the most standard neo-classical business cycle models changes in expectations cannot generate positive co-movement between consumption, investment and employment. In the standard real business cycle (RBC) model there are no imports or exports and no government spending, so the aggregate resource constraint requires that output must rise to allow consumption and investment to rise simultaneously. The only option for an increase in output is for hours worked to rise as the technological opportunities are initially unchanged and the capital stock is predetermined by what was installed in the previous period. However, consumption and leisure are normal goods under standard preferences, so that at a given wage (marginal product of labor) a household will choose to adjust consumption and leisure in the same direction, i.e., consumption and hours in opposite directions.

The standard one-sector model introducing news makes current consumption and current investment move in opposite directions. Intuitively, upon the arrival of the good news, agents want to increase consumption via a dominating positive wealth effect. Since leisure is a normal good, simultaneously they want to increase consumption while decreasing the hours worked. As long as the capital is predetermined and there have been no changes in fundamentals yet, lower worked hours means lower output. As the identity $Y = C + I$ relates output, consumption and investment, since output decreases and consumption increases, it must be the case that investment decreases. In that setting of the RBC model good news about the future sets off an output recession today as it induces consumption on one hand, and investment, hours worked, and output on the other hand to move in opposite directions. Therefore, the task is on one hand, to solve the co-movement of current consumption and current investment, which are moving in opposite directions, and on the other hand, to see how good news about the future sets off an output expansion today.

Beaudry and Portier (2004) propose the first model that produces an expansion in response to news. Their model features two complementary consumption goods, one durable and one non-durable. Both goods are produced with labor and a fixed factor but with no physical capital. The model generates a boom in response to good news about TFP in the non-durable goods sector. Beaudry and Portier (2004) model features a low short-term elasticity of substituting consumption and investment in conjunction with news shocks. The model simulation calibrated for the Spanish economy shows, that news shocks can generate expectation led business cycles in a three-sector economy; i.e. output, investment, and consumption respond positively to good news. The model simulates moments of output, consumption, aggregate labour and capital reasonably close to what is observed in real Spanish data.

The part is organized as follows. Chapter 2 describes the database, some relevant features of the Spanish economy, and provides some reduced form empirical evidence that is consistent with the idea of news view of Spanish business cycles. Chapter 3 presents the structural VECM framework and discusses the identifying assumptions for the two basic identification schemes. Chapter 4 presents a model of a three-sector economy, its calibration, and the model's news driven business cycle fluctuations. Chapter 5 concludes.

Chapter 2

Data and Preliminary Evidence

The goal of this section is to provide some descriptive evidence of the news shocks to the macroeconomic fluctuations of the Spanish economy. I use data series from the EU KLEMS database, the 2017 release, from 1974 to 2015 of the total factor productivity as the measure of productivity denoted by TFP, and the IBEX 35 as stock price[1]. The later series is deflated by the CPI and transformed in per-capita terms by dividing it by the working population aged 16-64 in order to account for the increasing number of investors over time. I will call SP the log of this index.

2.1 Reduced form evidence

To illustrate the news shocks view of business cycle, I analyze the fluctuations of the ratio aggregate capital to total factor productivity[2], K/TFP. When a surprise shock improves the TFP, $(TFP^* > \overline{TFP})$, while the capital stock

[1] Appendix A presents the data

[2] I consider the following production function where B represents the total factor productivity, TFP:

$$Y = K^\alpha (BN)^{1-\alpha} = B^{1-\alpha} K^\alpha N^{1-\alpha} = B \left(\frac{K}{B} \right)^\alpha N^{1-\alpha}$$

is low relative to the new state of technology[3], $(K/TFP^{*} < K/\overline{TFP})$, the agents find good opportunities for investment and employment. In order to catch up to the level of technology, the relatively low state of the capital stock creates demand for investment, generating a positive swing of the economy, as capital and employment are both increasing: as such, hours worked and K/TFP should be strongly negatively correlated in a supply shock.

On contrary, when a demand shock hits the economy, as the total factor productivity does not change, the capital and the hours worked increase in the same proportion[4]. Consistent with the RBC model, when demand shocks hit the economy there should be a strong positive correlation between hours and K/TFP.

The news shock view instead is close to a demand shock in short run, while in the long run is close to a supply shock suggesting that opposed dynamics make these variables to have a modest positive correlation. Looking from the capital accumulation perspective, when agents are acting on news - same effects as a demand shock - the capital accumulation anticipates TFP growth (the correlation is positive), but sometimes if agents are reacting to realizations as a supply shock, capital is lagging and the correlation is

[3]Technological surprise shock ($B_t > \bar{B}$): the $\frac{K}{TFP}$ is low relative to the new state of technology and compared to its long run level. This relatively low state of the capital stock creates incentives to invest and work more so the capital stock can catch up to the level business cycles. The RBC model predicts that employment should be high, as it is a desirable to work to produce capital goods. If the ratio is high, then employment should but be low, as there are low returns to capital accumulation. So according RBC view, employment and $\frac{K}{TFP}$ should be strongly negatively correlated.

$$B_t > \bar{B} \Rightarrow \begin{cases} B \uparrow, \text{ low values } \frac{K}{B} \\ N \uparrow, \text{ high values } N \end{cases} \Rightarrow \rho < 0 \text{ (strong negative correlation)}$$

[4]A positive demand shock:

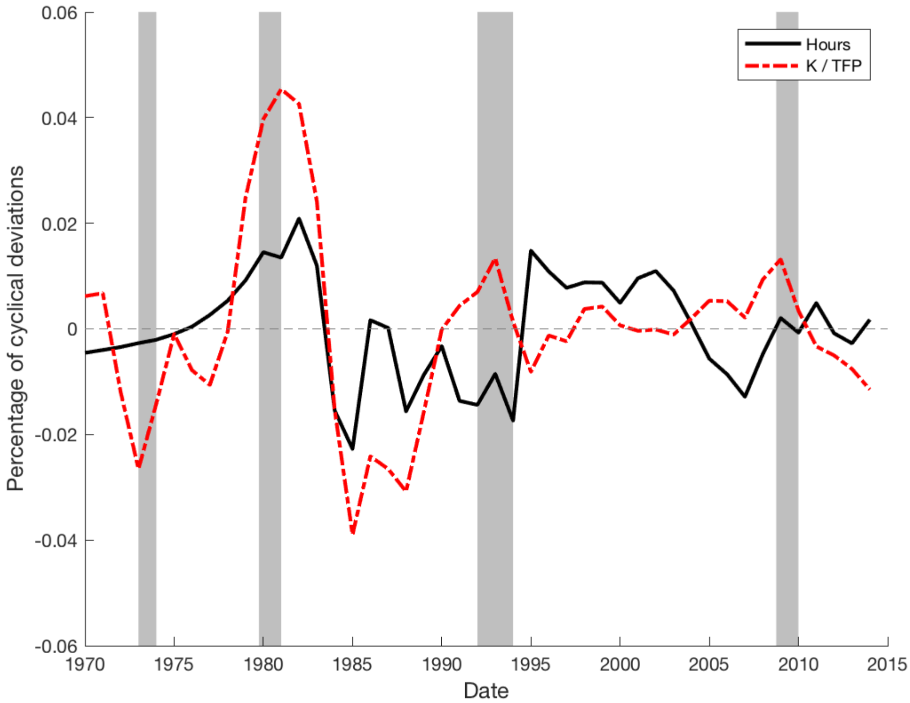
$$B_t = \bar{B} \Rightarrow \begin{cases} \frac{K}{B} \uparrow; \; K \uparrow \\ N \uparrow \end{cases} \Rightarrow \rho > 0 \text{ (large positive correlation)}$$

negative.

From the employment perspective, on the one hand, if employment booms arise because capital accumulation anticipates growth in TFP, then employment and K/TFP should be positively correlated in booms. On the other hand, major recessions in the news view of business cycles arise when K/TFP is already high and expectations no longer support such a high capital stock, leading to a recession. The second force should contribute to a negative correlation between employment and K/TFP. As stated by Beaudry and Portier (2014), since on average agents should be right more often than wrong, it suggests that employment and K/TFP should be positively correlated if the news view is central to fluctuations.

Following that reasoning, Figure 2.1 shows the Spanish data for per capita hours worked and the ratio K/TFP between 1970 and 2015. I used the HP-filter to remove low-frequency fluctuations not related to business cycles and plot the per cent deviations from the HP-filter trend. According to the news view of business cycles, recessions should arise after periods when the ratio K/TFP is high due to increased speculative investment.

Figure 2.1: Spain: Cyclical fluctuations for hours worked and capital /TFP ratio



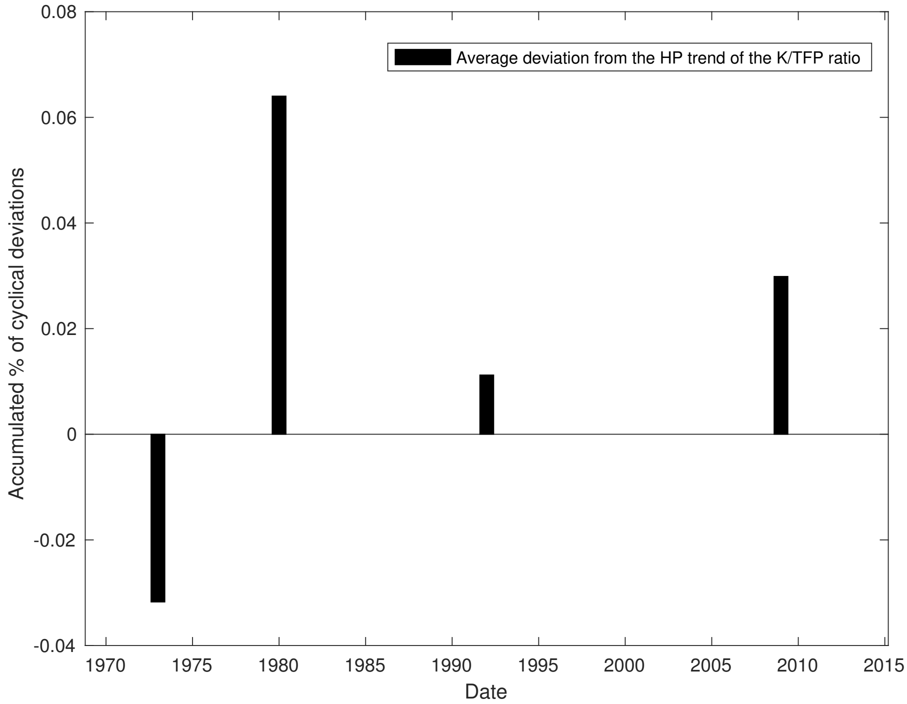
Note: Figure 2.1 displays the Hodrick-Prescott cycle (with smoothing parameter 100) of the ratio capital/TFP and of total hours. Grey areas correspond to Spanish economy recessions.

As it can be observed in the figure 2.1, the grey areas are marking the Spanish recessions. With the exception of the 70s recession that was triggered by the oil crisis, the 80s, the 90s and the 2009 crisis come after periods of capital stock accumulation. As can be seen from the figure, these two variables do not exhibit the strong negative correlation that would be predicted by RBC theory. In fact the correlation between the two is actually positive and equal to 0.33. In their survey, Beaudry and Portier (2014), found supportive evidence for the news view analyzing the US economy with a coefficient of correlation of 0.3. That fact indicates that, on average, periods when employment is high are periods where the capital stock is high at least relative to a current fundamental measured by TFP. Beaudry and Portier (2014) found that fact potentially consistent with the news view, although is contrary to the RBC view of fluctuations.

It is worth mentioning that when we examine the correlation between K/TFP at time t, with the rate of growth in hours worked in the next period (growth between t and $t+1$) it can be found a very close coefficient to the one presented by Beaudry and Portier (2014). Spain exhibits a positive correlation of 0.26, while the US coefficient of correlation is 0.24. The meaning of that correlation is that on average a high K/TFP ratio predicts further expansion, even though most recessions are preceded by high values of K/TFP. The pattern shown by the Spanish economy when the ratio K/TFP and hours worked is analyzed appears to be more consistent with a news view than with an RBC view.

To explore further the information content of the K/TFP ratio, in figure 2.2 I plot the average value of this ratio in the three preceding years prior to recessions. According to the news view of business cycles, recessions should arise after periods where there has been substantial speculative investment, that is, when K/TFP is high. As can be seen in the figure, almost all the Spanish recessions have been preceded by a period where capital accumulation outstripped growth in TFP. The only exception is the recession of 1973 that have been driven by the oil price crisis.

Figure 2.2: Spain: Average deviation from the HP trend of the K/TFP ratio over the three years preceding a recession



Next step, and following Beaudry and Portier (2014), I look for evidence over the behavior of relative prices in order to differentiate between the business cycle driven by the supply of investment goods versus the demand for investment goods. In order to check whether Spain had gone through a structural change over that period, I report the correlations for two time windows, one starting in 1974 and the other one starting in 1985[5] that corresponds to a period that the news about Spain becoming a member of the monetary union

[5] Zivot and Andrews (1992) Endogenous Structural Break Test is a sequential test that utilizes the full sample and uses a different dummy variable for each possible break date. The break date is selected where the t-statistic from the ADF test of unit root is at a minimum (most negative), where the evidence is least favorable for the unit root null. Consequently, a break date will be chosen as the outcome of an estimation procedure rather than predetermined exogenously.

was already incorporated into the agents' expectations. The date of 1985 as a structural break was chosen according to Zivot and Andrews (1992) unit root sequential test. In this setting, I consider the correlation of per capita hours worked and the investment prices of structures, equipment, residential structures and also the stocks price represented by the IBEX 35 as a measure of the price of investment. That model is giving a possible picture of how the capital goods installed in firms is driving the fluctuations. All these prices are deflated by the CPI and HP-filtered. What it can be seen in Table 2.1 and 2.2 it is a mixed set of results for the cyclical pattern of the relative price of investment.

Table 2.1: Coefficient of correlation: Period 1974 - 2015

	Equipment	Structures	Stock Prices	Hours
Equipment	1			
Structures	0.68	1		
Stock Prices	0.18	0.57	1	
Hours	-0.03	0.04	0.36	1

Table 2.2: Coefficient of correlation: Period 1985 - 2015

	Equipment	Structures	Stock Prices	Hours
Equipment	1			
Structures	0.87	1		
Stock Prices	0.14	0.65	1	
Hours	0.31	0.47	0.54	1

According to Beaudry and Portier (2014), the pattern consistent with the news view:

- The relative price of structures, and the stock prices index show a strong positive relation with employment movements.

- In contrast, the relative price of equipment shows a negative co-movement.

For the Spanish data set, if we focus on the most recent period, 1985-2015, where inflation has been more stable than in the full sample, we observe that the relative price of investment is positively correlated with hours worked for all of three indexes, with the weakest the relation being for the relative price of equipment. So over this latter period, if investment was driving the cycle then it appears most likely due to changes in the demand for investment goods as opposed to changes in their supply. However, over the full sample, the picture is less clear. The relative price of structures almost zero correlation with the hours, while the stock prices index shows a positive relation with employment movements over the longer sample. In contrast, the relative price of equipment and the hours shows a slightly negative co-movement. Hence, over the longer sample there is room for debate regarding which of the investment demand or the supply of investment goods have more likely played the greater role in fluctuations. If we consider the stock market index as representing the value of the firms, the behavior of this index is consistent with the pattern implied by the news view of fluctuations.

Chapter 3

Identification of the News Shock

3.1 Framework

Here I follow the empirical strategy of Beaudry and Portier (2006) and employ a structural vector autoregressive approach (SVAR) to identify the news shocks in the Spanish economy. I use real data series from 1970 to 2015 of the Total Factor Productivity as the measure of productivity denoted by TFP, and the IBEX 35 as stock price and denote the log of this index by SP[1].

I start with a bivariate time series model for these variables. In order to recover news shocks, I sequentially impose two separate identification restrictions, described as the short-run and long run. Since stock prices have the forward-looking property, they will respond to the changes in expectations earlier than the realized changes in macroeconomic fundamentals will affect the other economic variables. News about technology shocks can have an impact on stock prices, but it may need some time to actually affect total factor productivity (TFP) because of an implementation lag. Thus, stock prices are very helpful for our understanding on that expectations drive economic fluctuations.

To look at the quantitative relevance of technological news, one can look

[1]Appendix A presents the data

at the extent to which innovations in stock prices contain information about future technological growth, or alternatively whether periods of high technological growth are preceded by increase in stock prices. Beaudry and Portier (2006) implemented this idea using alternatively a short run and a long run identification scheme in a bivariate setting. They show that the news driven fluctuations are typically displaying co-linearity between ϵ_2 and $\tilde{\epsilon_1}$, the two disturbances obtained from the short-run and long-run identification schemes (where the tilde denotes long-run, and the subscripts 1 and 2 refer to TFP and SP, respectively). Such a result favours a view of business cycles driven largely by a shock that does not affect productivity in the short run - and therefore does not look like a standard technology shock - but affects productivity with substantial delay, and therefore does not look like a demand shock. It can be thought on this shock as a news representation about future technological opportunities that is first captured in stock prices.

Beaudry and Portier (2006) further show that, for the aggregate US economy, ϵ_2 and $\tilde{\epsilon_1}$, obtained from the bivariate identification schemes are highly correlated, and induce nearly identical dynamic responses of TFP and stock prices. An important result for my analysis that would support the news driven fluctuations, is that the correlation between the two disturbances for the Spanish economy is very high, 0.98, indicating almost a perfect colinearity.

3.2 Identification strategy in a bivariate VECM

From the data on TFP and SP, we need to recover the Wold moving average representation for ΔTFP and ΔSP. The augmented Dickey-Fuller unit root tests suggests that these two variables are integrated of order one, I(1) variables, stationary in the first difference. The Johansen's cointegration test indicates that TFP and SP are likely cointegrated of order one, so I adopt the specification of bivariate vector error correction models (VECM) in the estimation. The other specification choice concerns the number of lags to include in the VECM. According to a likelihood ratio test one lag is chosen for Spanish data, while Beaudry and Portier (2006) for the US data have chosen five lags [2].

The reduced form moving average, the Wold representation for the bivariate system $(\Delta TFP_t, \Delta SP_t)$ is as follows:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = C(L) \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix}, \quad E(\mu_t, \mu_t') = \Omega \tag{3.1}$$

where $C(L) = I + \sum_{i=1}^{\infty} C_i L^i$. The estimation is based on a moving average representation derived from the vector error correction model (VECM) between measured TFP and stock prices, SP. Furthermore, I assume that the system has at least one stochastic trend and therefore C(1) is not equal to zero as the unit root and cointegration test confirm that fact.

To describe the short-run restriction, I assume that the two variables can be represented in log first differences, by the Wold representation:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \Gamma(L) \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}, \quad E(\varepsilon_t, \varepsilon_t') = I \tag{3.2}$$

where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma_i L^i$ the two shocks, $\epsilon_{1,t}$ and $\epsilon_{2,t}$, are mutually orthogonal and have unit variance. The short run restriction imposes that ϵ_2 has no short run effect on TFP. Formally, this restriction is imposed by setting the 1,2 element of the matrix Γ_0 to zero.

The long-run restriction is based on an alternative Wold representation

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \tilde{\Gamma(L)} \begin{pmatrix} \tilde{\varepsilon}_{1,t} \\ \tilde{\varepsilon}_{2,t} \end{pmatrix}, \quad E(\tilde{\varepsilon}_t, \tilde{\varepsilon}_t') = I \tag{3.3}$$

where $\tilde{\Gamma}(L) = \sum_{i=1}^{\infty} \tilde{\Gamma}_i L^i$ and the two shocks $\tilde{\varepsilon}_{1,t}$ and $\tilde{\varepsilon}_{2,t}$, are mutually orthogonal and have unit variance. The long run restriction is that only $\tilde{\varepsilon}_{1,t}$,

[2]The Augmented Dickey-Fuller test, the Johansen test and the choice of lag test are reported in Appendix E: (TFP and stock prices - SP) are integrated of order one and cointegrated with each other, i.e. $(\Delta TFP_t, \Delta SP_t)'$ is $I(0)$

has a long run effect on TFP. This restriction is imposed by setting the 1, 2 element of the matrix $\tilde{\Gamma}(L) = \sum_{i=1}^{\infty} \tilde{\Gamma}_i L^i$ to zero.

Therefore, ε_2 and $\tilde{\varepsilon}_1$ are referred to as the stock prices innovation and the permanent shock to TFP, respectively. The procedure above is not applied simultaneously, but sequentially to describe the joint behaviour of measured TFP and stock prices.

Suppose that it happens to be the case that the two recovered disturbances, ε_2 and $\tilde{\varepsilon}_1$, are extremely highly correlated, or effectively the same. This suggests that the procedure has recovered a single shock that, since it satisfies the short-run restriction, and, it satisfies the long-run restriction, it captures all-important long-run information about productivity. Given these characteristics, the shock satisfies the two characteristics of a news shock described above. Of course, the procedure only delivers plausible measures of news if the two shocks happen to be highly correlated.

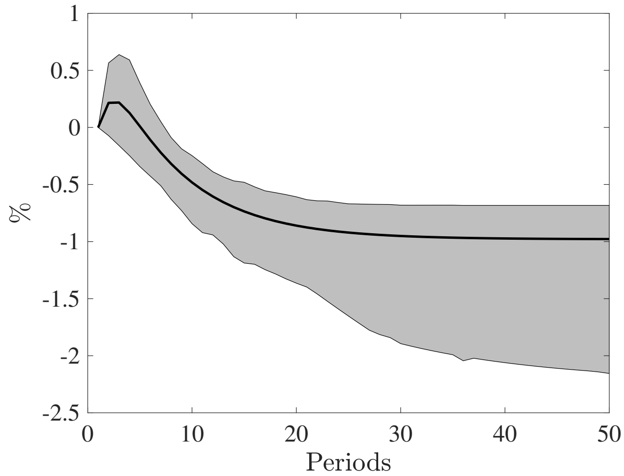
3.3 Evidence from the bivariate VECM: TFP and SP

The resulting impulse responses on (TFP, SP) associated with the ε_2 and $\tilde{\varepsilon}_1$ shock for the Spanish economy are displayed on figure 3.1 and 3.2. A first striking observation is that those responses appear very similar when comparing one orthogonalization to another. The upper panel in Figure shows the dynamics associated with the ε_2 shock, the short - run restriction, which seems to have no effect on TFP on impact and then gradually decreasing. This shock has a strong immediate effect on stock prices, having a permanent positive effect. These results suggest that ε_2 contains information about future stock prices reflected in instantaneously positively growth. The dynamics associated with the $\tilde{\varepsilon}_1$ shock - which by construction should have a permanent effect on TFP - has essentially no impact effect on TFP, followed by a gradually decrease. The effect on SP is substantial with a permanent increase as stock markets anticipate future profits.

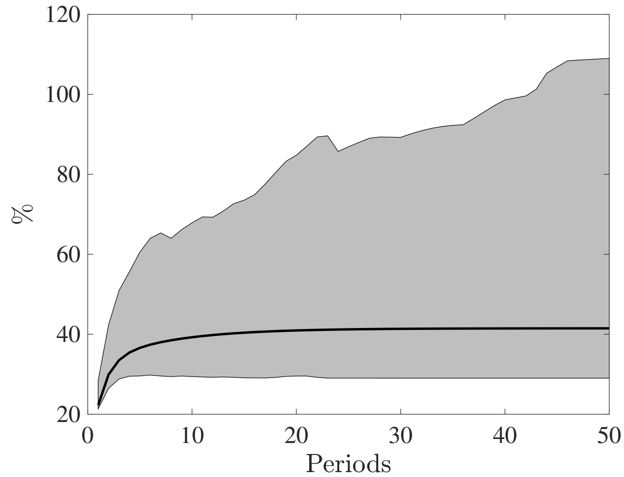
The next graphs presents the impulse response of TFP corresponding to the ε_2 shock (from short-run identification) in fig. 3.1, while the $\tilde{\varepsilon}_1$ shock (from long-run identification) in fig. 3.2.

Figure 3.1: IRF Short-run restrictions 2-VAR: TFP IBEX 35

(a) IRF TFP short run



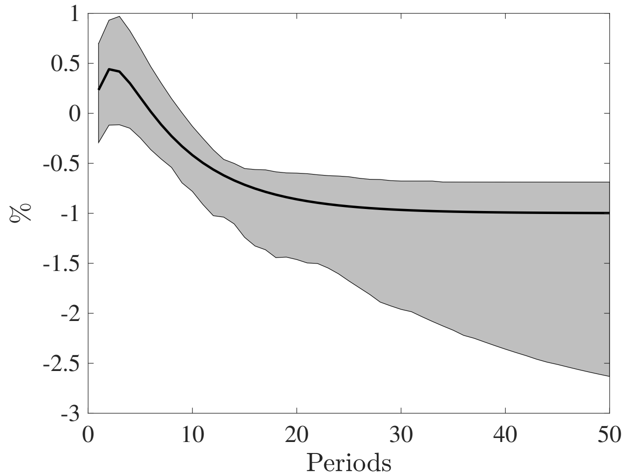
(b) IRF IBEX 35 short run



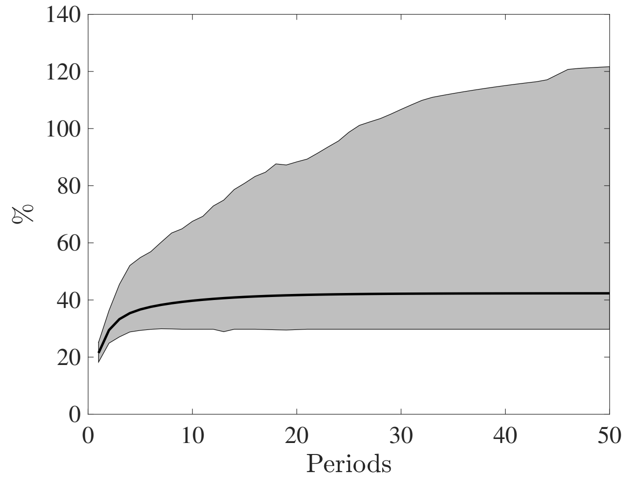
Note: The solid black lines represent the impulse responses functions of the TFP and IBEX 35 Index to a unit aggregate news shock. The gray area represents the 5%-95% confidence intervals. Impulse responses of TFP to a unit aggregate news shock are given in the upper panel; the responses of stock prices indices are given in the lower panel.

Figure 3.2: IRF Long-run restrictions 2-VAR: TFP IBEX 35

(a) IRF TFP long run



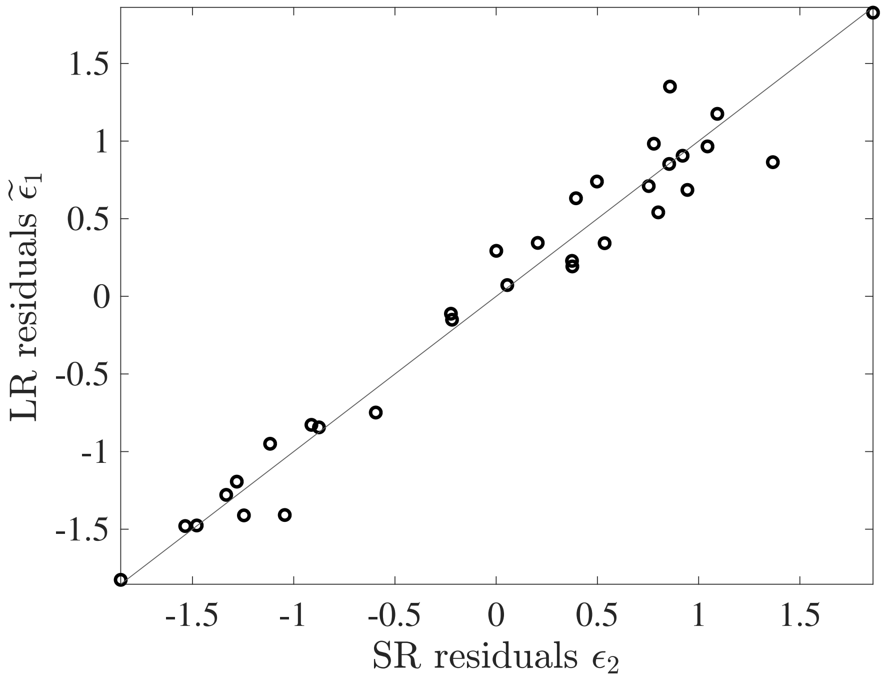
(b) IRF IBEX 35 long run



Note: The solid black lines represent the impulse responses functions of the TFP and IBEX 35 to a unit aggregate news shock. The gray area represents the 5%-95% confidence intervals. Impulse responses of TFP to a unit aggregate news shock are given in the upper panel; the responses of stock prices indices are given in the lower panel.

The scatter plots of ε_2 and $\tilde{\varepsilon}_1$ are shown in figure 3.3. As can be seen from the figure, the ε_2 and $\tilde{\varepsilon}_1$ line is up on the 45 degrees line. Hence, as the coefficient of correlation between these two series is 0.98, practically the two orthogonalization techniques recover essentially the same shock.

Figure 3.3: Identified structural residuals: SVAR analysis of TFP and IBEX 35

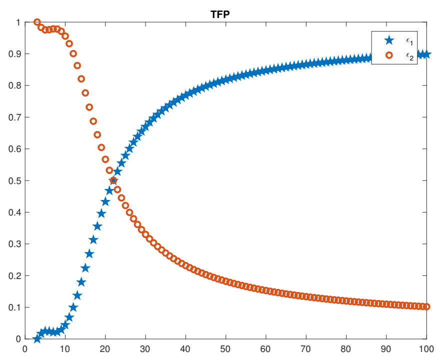


Note: Figure 3.3 displays the two shocks, the ε_2 and $\tilde{\varepsilon}_1$. The coefficient of correlation between these two series is 0.98 (with a standard deviation of 0.012).

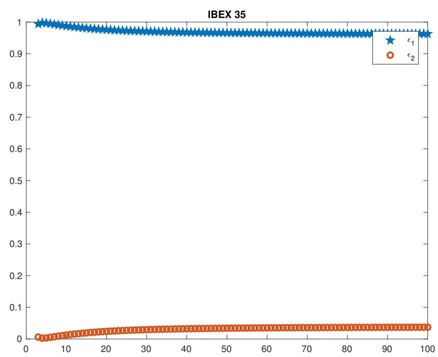
Figures 3.4 and 3.5 display the fraction of the FEV of the TFP (left panel) and IBEX 35 (right panel) explained by a TFP news shock. Looking at the impact on the TFP, left panel on figures 3.4 and 3.5, the news shock explain almost none of the movement in TFP on impact but reaches up to 90% of TFP variations after 40 periods. This news shock explains over 90% of the FEV of IBEX 35 on impact, decreasing fast after 15 periods. Looking at the impact on the IBEX 35, right panel on figures 3.4 and 3.5, the TFP news shock explain almost all of the movement in IBEX 35 at all horizons, while the IBEX 35 shock on IBEX 35 have practically no effect at all horizons. The two figures imply that news shock is sufficient to describe the majority of TFP and IBEX 35 movements.

Figure 3.4: FEV Short-run restrictions 2-VAR: TFP IBEX 35

(a) FEV TFP short run



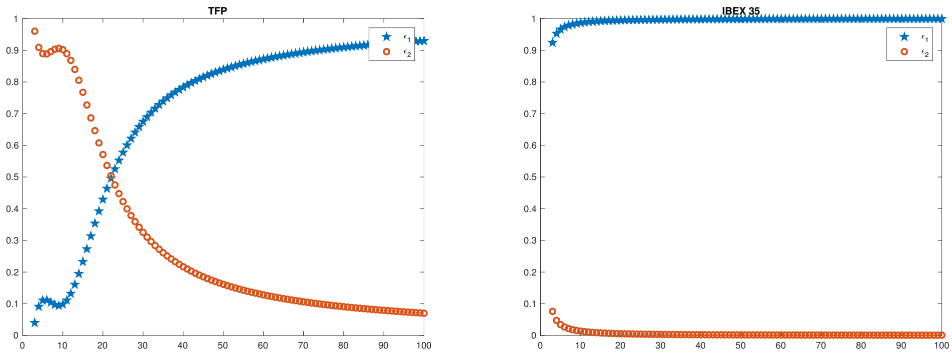
(b) FEV IBEX 35 short run



Note: Forecast error decomposition of the TFP (left panel) and IBEX 35 (right panel) to a unit aggregate news shock.

Figure 3.5: FEV Long run restrictions 2-VAR: TFP IBEX 35

(a) FEV TFP long run (b) FEV IBEX 35 long run



Note: Forecast error decomposition of the TFP (left panel) and IBEX 35 (right panel) to a unit aggregate news shock. I

The results from the IRF bivariate vector autoregression model of TFP and stock prices by employing two different orthogonalization schemes indicate that the procedure has recovered a single shock that given the short-run and long-run restrictions, captures the empirical evidence of the Spanish news shocks TFP. Those results are confirmed by the forecast error variance decomposition (FEV)[3]. At the same time, it captures the empirical evidence of the Spanish TFP stagnation over the two last decades as showed by Díaz and Franjo (2016).

[3]FEV is an alternative way to represent impulse response functions. In a linear model with multiple exogenous driving forces, the fraction of the forecast error variance of an endogenous variable due to a particular shock equals the sum of squared impulse response functions to that shock up to a given forecast horizon divided by the sum of squared impulse response functions to all shocks up to the same forecast horizon. As the forecast horizon tends towards infinity, the variance decomposition is often said to be unconditional in that it shows the fraction of the unconditional variance of an endogenous variable attributable to each shock. Variance decompositions are frequently employed to evaluate the relative importance of different exogenous shocks in accounting for business cycles.

3.4 Evidence from the trivariate VAR system

In order to assess the relevance of news shock for macroeconomic fluctuations, I examine, like Beaudry and Portier (2006), whether these observations exist in higher dimensional systems. I extend the system to a trivariate setting in which the third variable is one of the main macro aggregates, consumption, investment, output and hours[4] alternatively in addition to TFP and SP. The comovement of different macroeconomic variables is an important feature for the business cycles, while those patterns may include the significant clues about the mechanisms and shocks that generate business fluctuations. Hence, investigating the comovement of these macro variables to news shocks is very important to study the business cycle fluctuations. I first checked the cointegration properties of such systems. Running trivariate Johansen tests with lags indicated by the Schwarz Criterion I found evidence of two cointegrating vectors if it was added output, investment, consumption, hours or residential capital as a third variable. Hence, I treat all trivariate systems as having two cointegrating vectors.

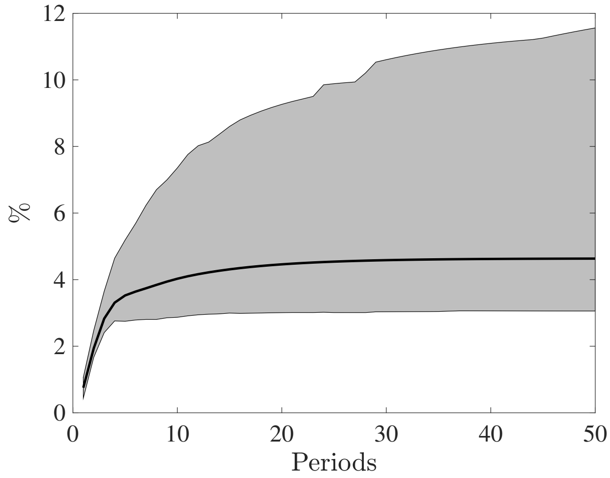
From the IRF analysis on the macroeconomic variables, GDP, investment, consumption and residential investment, do not react on impact of the shock but then gradually rises further towards a higher permanent level. In terms of macroeconomic implications it predicts sustained future growth, accounting for a large share of macroeconomic fluctuations at medium and longer horizons. Although on hours worked the shock have no statistically significant effect, it generates sharp response of residential investment.

Consistent with my argumentation, these responses suggest that the news hypothesis therefore seems natural. In line with Beaudry and Portier (2006) the interpretation of those facts is that the news shocks drove economic fluctuations by enhancing the creation of new investment opportunities, i.e. increasing investment in residential structures in Spain.

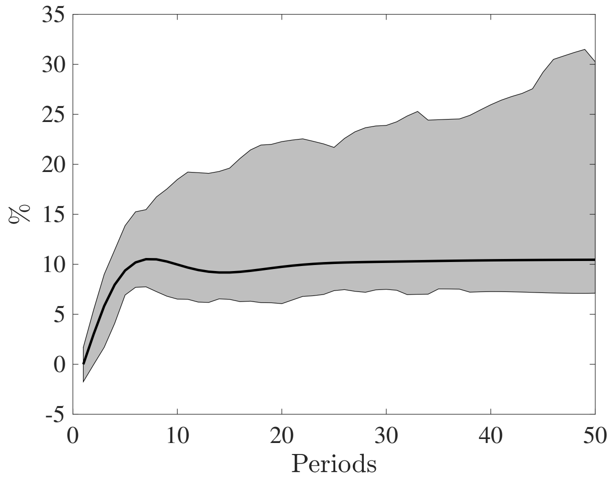
[4] Appendix A.2 presents the data

Figure 3.6: 3-VAR system: TFP IBEX 35 GDP / I

(a) IRF GDP



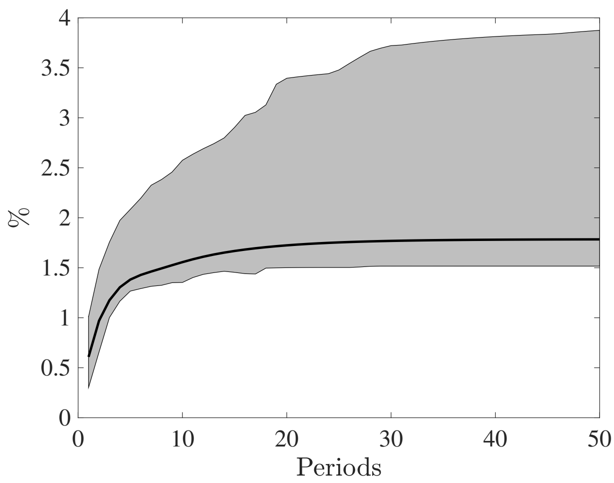
(b) IRF I



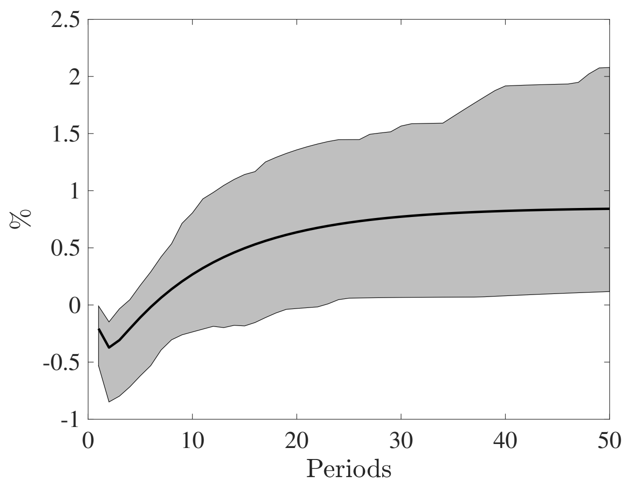
Note: The impulse response functions of a trivariate VAR system when OUTPUT and INVESTMENT are added. The solid black lines represent the impulse responses functions to a unit aggregate news shock. The gray area represents the 5%-95% confidence intervals.

Figure 3.7: 3-VAR system: TFP IBEX 35 C / H

(a) IRF C



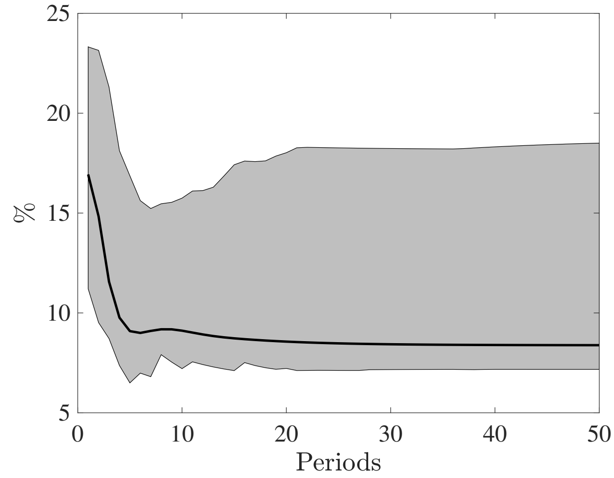
(b) IRF HOURS



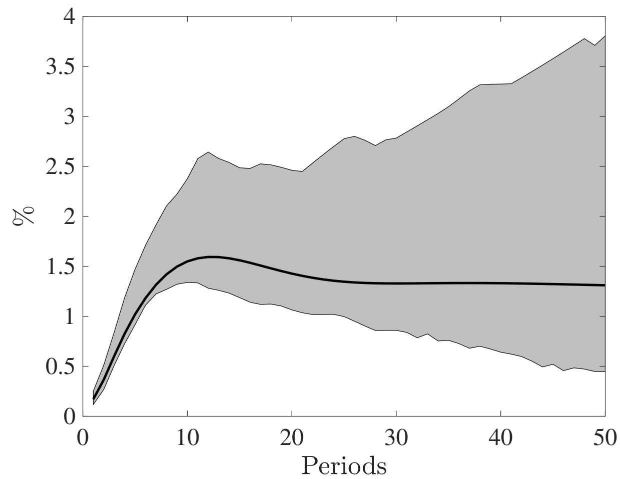
Note: The impulse response functions of a trivariate VAR system when CONSUMPTION and HOURS are added. The solid black lines represent the impulse responses functions to a unit aggregate news shock. The gray area represents the 5%-95% confidence intervals.

Figure 3.8: 3-VAR system: TFP IBEX 35 Residential I

(a) IRF IBEX 35



(b) IRF Residential Capital



Note: The impulse response functions of a trivariate VAR system TFP, IBEX and RESIDENTIAL CAPITAL. The solid black lines represent the impulse responses functions to a unit aggregate news shock. The gray area represents the 5%-95% confidence intervals.

Chapter 4

The Benchmark Model with News Shocks

In this section I will examine whether a reasonably calibrated version of a theoretical news model can reproduce the certain observed pattern of the Spanish economy while being able to capture its variances and co-movements. I start from the idea that the Spanish economy meets the two conditions to be subject to a model that generates Pigou cycles:

a) The agents received news that lead them to increase their current demand for investment, and

b) This increase in investment demand was done by an increase in employment, not a decrease in consumption.

I build on Beaudry and Portier (2004) (henceforth BP) relying heavily on theirs notations, constructing a three sector real economy capable of generating Pigou cycles with the following characteristics:

i) a forecast of future technological improvement first leads to a boom defined as an increase in aggregate output, employment, investment and consumption,

ii) the realization that a forecast is too optimistic leads to a recession defined as a fall in all the same aggregate quantities.

4.1 Environment

In the BP economy the production of investment and consumption takes place in separate sectors. Investment is produced with labour and a fixed factor, both supplied by a representative household. The production of consumption in turn requires services and capital stock as factors. The capital stock accumulates according to investment made. Services are produced in the third sector with a technology using again labour and a fixed factor. Labour is perfectly mobile across the service and the investment sector. The households' decisions to shift workforce will influences the level of output, i.e. the sum of investment and consumption, although since the technology in the consumption-sector will constrain the substitution of services with the capital stock as this relation is fairly fixed in the short run.

The model by construction exhibits a low elasticity of substituting consumption and investment in order to produce expectation-led business cycles. A representative household populates the economy. One firm producing a non-durable good, a firm producing investment goods, and a firm producing a final consumption good. Production of the durable investment good can be considered as plant or housing infrastructure, while the production of the non-durable good could be seen as trading activities and/or the provision of services.

The firm producing the consumption good uses both the durable and the non durable good as production inputs. The model represents a closed economy and abstracts from a government sector. Consumption is used as numéraire.

4.2 Production sector

As the capital is accumulated in the sector producing the durable investment good, in the Spanish economy case could be associated with the structures investment sector. The household owns the entire stock of capital since it buys every output unit produced in the durable investment good sector at a price p_t , and it rents capital at the rate r_t to the final good producing firm.

The service sector, in which the non-durable good is produced, can be thought of as directly accompanying the sector in which the consumption good is finalized. My assumption is that this sector is related with the utilities sector of the Spanish economy, like for example the electricity and water supplies, sewage and gas services, mobile and internet, banks territorial branches, roads new construction and maintenance, etc.

In every period the household receives a signal about future total factor productivity - the news shock. The signal correctly indicates TFP with a certain probability.

The final good, denoted C_t, is produced as a constant elasticity of substitution (CES)[1] composite of the non-durable good (or service) X_t and the stock of infrastructure, durable investment good, K_t:

$$C_t = (\alpha X_t^{\nu} + (1-\alpha) K_t^{\nu})^{\frac{1}{\nu}}, \qquad \nu \leq 0 \tag{4.1}$$

The final good C_t is a flow of consumption services, which could be mod-

[1]The CES production function allows to control the degree of substitutability of the inputs. The elasticity of substitution between non-durable good (X) and the stock of infrastructure (K) in the final good (C) is a critical parameter that plays an important role in a model that displays Pigou cycles. In RBC models news about the future productivity trigger a positive income effect that leads to contemporaneous increase in consumption and leisure. As such, in this framework news fail to produce the comovement characteristic of the business cycle fluctuations. Beaudry and Portier (2004) identify the high elasticity of substituting consumption and investment as the main element driving this result. Therefore, a model that exhibits a low elasticity of substituting consumption and investment is able to produce business cycle comovements in the presence of news shocks.

eled as being either produced inside the household - by households purchasing X_t and K_t - or in the market. I choose to treat C_t as being produced in the market. Here, α, belongs to the unit interval and denotes the relative weight of each input.

The provision non-durable good X_t, or services, follows a Cobb-Douglas technology that uses labour $l_{x,t}$ and the sector-specific factor $\tilde{l}_x$, both supplied by the household, as inputs:

$$X_t = \theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{(1-\alpha_x)}, \qquad 0 < \alpha_x \leq 1$$

where $\theta_{x,t}$ is the state of technology (TFP) in the non-durable goods sector, while α_x is the income share of labour. The non-durable good X_t production function has constant returns to scale, but decreasing returns to scale in the variable factor.

Production in the durable good or construction sector is organised according to a Cobb-Douglas technology using labour $l_{k,t}$ and a fixed factor $\tilde{l}_k$as inputs.

$$I_t = \theta_{k,t} l_{k,t}^{\alpha_k} \tilde{l}_k^{(1-\alpha_k)}, \qquad 0 < \alpha_k \leq 1$$

Production in the construction sector depends on the state of technology (TFP) in this sector, $\theta_{k,t}$, and α_k is labour income as a share of total durable output. The household supplies both inputs and the firm resells its total output I_t at the price of p_t consumption units to the household.

The capital good accumulates according to:

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

where δ is the rate of depreciation and I_t is investment which is provided by the construction sector.

Beaudry and Portier (2004) restrict attention to cases where the elasticity of substitution between K_t and X_t in the final goods sector is no greater that one, which seems reasonable given our interpretation of K_t as infrastructure. Both the non-durable good sector and the construction sector should have production technologies that use both physical capital (machines) and labour. However, in order to make the model concise they exclude this possibility and instead introduce fixed factors. This simplifies exposition greatly since it allows remaining in the family of models with only one capital stock.

4.3 Household Sector

The representative household preferences are defined over consumption of the final good and over the labour supplied in each of the two sectors. The household's objective is to maximize:

$$E_0 \left[\sum_{t=0}^{\infty} \beta^t \left\{ log(C_t) + \nu_0(\bar{l} - l_{x,t} - l_{k,t}) \right\} \right] \tag{4.2}$$

where C_t is the level of consumption of the final good, $\bar{l}$ is the endowment of labor available in each period, β is the discount factor and ν_0 is a positive constant.

Following Hansen (1985) and Rogerson (1988) the household preferences are assumed to be separable in consumption and in leisure. I also assume that preferences are linear with respect to labour at the representative agent level.

The household's within period budget constraint is:

$$C_t + p_t l_t = w_{x,t}(l_{x,t}) + w_{k,t}(l_{k,t}) + r_t K_t + \Pi_{x,t} + \Pi_{k,t}$$

where the final good C_t is the numéraire, p_t is the price of capital, r_t is the rental rate of capital. $w_{x,t}$ and $\Pi_{x,t}$ are respectively the wage rate and returns to the fixed factor in the intermediate goods sector, and finally $w_{k,t}$ and $\Pi_{k,t}$ are the wage rate and returns to the fixed factor in the construction sector.

4.4 Information Structure

The information structure lays out what agents at which points in time know and what kind of uncertainty agents face. Since the processes driving TFP in the model are part of the stochastic environment and since it appears natural to specify the news shock such that it provides new information about future TFP innovations.

TFP in the investment sector. Total factor productivity $\theta_{k,t}$ in the durable good sector is non-stochastic and evolves according to:

$$log\ \theta_{k,t} = g_{0,k} + g_1 t$$

Beaudry and Portier (2004) justify the assumption of no stochastic variation in the durable good sector by on one hand because it seems unreasonable to study the model with shocks perfectly correlated among sectors, and on the other hand because expectations about future increases of TFP that concern the durable good sector do not appear relevant to the evolution of business cycles.

The TFP innovations or technological improvements in the non-durable good sector could be seen as a higher degree of goods-differentiation from which the agents increase theirs utility. In this interpretation, the Pigou cycle then is the result of higher variety of goods expectations and the necessary adjustments in the infrastructure good sector.

TFP in the non-durable sector. In the intermediate goods sector the technology evolves stochastically according to:

$$log\ \theta_{x,t} = g_{0,x} + g_1 t + log\ \hat{\theta}_{x,t}$$

$$log\ \hat{\theta}_{x,t} = \lambda\ log\ \hat{\theta}_{x,t-1} + \epsilon_t, \qquad 0 < \lambda < 1$$

where ϵ_t is a zero mean i.i.d random variable and variance σ_ϵ. ϵ_t takes a value that shifts TFP in period t either above or below the average growth rate g, i.e. either high level, ϵ_t^H, or low level, ϵ_t^L.

One of the BP question was if news shocks could generate real business cycles even though TFP never regresses, and for that they restrict the realisation of ϵ in a situation of regress to be larger than g. As my question is to see if news shocks could explain the developments of the particular Spanish economic structure, I believe that I could ignore this restriction.

4.5 Introducing the news shock

As in BP, in every period the household receives a signal about a future innovation to TFP, ϵ_t, can either take on a high level, which implies growth, or a low level, which implies no growth. The signal is assumed to only take on two values: one indicating a future high growth state and one indicating a future no growth state. I denote by q the probability that the signal indicates the correct state, while $1 - q$ is the probability of a signal indicating an erroneous state.

The probabilities of the different states of ϵ_t are $1 - p$ and p. There is a restriction which says that on average, technology grows at factor g_1, while bad times are considered periods with no productivity growth. As such, the p fully characterizes the distribution of technological innovations. In effect, these restrictions imply that ε_t takes on the value $g_1 \times p/(1 - p)$ in the growth state. The economy can therefore go through one of the following four realizations of signal and subsequent growth: a growth signal at time t which is validated by technological growth at time $t+n$ (probability $(1-p)q$), whereas a signal at time t but no realized growth at time $t + n$ (probability $(1 - p)(1 - q)$); a no-growth signal at time t but a growth realization at time $t + n$ (probability $p(1 - q)$ while a no-growth signal at time t and a no-growth realization at time $t + n$ (probability pq). As for the parameters (p, q) I cannot infer from previous studies of the Spanish economy, I will use the BP calibrated values.

4.6 Household's problem

The household maximizes utility with arguments $C, l_{x,t}, l_{k,t}$ subject to the constraints imposed by production of the consumption and the investment good.

$$\max_{C_t, l_{x,t}, l_{k,t}} E_0 \left[\sum_{t=0}^{\infty} \beta^t \left\{ log(C_t) + \nu_0(\bar{l} - l_{x,t} - l_{k,t}) \right\} \right]$$

subject to:

$$C_t = \left[\alpha \left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \right)^{\nu} + (1-\alpha) K_t^{\nu} \right]^{\frac{1}{\nu}},$$

$$K_{t+1} = (1-\delta) K_t + \theta_{k,t} l_{k,t}^{\alpha_k} \tilde{l}_k^{1-\alpha_k}$$

As a perfect competition problem, the budget constraint holds in every period. The period endowment consists of the two fixed factors and the accumulated capital stock. In every period the household receives a signal about that state of future TFP.

I start here with the setup of the social planner problem and the derivation of the first order conditions (FOCs).

4.6.1 Equilibrium and First Order Conditions

The competitive model equilibrium is determined by a sequence of quantities $\{K_t, C_t, L_{x,t}, L_{k,t}\}_{t=0}^{\infty}$ and prices $\{p_t, r_t, w_{x,t}, w_{k,t}\}_{t=0}^{\infty}$ such that:

1. allocations are optimal given prices (that is, consumers maximize utility and firms maximize profits)

2. markets clear i.e.

   - good markets clear, i.e. $Y_t = C_t + p_t I_t$,
   - labour markets clear, i.e. labour supply equals labour demand,
   - the problem (4.2) is solved.

Starting conditions $K_0, \theta_{x,0}, \theta_{k,0}$ are assumed to exist and the time paths of $\theta_{x,0}, \theta_{k,0}$ are exogenous.

I consider that $\tilde{l}_x$ and $\tilde{l}_k$ are normalized to unity and I assume interior solutions for $\tilde{l}_{x,t}$ and $\tilde{l}_{k,t}$. In this model the competitive equilibrium and the solution to the social planner problem coincide.

The Lagrangian for this problem is:

$$\begin{aligned}\mathcal{L}\left(\{C_t, l_{x,t}, l_{k,t}, K_{t+1}, \lambda_t, \mu_t\}\right):\\ E_0\Bigg[\sum_{t=0}^{\infty}\beta^t\left\{log(C_t)+\nu_0(\bar{l}-l_{x,t}-l_{k,t})\right\}\\ -\lambda_t\left\{C_t-\left[\alpha\left(\theta_{x,t}l_{x,t}^{\alpha_x}\tilde{l}_x^{1-\alpha_x}\right)^{\nu}+(1-\alpha)K_t^{\nu}\right]^{\frac{1}{\nu}}\right\}\\ -\mu_t\left\{K_{t+1}-(1-\delta)K_t-\theta_{k,t}l_{k,t}^{\alpha_k}\tilde{l}_k^{1-\alpha_k}\right\}\Bigg]\end{aligned} \tag{4.3}$$

I define an auxiliary variable: $H_t = \frac{\partial C_t}{\partial K_t}$

FOC

$$\lambda_t = \frac{1}{C_t} \tag{4.4}$$

$$\nu_0 = \lambda_t \frac{\alpha\alpha_x N_t^{\nu}}{l_{x,t}}\left[\alpha N_t^{\nu}+(1-\alpha)K_t^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{4.5}$$

$$\mu_t = \nu_0 \frac{l_{x,t}}{\alpha_x D_t} \tag{4.6}$$

$$\mu_t = \beta E_t\left[\mu_{t+1}(1-\delta)+\lambda_{t+1}H_t\right] \tag{4.7}$$

$$C_t = \left[\alpha N_t^{\nu}+(1-\alpha)K_t^{\nu}\right]^{\frac{1}{\nu}}$$

$$K_{t+1} = (1-\delta)K_t + D_t$$

$$N_t = \theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x}$$

$$D_t = \theta_{k,t} l_{k,t}^{\alpha_k} \tilde{l}_k^{1-\alpha_k}$$

$$H_t = (1-\alpha)K_{t+1}^{\nu-1}\left[\alpha\left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x}\right)^{\nu} + (1-\alpha)K_{t+1}^{\nu}\right]^{\frac{1-\nu}{\nu}}$$

In a Walrasian economy the marginal rate of substitution between consumption and investment equals the relative price that is equal to the ratio of shadow prices.

Normalizing the price of consumption to unity gives:

$$p_t = \frac{\mu_t}{\lambda_t}$$

The first derivative C.2 equates λ_t with the marginal utility of consumption, i.e. λ_t is the shadow price of a consumption unit at the margin, while C.4 represents the disutility of labour and the utility of consumption produced with this labour contemporaneously.

The C.6 represents the Euler equation and formalizes the inter-temporal adjustment.

4.6.2 Steady state

At this point, the next step towards a numerical solution of the model is obtaining the steady state from the FOC. According to BP a number of additional requirements are assumed to hold in the steady state:

$\nu_0 = 1$;

$\tilde{l} = \tilde{l}_x + \tilde{l}_k = 2$ is the total time amount of household;

$(\tilde{l}_x + \tilde{l}_k)/3$ is the working time in the steady state;

$\theta_{x,ss} = 1$;

$\theta_{k,ss} = 1$ (arbitrarily normalized);

$$C_{ss} = \frac{\alpha\alpha_x N_{ss}^{\nu}}{l_{x,ss}} \left[\alpha N_{ss}^{\nu} + (1-\alpha) K_{ss}^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{4.8}$$

$$\frac{l_{k,ss}}{\alpha_k D_{ss}} = \beta \frac{H_{ss}}{C_{ss}(1-\beta(1-\delta))} \tag{4.9}$$

$$K_{ss} = \frac{D_{ss}}{\delta} \tag{4.10}$$

$$N_{ss} = l_{x,ss}^{\alpha_x} \tag{4.11}$$

$$D_{ss} = l_{k,ss}^{\alpha_k} \tag{4.12}$$

$$H_{ss} = (1-\alpha) K_{ss}^{\nu-1} \left[\alpha N_{ss}^{\nu} + (1-\alpha) K_{ss}^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{4.13}$$

Then I use a Taylor approximation around the steady state to replace the equations by approximations as log-deviations of the variables. Log-linearized equations are given in appendix C. The last steps consists in solving for the recursive equilibrium law of motion using the undetermined coefficients method by H. Uhlig, and analyzing the solutions via impulse-response analysis by implementing the Uhlig (1998) Toolkit MATLAB programs to carry out these calculations.

4.7 Calibration

I start the calibration exercise acknowledging that a three-sector model is an extreme simplification of reality and that it omits many important elements that could be very well introduced in the model like for example: adjustment costs, variable rates of factor utilization, inventories, additional capital stocks.

Many parameters are based on known estimates in line with other calibrations for the Spanish economy for example Puch and Licandro (1997) and Díaz-Giménez and Puch (1998). In particular, the discount factor β is set equal to 0,9891, the depreciation rate δ is set to 0.0222. Total disposable time, $\tilde{l} = \tilde{l}_x + \tilde{l}_k$ is is normalized to 2, and the disutility of labour scale parameter ν_0 is set to 1, so that one third of total time is devoted to work in the steady state. Like Beaudry and Portier (2004) I set the ratio $\frac{\theta_{0,x}}{\theta_{0,k}} = 1$. The relative weight of K and X in the CES production function, that is the parameter α, is set so that the labour share is 65.29% and consumption's share in total output is 75%.

Following the literature on scale parameters, which says that the short-run returns to labour are close to the labour share in output, I set $\alpha_x = 0.6$. From the data it can be seen that are little decreasing returns to labour in the construction industry and I believe that by setting $\alpha_k = 0.97$ it will reflect that fact. The model considers that the infrastructure K and other goods X are strong complements, with an elasticity of substitution close to 0.2.

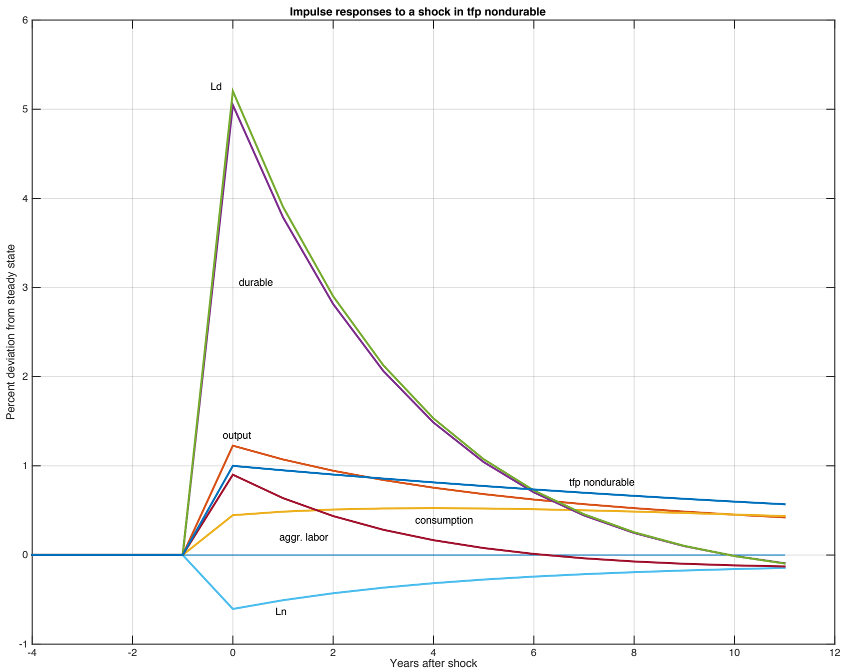
Using impulse response functions derived from the model I will try to illustrate key properties of the model.

4.8 News driven business cycle fluctuations

In this model, an increase in investment demand will arise following a signal when the signal received does not relate to productivity improvement in the capital good sector. In the figure it can be observed how the economy responds to an anticipated increase in technology in the non-durable good sector, induced by a positive realization of the signal v_t. As a result of the signal, a technological improvement is expected to arise in $t = 1$ period time[2]. The figure shows the dynamics associated with the case where the expected increase is actually realized (time $t = 0$ in the graph). As can be seen from the figure 4.1, employment in the construction sector and the structures sector immediately jumps.

4.8.1 Benchmark Model Simulation

Figure 4.1: The effects of a news shock in non-durable TFP



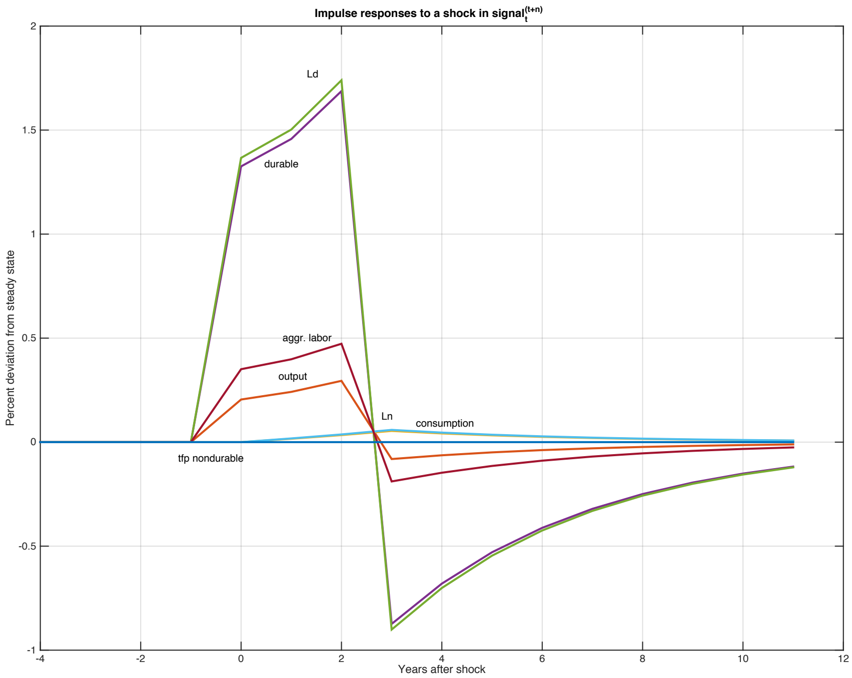
The dynamics are such that anticipated technological improvement can be said to cause an expectation lead boom, that is, from period $t - 1$, total output (defined as $C_t + p_t I_t$), investment and consumption are all increasing even though technology has not yet improved, and then gradually decrease

[2] Appendix D illustrates a simulation with 3 periods signal timing

to its steady-state level while the aggregate labour is increasing although the employment in the non-durable sector is decreasing.

If at period $t = 3$, instead of technology improving as anticipated, individuals learn that their forecast is incorrect and that technology does not actually change and it remains at the same initial level, the situation changes. In the figure 4.2 it can be seen that dynamics of non realization of the TFP news.

Figure 4.2: The effects of a non-realized shock in non-durable TFP



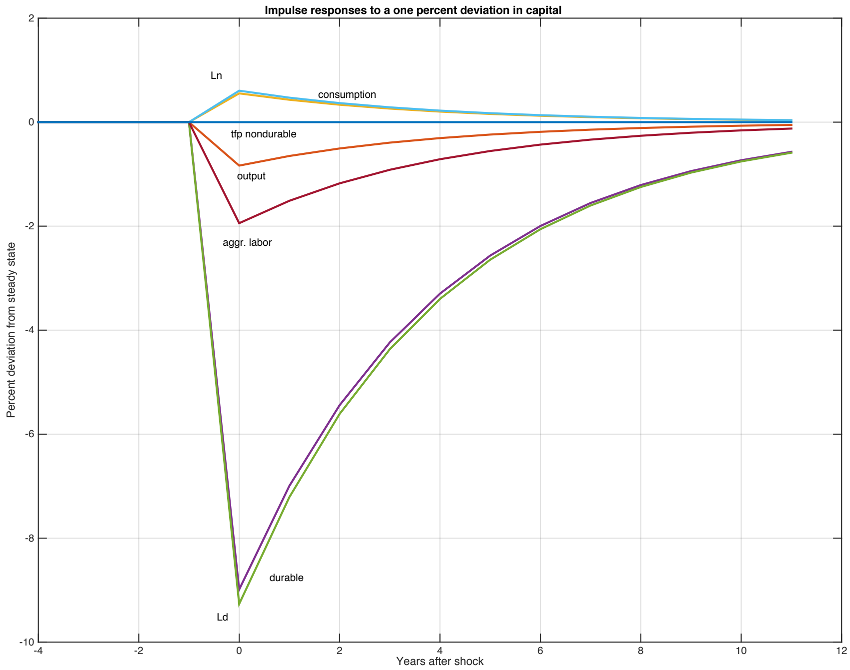
The economy first experiences an expansion and then a recession without ever having experienced an actual change in technology. It can be seen a sharp fall in output, employment in the construction sector, and durables at period $t = 3$, as individuals realize that they previously over-accumulated. Following this drop, the output gradually returns to its previous steady state and the durables and the employment in durables returns very slowly to its initial level after more than 12 periods. In particular, at period $t = 3$ aggregate output, investment and employment all fall, while consumption starts to fall with a lag.

In this model, an expansion and a recession can arise as the result of overly optimistic expectations about future technological growth. These dynamics capture the idea, suggested by Pigou and others, that forecast errors might be key in understanding recessions.

In the case of news about improvement in the structures good sector, good news would lead to a recession not an expansion.

The figure 4.3 shows how the economy responds to signal only to an improvement in the capital good sector: output, investment in durable, and labour in durable move together, but downwards. The only consumption and employment in the non-durable sector are increasing. It results that in a multi-sector model like the one presented, expected improvement in the non-durable good is not in itself sufficient to guaranty increased demand for current investment. In effect, in order to guaranty that investment increases following news about future productivity in the nondurable good sector, the production structure must exhibit enough complementarity between capital and the non-durable good.

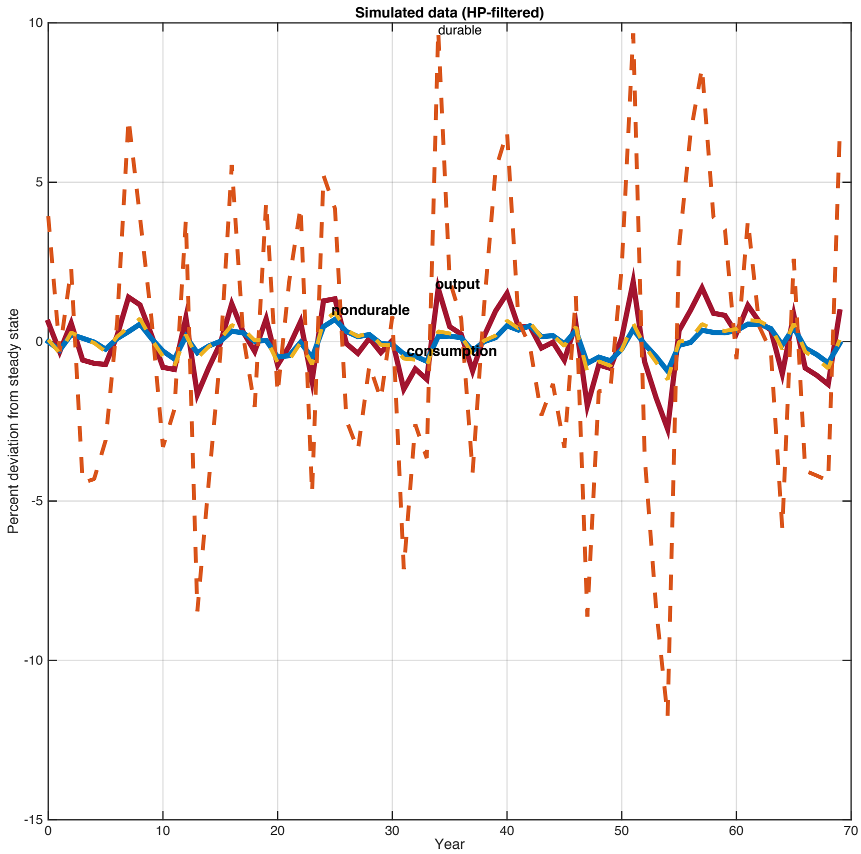
Figure 4.3: A shock in capital that produces a recession



Emerge from the model that having high labour supply elasticity is a feature that helps the decoupling of investment and consumption decisions in the model and thereby favors the emergence of Pigou cycles, although he model does not require an infinite elasticity of labour supply to have expectations generate substantial fluctuations. If instead agents valued smooth leisure sufficiently, they would be less willing to work harder in both sector following a news and this would limit the possibility of Pigou cycles.

In the graph below (figure 4.4) it can be observed the simulated data, HP-filtered, where the variation of durable goods is by far largest, followed by the one in output; consumption evolves smooth matched closely by the non-durable. This order mirrors relative variation in real data. Studying the quantitative properties of the model shows that the model is capable of reproducing basic stylized facts of real business cycles. Focusing on the relative size of standard deviations, it appears that the model captures real data rather convincingly. The empirical moments of the BDREM[3] dataset of the Spanish economy are described in the following table beside to the simulated moments of the model.

Figure 4.4: Simulated Output, Consumption, durables and non-durables



The table 4.1 displays series for consumption, capital, aggregate labour and output as coming out of a model simulation with a signal leading the factual TFP innovation by three periods.

[3] Boscá et al. (2007)

Table 4.1: Targeted and simulated moments (standard deviation of HP-filtered data)

	Spanish data	Model simulation
Consumption	0.637	0.631
Capital	0.296	0.281
Aggregate labour	0.767	0.71
Output	1.19	1.21

Note: The Spanish data is taken from the BDREMS data base;

Comparing column of the Spanish data with and simulation it can be seen that the model very slightly overstates the standard deviations of output (Y). The model matches very much the consumption (C) while for the capital (K) and aggregate labour the empirical data show a slightly higher standard deviation.

Focusing on the relative size of standard deviations, it appears that the model captures real data rather convincingly.

The model simulation produces correlations that lie somewhat below the respective empirical moments as it can be seen from the table 4.2.

Overall, the model simulates moments of output, consumption, aggregate labour and capital reasonably close to what is observed in real data.

Table 4.2: Model Autocorrelation and Comovement: corr($v_{t+j}Y_t$)

Model and Data Autocorrelation and Comovement

	-3		-2		-1		0		1		2		3	
v_{t+j}	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
Y	0.14	0.09	0.36	0.37	0.64	0.76	1	1	0.64	0.76	0.36	0.37	0.14	0.09
C	-0.01	0.22	0.19	0.36	0.47	0.52	0.85	0.5	0.75	0.57	0.63	0.50	0.49	0.42
K	-0.22	-0.31	-0.06	-0.14	0.19	0.04	0.54	0.24	0.71	0.35	0.74	0.38	0.68	0.37
L	0.21	0.35	0.39	0.42	0.61	0.54	0.87	0.63	0.39	0.61	0.06	0.55	-0.18	0.50

Chapter 5

Conclusion

The purpose of this study was to analyze the relevance of news shocks as driver of macroeconomic fluctuations for the Spanish economy for the period 1970 - 2015. Following Beaudry and Portier (2006) approach, the baseline specification identifies news shocks under the assumption that these shocks do not have a contemporaneous effect on TFP but still generate an increase in stock prices.

Quantitatively, the impulse response analysis suggests that a substantial part of the total TFP response is delayed rather than immediate. While there is evidence of a gradually decreasing response of TFP to news shocks, there is none effect on impact. Nevertheless there is a high correlation between a shock with permanent effects on TFP in the long run and a shock which has an immediate effect on stock prices but doesn't affect TFP on impact. Under Beaudry and Portier (2006) interpretation, the results are quite supportive for the news-driven business cycle hypothesis for the Spanish economy.

In a VAR with TFP and IBEX 35 augmented successively with GDP, investment, consumption and residential investment, both types of shocks seem to account for important fractions of the total variance of macroeconomic variables at medium and longer horizons, while it generates sharp response of residential investment.

Consistent with my argumentation, these responses suggest that the news shocks drove economic fluctuations by enhancing the creation of new investment opportunities, i.e. increasing investment in residential structures in Spain.

A three-sector model economy, similar to the model in Beaudry and Portier (2004), with a low substitutability of consumption and investment, and calibrated for the Spanish economy is capable to simulate medium to long run variation in the data.

Part III

EVALUATION OF THE NEWS SHOCKS IDENTIFICATION METHODOLOGIES

The third part of this dissertation provides a comprehensive overview of two different structural VAR methodologies that have been developed to identify news shock dynamics since the seminal work of Beaudry and Portier (2006). In the preceding part I use Beaudry and Portier (2006) methodology to empirically identify news shocks in a bivariate and trivariate SVAR. In that sense, in a VAR including TFP, IBEX 35 and various macroeconomic aggregate variables, I find that imposing sequentially short- and long- run restrictions in a VECM model, the impulse response functions recovered are consistent with the news shock view of the business cycle. Although the results of the methodology used indicate that the news shocks have an important role in explaining the Spanish business cycle fluctuations, it is important to note a number of potential issues related to news shocks identification methods. As the first part show, the goal of news shocks identification are often quite ambitious, in the sense that the econometrician does not observe all variables in economic agents' information sets, which means that strong assumptions typically underlie these types of exercises. In order to deepen the understanding of the mechanisms underlying news shocks identification methods, in this part I analyze the assumptions for identification schemes using in the first place the short-, and long run restrictions, and then, the maximum forecast error variance approach. I compare those two strategies for isolating news shocks by illustrating the empirical problems of identifying them and contrast the results. Detailing on each identification methodology, I use Spanish data to test these SVAR techniques analyzing to what extent different orthogonalization schemes can lead to quite different results. In this part, the VAR specification includes the investment specific technical change (ISTC) instead of TFP in order to test if news regarding future ISTC are a major source of business cycle fluctuations.

Chapter 1

Introduction

In the news shocks literature there is no consensus over how to best identify news shocks dynamics within SVAR settings as different structural VAR approaches show contrasting results. For example, Beaudry and Portier (2006) find that total factor productivity (TFP) news shocks are important drivers of business cycles, while Barsky and Sims (2011) find they are not. Specifically, Beaudry and Portier (2006) condition on stock prices to capture news about expected changes in technology. By contrast, Barsky and Sims (2011) identify news about productivity as the shock orthogonal to current productivity that best explains future variations in productivity. This debate motivates my analysis of two of the most used methodologies to identify news shock dynamics: Beaudry and Portier (2006) (henceforth BP) and Barsky and Sims (2011) (henceforth BS). The aim of the present paper is to highlight the key similarities and differences in the context of vector autoregressive (VAR) methodologies. I apply alternative identification strategies using Spanish annual data for the period 1970 - 2015, examining why and to what extent these SVAR approaches differ in the results they deliver. My contribution is to identify news shocks on the investment specific technical change (ISTC) while conditioning not only on stock prices, but on other forward looking variables like aggregate investment, consumption, residential investment or hours.

The basic idea of the news view of business cycles is that agents receive information that relates to future developments in the economy. The appealing feature of the news-driven business cycle literature is the possibility to generate boom-bust cycles without any observable change in fundamentals ex-post. In particular, if good news about future productivity generates an expansion but ex-post that exogenous fundamental does not change, then one might observe business cycle dynamics (i.e. output expanding and then contracting) with no observable change in fundamentals.

The origins of current empirical studies starts with the seminal paper of Beaudry and Portier (2006). They present evidence that news of productivity shocks anticipate actual changes to productivity raising fundamental questions about the empirical relevance of the news driven real business cycle hypothesis. Since then, there has been an increasing interest in studying the role anticipated shocks play in generating cyclical movements in macroeconomic data with different modeling tools.[1]

A large body of empirical work relies on reduced form time series techniques suggesting news about the future changes in fundamentals - such as total factor productivity (TFP), taxes, or government spending - might be an important driver of the business cycle[2].

This literature explores two general strategies for isolating news shocks. The first one follows Beaudry and Portier (2006) which involves two identifying restrictions. First, they impose the restriction that one shock has no long-run effects on total factor productivity (TFP) and label the orthogonal shock as the news shock; then they impose the restriction that one shock has zero short-run effect and label that shock as the news shock. As it turns out, the two restrictions lead to similar results. They then look at the effect of

[1] Recent papers document the importance of news shocks: Beaudry and Portier (2004, 2006, 2014); Schmitt-Grohé and Uribe (2012); Jaimovich and Rebelo (2009); Christiano et al. (2008); Fujiwara et al. (2011); Barsky and Sims (2011); Kurmann and Otrok (2013); Forni et al. (2014a)

[2] Pigou (1927) was one of the first authors to propose that agents' expectations about the future are an important source of business cycle fluctuations.

the two shocks on standard macroeconomic aggregates, including consumption, investment, and employment, finding that the identified news shock leads to positive conditional comovement among macroeconomic aggregates on impact. Hence, the aggregate variables strongly anticipate movements in technology while they find that the news shocks account for a large fraction of the variance of aggregate variables at business cycle frequencies.

Further work by Beaudry and Lucke (2010) and Beaudry et al. (2011) has confirmed these findings; Beaudry et al. (2011) look at non-U.S. international data, while Beaudry and Lucke (2010) consider a richer identification strategy in a five-variable SVAR, allowing for several shocks, including both neutral and investment-specific technology shocks, and monetary and preference shocks, along with their news shock.

Barsky and Sims (2011) challenge Beaudry and Portier (2006) results using different identification assumptions. They choose the news shock as the shock orthogonal to the current TFP innovation that has the most predictive power in explaining future TFP. They apply a principal-components approach to identify their news shock, choosing the one that maximizes the sum of contributions to the TFPs forecast error variance (FEV) over a finite horizon. Although theirs findings are in contrast with those of Beaudry and Portier (2006), are in line with the predictions of the standard neo-classical model: following a news shock consumption increases, but output, investment, and hours fall slightly.

BP and BS schemes identify the surprise technology shock identically but may differ in the identification of the news shock. With respect to the latter shock, both approaches share the restriction that it has no impact effect on TFP. The BS approach furthermore embraces the solution of a maximization problem, whereas the BP approach imposes that no other shock than surprise and anticipated technology can have a long-run impact on TFP.

Most of this literature focuses on news shocks about neutral productivity, although the concept of a news shock may apply to any exogenous driving force. For example, Beaudry and Portier (2006) extracted news about future technology from stock prices; Ramey (2011) created a series of news about future government spending by reading *"Business Week"* and other periodicals; Fisher and Peters (2010) created news about government spending by extracting information from stock returns of defense contractors; Poterba and Summers (1986) and Leeper et al. (2012) used information from the spread between federal and municipal bond yields for news about future tax changes; and Mertens and Ravn (2012) decomposed Romer and Romer (2010) narrative tax series into one series in which implementation was within the quarter ("unanticipated") and another series in which implementation was delayed ("news"). In the monetary shock literature, many papers use high frequency financial futures prices to extract the anticipated versus unanticipated component of interest rates changes (e.g. Rudebusch (1998), Bagliano et al. (1999), Kuttner (2001), and Gürkaynak et al. (2005), while Kurmann and Otrok (2013) identify news shocks in a framework of a vector autoregression (VAR) that combines measures of the term structure slope and productivity with prominent macro aggregates.

The central insight for the purpose of this part of the dissertation is that investment-specific technical change (ISTC) constitutes news in as much as these developments are known in advance and therefore lead to predictable changes in productivity growth. Hence, as long as long-run investment-specific technical change (ISTC) is primarily driven by actual productivity-enhancing changes, increase in factor input quality and efficiency of allocations, then a shock that accounts for the majority of changes in long-run fluctuations in productivity should capture news. For that reason, in this part I look at the extent to which innovations in forward looking variables contain information about future ISTC, or alternatively whether periods of high investment specific technical change growth are preceded by increase in macroeconomic variables. I consider the ISTC as a productivity indicator that provides economic agents clear signals about how output, consumption, hours, investment in residential capital, business structures and equipment can evolve in the future.

In particular, I focus on the propagation of the news shocks to ISTC through alternative identification methods. The first one is imposing short and long run restrictions on a reduced form VAR of two, three and four variables. Then, I use the maximum forecast error variance (MFEV) identification approach in the same setting and compare the two results.

I focus on ISTC for various reasons. A large body of literature has considered its relevance for growth, business cycles, and asset prices. Greenwood et al. (1988) were the first to suggest that investment shocks could be a viable alternative to neutral technology shocks as sources of business cycles in a general equilibrium environment. The appeal of these disturbances was later enhanced by the work of Greenwood et al. (1997) and Fisher (2006). The former suggested that investment-specific technical progress - a kind of investment disturbance identified with trend reductions in the price of investment relative to consumption - is responsible for the major share of growth in the post-war U.S. Fisher (2006) using structural VARs identifies unanticipated ISTC shocks using data on the real price of investment, and finds that they have accounted for over two-thirds of business cycle fluctuations in output over the 1982-2000 period. Both these contributions rely on the observation that, in equilibrium, technology improvements in the production of investment goods should be reflected in their relative price. The relative importance of identified ISTC news shocks has been determined by Khan and Tsoukalas (2012). They provide strong support for ISTC news shocks when investigating the role of news in driving U.S. business cycles. The ISTC news shocks have been introduced in the DSGE literature (see, e.g., Davis (2007), Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), Khan and Tsoukalas (2012), but they have not yet been identified in the data using the VAR methodology, which has the advantage that it imposes minimal restrictions to identify shocks.

I focus on the performance of identification schemes with respect to impulse response functions as it is the convention in the related literature. I present the impulse response from the simulations corresponding to each empirical methodology graphically. To be more precise, I plot the median estimated response corresponding to each empirical model. Hence, I report the innovations coefficient of correlation between estimated news shock series for each simulation. Although this correlation can never be perfect in the framework due to the non-fundamentalness problem, a high correlation would very likely indicate that the problem is negligible in practice.

The paper is organized as follows. Chapter 2 presents the structural vector autoregression (SVAR) approach, the vector error correction models (VECM), and the problems related to the non-fundamental representation of a SVAR identifying news shocks. Chapter 3 reviews the Beaudry and Portier (2006) news shocks identification scheme. Chapter 4 presents BP identification scheme results. Chapter 5 reviews the Barsky and Sims (2011) news shocks identification scheme. Chapter **??** reports the results of BS methodology, and chapter 7 concludes.

Chapter 2

Structural Vector Autoregression Approach

The structural vector autoregression (SVAR) approach used to identify news shocks as well as the dynamic response of macroeconomic variables to them employs simple time series procedure. Using the economic theory to sort out contemporaneous links among the variables (Stock and Watson (2001)), the SVARs are an empirical tool to analyze the effects of the economy as a dynamic, stochastic system which responds to present and past structural shocks[1]. The idea behind the procedure is to run vector autoregressions in the data and impose identifying assumptions to back out impulse responses to news shocks. Empirical findings about the dynamic effects of structural economic shocks are typically reported in terms of point estimates of those impulse response functions, surrounded by error bands. These SVAR impulse responses are then compared with theoretical impulse responses from economic models.

The BP approach uses short and long-run restrictions to identify news shocks with stock price innovations orthogonalized with respect to productivity measure growth. The long-run restrictions in a vector autoregressions

[1] Leeper et al. (1996), Christiano et al. (1999) and Favero (2001) provide excellent surveys.

(VARs) started with the seminal work of Blanchard and Quah (1989) that estimate a two-variable model. Theirs method is often applied to small-dimension VARs that permit the identification of only a limited number of shocks. As this approach does not require a fully-articulated structural model or numerous model-specific assumptions it is used extensively in empirical research. However, Faust and Leeper (1997) discuss potential limitations of imposing long-run restrictions. They show that identification via long-run restrictions could be unreliable as the shocks are aggregation of many underlying types of shocks that may be poorly identified. Additionally, Erceg et al. (2005) show that it is difficult to estimate precisely the long-run effects of shocks when available samples may be too short or unstable to credibly impose such restrictions. The intuition is that finite samples generate imprecise measures of the VAR moving-average parameters at very long horizons, which when are used for identification purposes, translate into imprecise and potentially spurious inference.

Additionally, the zero-restriction based approach in Beaudry and Portier (2006) is difficult to implement beyond a bi-variate system and has been criticized for this reason. If there are more than two variables, there are typically many disturbances that have no effect on measure of the productivity - ISTC in my case - in the short-run and anticipate future changes in the ISTC. In other words, there are different linear combinations of past observable variables that are orthogonal to current ISTC innovations and may help to forecast future productivity.

In contrast, the Barsky and Sims (2011) methodology it is an alternative to zero restrictions approach to identify structural shocks and their associated impulse response functions which can be easily implemented on VARs of different sizes. In particular, they use a variant of the maximum forecast error variance (MFEV) method introduced by Francis et al. (2010) which builds on Faust (1998) and Uhlig (2004b,a). The maximum forecast error variance method of Francis et al. (2014) was developed as an alternative to using standard long-run restrictions - as for example used in Blanchard and

Quah (1989) or Galí (1999) - to identify technology shocks. The method aims to isolate shocks that maximize the forecast error variance of a variable attributable to those shocks at a long but finite forecast horizon.

BS methodology identifies the news shock as the innovation associated with the maximum forecast error variance share (MFEV) of the ISTC over 40 quarters forecast horizon, but with the additional restriction that the innovation is orthogonal to current productivity. In particular, the ISTC news shock is identified as the linear combination of reduced-form innovations orthogonal to current ISTC that maximizes the sum of contributions to productivity measure forecast error variance over a finite horizon.

The restriction is based on the assumptions that (i) only a limited number of shocks affect ISTC and (ii) the ISTC news shocks do not affect ISTC contemporaneously but anticipate future changes in it. The main advantage of the MFEV approach is that unlike the long-run restrictions approach, it does not rely on the precise assumptions about the stochastic trend in the variable of interest or the number of common stochastic trends among the variables of interest. Barsky and Sims (2011) methodology builds on a level VAR estimation, while Beaudry and Portier (2006) estimate VECMs. As Hamilton (1994) emphasizes, if the evidence about cointegration is unclear, it may be preferable to estimate the system without cointegration restrictions - i.e., a VAR in levels - so as to avoid misspecification bias.

Francis et al. (2010) show that medium run identification similar to that of BS methodology performs better in finite samples than does long-run identification. At the same time, because identification is not based on the zero frequency, one need not take an explicit stance on the order of integration of variables or on the cointegrating relationships among them. As noted by Fisher (2010), when a vector error correction models (VECM) is used as in BP case, the conclusions regarding the importance of news shocks greatly depend on the number of cointegration relationships imposed.

Next two sections investigate the properties of the vector error correction model (VECM) and presents the problem known as a non-fundamentalness problem that limits the SVAR methods in identifying the news shocks.

2.1 Vector Error Correction Models - VECM

Although estimation of the parameters of the VAR requires that the variables in are covariance stationary, with their first two moments finite and time-invariant, many economic time series appear to be "first-difference stationary" with their levels exhibiting unit root or nonstationary behavior. If the variables in the VAR are not covariance stationary, but their first differences are, they may be modeled with a vector error correction model (VECM).

Applied to covariance-stationary time series, the VARs regression estimators have good properties, but encounter difficulties when applied to non-stationary or integrated processes. When Granger and Newbold (1974) introduced the concept of spurious regressions, they illustrated that if you have two independent random walk processes, a regression of one on the other will yield a significant coefficient, even though they are not related in any way. Together with the fact that Nelson and Plosser (1982) show that unit roots might be present in a wide variety of macroeconomic series in levels or logarithms, imply that variables should be rendered stationary by differencing before they are included in an econometric model.

Engle and Granger (1987) demonstrated that two or more integrated, nonstationary time series might be cointegrated, so that some linear combination of these series could be stationary even though each series is not. If two series are both integrated - of order one, or I(1) - one could model their interrelationship by taking first differences of each series and including the differences in a VAR or a structural model. However, this approach would be suboptimal if it was determined that these series are indeed cointegrated. In that case, the VAR would only express the short-run responses of these series to innovations in each series. This implies that the simple regression in first differences is misspecified. If the series are cointegrated, they move together in the long run. A VAR in first differences, although properly specified in terms of covariance-stationary series, will not capture those long-run tendencies.

Accordingly, the VAR concept may be extended to the vector error-correction model (VECM), when there is evidence of cointegration among two or more series. The model is fit to the first differences of the nonstationary variables, but a lagged error-correction term is added to the relationship.

In the case of two variables, this term is the lagged residual from the cointegrating regression, of one of the series on the other in levels. In the case of multiple variables, there is a vector of error-correction terms, of length equal to the number of cointegrating relationships, or cointegrating vectors, among the series. There must be two cointegrating relationships in trivariate models, while for four-variable models there must be three cointegrating vectors.

2.1.1 Structural Vector Error Correction Model - SVECM

To begin, lets consider a K-dimensional vector of observable variables y_t is integrated of order one and can be represented as a vector autoregressive (VAR) process of order $p < \infty$. Allowing for $r > 0$ cointegrating vectors, the error-correction representation of the process is given by

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + u_t, \tag{2.1}$$

where α and β are $K \times r$ matrices of loading coefficients and cointegrating vectors, respectively; the $\Gamma_j's, j = 1, ..., p-1$, are $K \times K$ coefficient matrices; and u_t are the reduced-form error terms. These can be thought to be linear combinations of the structural shocks, ε_t, we are interested in. As is common in the literature, it is assumed that the covariance matrix of ε_t is the identity matrix I_K. Since the covariance matrix of u_t is non-diagonal, there exists a nonsingular matrix B such that $u_t = B\varepsilon_t$. This matrix is not unique, and suitable assumptions must be imposed on its coefficients to identify structural shocks. The structural model, a B-model in the sense of Lütkepohl (2005) is then obtained from (2.1) by applying the Granger representation theorem:

$$y_t = L \sum_{\tau=1}^{t-1} \varepsilon_\tau + B\varepsilon_t + \sum_{\tau=1}^{\infty} \Xi_\tau^* B\varepsilon_{t-\tau} + y^0, \tag{2.2}$$

where y^0 is a vector of initial conditions, $L := \beta_\perp \left[\alpha'_\perp \left(I_K - \sum_{I=1}^{p-1} \Gamma_i\right) \beta_\perp\right]^{-1} \times \alpha'_\perp B$ is a $K \times K$ matrix with a rank $K - r$, $\alpha_\perp, \beta_\perp$ denote orthogonal complements of α, β, respectively, and the matrices $\Xi_j^*, j = 1, ..., \infty$, are absolutely summable; that is, $lim_{\tau\to\infty}\Xi_j^* = 0$. Hence, in terms of structural interpretation, L is the long-run multiplier matrix of the structural shocks, ε_t and B is the corresponding short-run impact matrix. We have to propose and justify (at least) $K(K-1)/2$ restrictions on $B =: (b_{ij})$ and $L =: (l_{ij})$ to identify the structural shocks. Thus for $K = 2$ we need at minimum one restriction to identify the structural shock of interest.

2.2 Non-fundalmentalness

The BP methodology uses small-scale VAR or vector error correction (VECM) models to identify news shocks. Forni et al. (2014a) point out that small-scale VAR models suffer from the non-fundamentalness issue, which is clearly an important concept in time series econometrics. Non-fundamentalness means that the variables used by the econometrician do not contain enough information to recover the structural shocks and the related impulse response functions.

The problem is essentially whether the structural moving average (MA) representation of such variables can be inverted or not. If not, the variables do not have a VAR representation in the structural shocks, implying that such shocks cannot be obtained by estimating a VAR with these variables.[2] One way to mitigate the invertibility/fundamentalness problem is by adding

[2] A partial list of references on non-fundamentalness includes Sargent and Hansen (1991), Lippi and Reichlin (1993, 1994), Giannone and Reichlin (2006), Fernández-Villaverde et al. (2007) and Forni et al. (2014b).

variables to the information set as is highlighted by Fernández-Villaverde et al. (2007) or Leeper et al..

Fève and Jidoud (2012) show that identifying news shocks may induce a non-fundamental time series representation of the data. The identification of structural shocks from past and current data may fail because these data cannot reveal the current and past shocks, an assumption taken as given in the VAR analysis.

Nevertheless, this issue has been analysed by Beaudry and Portier (2014) and in particular by Beaudry et al. (2015), where they show that although the non-fundamentalness problem is present, it is quantitatively almost irrelevant because impulse response functions do not change much even when the three most important factors from the factor-augmented VAR proposed by Forni et al. (2015) are used.

As such, Beaudry et al. (2015) develop a diagnostic based on an R^2 to determine whether non-fundamentalness is quantitatively important. They argue that in some cases the non-fundamental representation is close to the fundamental representation, implying that the non-fundamentalness problem may cause only minor bias in the estimation of structural impulses. Theirs finding is that nonfundamentalness is not a serious problem in the identification of technological news shocks, even though there may remain debate on how best to use SVAR techniques to identify the effects of news.

Beaudry and Portier (2014) show that even when a model with news shocks gives rise to a non-fundamental representation, its fundamental representation can be very "close" to its non-fundamental one, implying that VAR methods may nonetheless deliver a good approximation of structural impulse responses even when the non-fundamentalness problem arises.

Forni and Gambetti (2011)[3] suggested a fundamentalness test that can

[3]The test verifyies whether the structural shock estimated with a VAR is an innovation with respect to available information. The information is summarized by computing the principal components; then is estimated the news shock with different VAR specifications and identification schemes; finally, is tested for orthogonality of the estimated shocks with respect to the lags of the principal components.

find if fundamentalness is rejected for small-scale VARs. They find that the only VAR specification surviving the test is a high dimension VAR estimated with Barsky and Sims (2011) methodology.

Chapter 3

Short- and Long-run Restrictions Methodology

In this section I analyze the approach that relies on quite standard techniques of imposing short- and long-run restrictions with Cholesky decomposition[1] proposed by Beaudry and Portier (2006). BP start from the idea that forward-looking variables and in particular stock prices should contain

[1] Cholesky decomposition: consider a zero mean VAR(p) process:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{3.1}$$

This process can be rewritten in such a way that the residuals of different equations are uncorrelated. For this purpose, we choose a decomposition of the white noise covariance matrix $\Sigma_u = W\Sigma_\varepsilon W$, where Σ_ε is a diagonal matrix with positive diagonal elements and W is a lower triangular matrix with unit diagonal. This decomposition is obtained from the Choleski decomposition $\Sigma_u = PP'$ by defining a diagonal matrix D which has the same main diagonal as P and by specifying $W = PD^{-1}$and $\Sigma_\varepsilon = DD'$. In the econometrics literature such a system is called a *recursive model* (Theil (1971)). Herman Wold has advocated these models where the researcher has to specify the instantaneous "causal" ordering of the variables. This type of causality is therefore sometimes referred to as Wold-causality. The ordering has to be such that the first variable is the only one with a potential immediate impact on all other variables. The second variable may have an immediate impact on the last $K-2$ components of y_t but not on y_{1t} and so on. To establish such an ordering it is not an easy exercise in practice.

valuable information for the identification of news shocks. They explicitly take into account that news about future productivity or technology may have effects today even though it does not show up in current productivity.

For this purpose, BP impose different identifying restrictions on the estimated lag polynomial of a moving average (MA) representation that provides a set of structural shocks to be compared. If under different identifying assumptions are found similar shocks, then the type of identifying assumption contains information about how a specific shock hits the economy.

For instance, I look at a vector autoregressive (VAR) model that includes a measure of productivity, ISTC, and a measure of stock prices index, the IBEX 35. Using this bivariate VAR, I experiment with two identifying restrictions finding two almost co-linear shocks. First, I impose the restriction that one shock has no long-run effects on IST and label the orthogonal shock as the news shock; second, I impose the restriction that one shock has zero short-run effect and label that shock as the news shock. I find a very high correlation between the news ISTC shock series identified by these two alternative schemes and that impulse responses to them of measures of economic activity are quite similar. It turns out that the two restrictions lead to similar results as the two shocks are co-linear. Hence, following the BP hypothesis, they represent a technical innovation which affects ISTC with delay. However, this technical innovation affects stock prices immediately and may therefore cause expectations-driven fluctuations. Therefore, like Beaudry and Portier (2006), I conclude that the common component of these two shocks represents an anticipated ISTC shock, suggesting that positive news shocks in productivity are preceded by stock market booms.

3.1 Baseline Identification

To implement the baseline identification scheme, the most natural choice of variables on which to base the procedure are a measure of productivity and some forward-looking variable that contains information about future developments. As such, the reduced-form two variables VAR specification consists of two endogenous variables ordered as follows: ISTC and IBEX 35 (henceforth SP)[2]. Since stock prices have the forward-looking property, they will respond to the changes in expectations earlier than the realized changes in macroeconomic fundamentals will affect the other economic variables. News about investment specific technical change shocks can have an impact on stock prices, but it may need some time to actually affect ISTC because of an implementation lag. Thus, stock prices are very helpful for the understanding of expectations driven economic fluctuations.

Later on, when introducing in the bivariate and trivariate VAR system beside the ISTC the GDP/Investment/Consumption/Hours/Residential Investment/Equipment Investment, it is reasonable to assume that an expected increase in the ISTC has an immediate effect on the macroeconomic variables mentioned stimulating the economy.

Next section presents the identification strategy consists in two steps. First, I apply sequentially short-run and long-run restrictions on the VAR model to identify the news shocks. Second, I compute the correlation between the two news shocks recovered from the two identification strategies.

3.2 Bivariate VECM of ISTC and IBEX 35

I assume that the two variables, ISTC and SP, can be represented in log first differences, $log\ \Delta ISTC$ and $log\ \Delta SP$, by the Wold representation.

[2] As Lütkepohl (2005) stated, one problem with this type of impulse response analysis is that the ordering of the variables cannot be determined with statistical methods but has to be specified by the analyst. The ordering has to be such that the first variable is the only one with a potential immediate impact on the second. In a multivariate setting to establish such an ordering may be a quite difficult exercise in practice. The second variable may have an immediate impact on the last $K-2$ components of y_t but not on y_{1t} and so on. The choice of the ordering, the *Wold causal ordering*, may, to a large extent, determine the impulse responses and is therefore critical for the interpretation of the system.

3.2.1 Reduced Form MA

The reduced form moving average for the bivariate system $[\Delta ISTC_t, \Delta SP_t]$ is as follows:

$$\begin{bmatrix} \Delta ISTC_t \\ \Delta SP_t \end{bmatrix} = C(L) \begin{bmatrix} \mu_{1,t} \\ \mu_{2,t} \end{bmatrix}, \quad E(\mu_t, \mu_t') = \Omega \tag{3.2}$$

where $C(L) = I + \sum_{i=1}^{\infty} C_i L^i$. The estimation is based on a moving average representation derived from the vector error correction model (VECM) between measured ISTC and stock prices, SP. Furthermore, I assume that the system has at least one stochastic trend and therefore $C(1)$ is not equal to zero as the unit root and cointegration test[3] confirms that fact.

Short-run restriction

To describe the short-run restriction, I assume that the two variables can be represented in log first differences, by the Wold representation:

$$\begin{bmatrix} \Delta ISTC_t \\ \Delta SP_t \end{bmatrix} = \Gamma(L) \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad E(\varepsilon_t, \varepsilon_t') = I \tag{3.3}$$

where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma_i L^i$ the two shocks, $\epsilon_{1,t}$ and $\epsilon_{2,t}$, are mutually orthogonal and have unit variance. The short run restriction imposes that ϵ_2 has no short run effect on IST. Formally, this restriction is imposed by setting the $1,2$ element of the matrix Γ_0 to zero:

$$\Gamma_0 = \begin{bmatrix} * & 0 \\ * & * \end{bmatrix}. \tag{3.4}$$

[3] The Johansen Cointegration Test are shown in the Appendix H

As such, the second shock of the system has no contemporaneous impact on the ISTC, but is not restricted in terms of its impact after the initial period. The second shock hence stands for a news shock.

The ***trivariate framework*** needs three restrictions for an exact identification together with the ones on the covariance matrix of the structural shocks. The additional three restrictions in the BP framework are given by:

$$\Gamma_0 = \begin{bmatrix} * & 0 & 0 \\ * & * & * \\ * & * & * \end{bmatrix} \text{ and } \Gamma(1) = \begin{bmatrix} * & * & 0 \\ * & * & * \\ * & * & * \end{bmatrix}. \tag{3.5}$$

Thus, only the first shock - the surprise ISTC shock - can have an impact effect on ISTC. The news shock, on the other hand, does not alter the ISTC at impact, but can have a long-run effect on it. Note that both surprise and anticipated technology shocks can have a long-run impact on ISTC according to this specification. Finally, the third shock can represent a measurement error or a linear combination of other structural shocks in the data.

The ***four-variable framework*** is quite similar to the trivariate one with the following restrictions:

$$\Gamma_0 = \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & * & 0 \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \text{ and } \Gamma(1) = \begin{bmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix}. \tag{3.6}$$

The first and second shocks are again labelled surprise ISTC and news, respectively, while the last two shocks could represent a measurement error or a linear combination of structural shocks other than technology shocks in the data. Although I arbitrarily set the $(2,4)$ element of Γ_0, it can be observed that whether the $(2,3),(2,4)$ or $(3,4)$ element of Γ_0 is set to zero does not make a difference in terms of the identification of surprise IST or news shocks within this structure.

Long-run restriction

The long-run restriction is based on an alternative Wold representation

$$\begin{bmatrix} \Delta ISTC_t \\ \Delta SP_t \end{bmatrix} = \tilde{\Gamma}(L) \begin{bmatrix} \tilde{\varepsilon}_{1,t} \\ \tilde{\varepsilon}_{2,t} \end{bmatrix}, \quad E(\tilde{\varepsilon}_t, \tilde{\varepsilon}_t') = I \tag{3.7}$$

where $\tilde{\Gamma}(L) = \sum_{i=1}^{\infty} \tilde{\Gamma}_i L^i$ and the two shocks $\tilde{\varepsilon}_{1,t}$ and $\tilde{\varepsilon}_{2,t}$, are mutually orthogonal and have unit variance. The long run restriction is that only $\tilde{\varepsilon}_{1,t}$, has a long run effect on IST. This restriction is imposed by setting the 1, 2 element of the matrix $\tilde{\Gamma}(L) = \sum_{i=1}^{\infty} \tilde{\Gamma}_i L^i$ to zero.

3.2.2 Short-run Identification

From (3.2) and (3.3) we have

$$\Gamma(L)\varepsilon_t = C(L)\mu_t \tag{3.8}$$

Since $C_0 = I$, and (3.8) must hold for all t, then

$$\Gamma_0 \varepsilon_t = \mu_t \tag{3.9}$$

If I square both sides and take expectations then it yields:

$$\Gamma_0 \Gamma_0' = \Omega$$

$$\Gamma_0 \varepsilon_t, \varepsilon_t' \Gamma_0' = \mu_t \mu_t' \quad \Rightarrow \quad \Gamma_0 \Gamma_0' E(\varepsilon_t, \varepsilon_t') = E(\mu_t \mu_t') \quad \Rightarrow \quad \Gamma_0 \Gamma_0' * I = \Omega$$

The short-run identification is done by estimating the Cholesky decomposition of Ω. I impose the $1, 2$ element of matrix Γ_0 to zero, meaning that the second disturbance ε_2 has no short run (contemporaneous impact on) effect on ISTC. The equations (3.8) and (3.9) also implies that $\Gamma_i = C_i\Gamma_0$, for $i > 0$ $(\Gamma(L)\varepsilon_t = C(L)\Gamma_0\varepsilon_t)$.

3.2.3 Long-run Identification

In the long run case, the distributed lag $\tilde{\Gamma}(L)$ is different from the one above. Since

$$\tilde{\Gamma}(L)\tilde{\Gamma}(L)' = C(L)\Gamma_0\Gamma_0'C(L)'$$

$$\Gamma_0\Gamma_0' = \Omega \quad \Rightarrow \quad \tilde{\Gamma}(L)\tilde{\Gamma}(L)' = C(L)\Omega C(L) \tag{3.10}$$

we do not know Ω, so we need to estimate $\hat{\Omega}$ and then the estimation will be:

$$\tilde{\Gamma}(L)\tilde{\Gamma}(L)' = C(L)\hat{\Omega}C(L) \tag{3.11}$$

Thus, for the long run multipliers we have,

$$\tilde{\Gamma}(1)\tilde{\Gamma}(1)' = C(1)\hat{\Omega}C(1) \tag{3.12}$$

where $\tilde{\Gamma}(1)$ is the lower triangular of Cholesky decomposition of $C(1)\hat{\Omega}C(1)'$.

For the long run identification, I impose the $1, 2$ element of the long run matrix $\tilde{\Gamma}^1_{12}$ to be equal to zero, which makes that the disturbance $\tilde{\varepsilon}_2$ has no long run effect on ISTC. From that it can be obtained $\tilde{\Gamma}(L) = C(L)C(L)^{-1}\tilde{\Gamma}(1)$.

Therefore, ε_2 and $\tilde{\varepsilon}_1$ are referred to as the stock prices innovation and the permanent shock to ISTC, respectively. The procedure above is not applied simultaneously, but sequentially to describe the joint behavior of measured IST and stock prices.

Suppose that it happens to be the case that the two recovered disturbances, ε_2 and $\tilde{\varepsilon}_1$, are extremely highly correlated, or effectively the same.

This suggests that the procedure has recovered a single shock that, since it satisfies the short-run restriction, and, it satisfies the long-run restriction, it captures all-important long-run information about productivity. Given these characteristics, the shock satisfies the two characteristics of a news shock described above. Of course, the procedure only delivers plausible measures of news if the two shocks happen to be highly correlated.

Chapter 4

Short- and Long-run Methodology Results

This section presents the empirical results of the BP identification methodology. I use real data series for the Spanish economy from 1970 to 2015 downloaded from the EU KLEMS data base, the 2017 release[1].

4.1 Evidence from Bivariate VECM

In order to recover news shocks, in a bivariate framework I sequentially impose two separate identification restrictions: short- and long-run. The first variable in the bivariate framework is the ISTC. However, as a measure of methodology robustness I use different forward looking variables as the second one. I start from the IBEX 35, but I consider alternative identification using GDP, Investment, Consumption, Hours, Residential Investment and Equipment Investment.

I show that the news driven fluctuations are typically displaying colinearity between ϵ_2 and $\tilde{\epsilon_1}$, the two disturbances obtained from the short-run and long-run identification schemes. In this setting, "the tilde", $\sim$ denotes long-run, and the subscripts 1 and 2 refer to ISTC and second variable, re-

[1] http://www.euklems.net

spectively. The result favors a view of business cycles driven largely by a shock when does not affect the measure of productivity in the short run - and therefore does not look like a standard technology shock - but affects the ISTC with substantial delay, and therefore does not look like a demand shock. It can be thought on this shock as a news representation about future investment specific technological opportunities that is first captured in the forward looking variable.

4.1.1 Bivariate VECM: ISTC and IBEX 35

In a bivariate structural vector autoregressive approach (SVAR) the variables are the investment-specific technical change (ISTC) as the measure of productivity denoted by ISTC, and the IBEX 35 as stock price and denote the log of this index by SP. Since stock prices have the forward-looking property, they will respond to the changes in expectations earlier than the realized changes in macroeconomic fundamentals will affect the other economic variables. News about ISTC shocks can have an impact on stock prices, but it may need some time to actually affect ISTC because of an implementation lag. Thus, stock prices are very helpful for our understanding on that expectations drive economic fluctuations.

The augmented Dickey-Fuller unit root tests suggests that these two variables are integrated of order one (I(1) variables, stationary in the first difference. The Johansen's cointegration test indicates that ISTC and SP are likely cointegrated of order one, so I adopt the specification of bivariate vector error correction models (VECM) in the estimation. The other specification choice concerns the number of lags to include in the VECM. The number of lags are been selected using information criteria, likelihood ratio test statistic, and Akaikes information criterion. According to a likelihood ratio test one lag is chosen for Spanish data.[2].

[2] The Augmented Dickey-Fuller test, and the Johansen test are reported in Appendix H - (ISTC and stock prices - SP) are integrated of order one and cointegrated with each other, i.e. $[\Delta ISTC_t, \Delta SP_t]'$ is $I(0)$

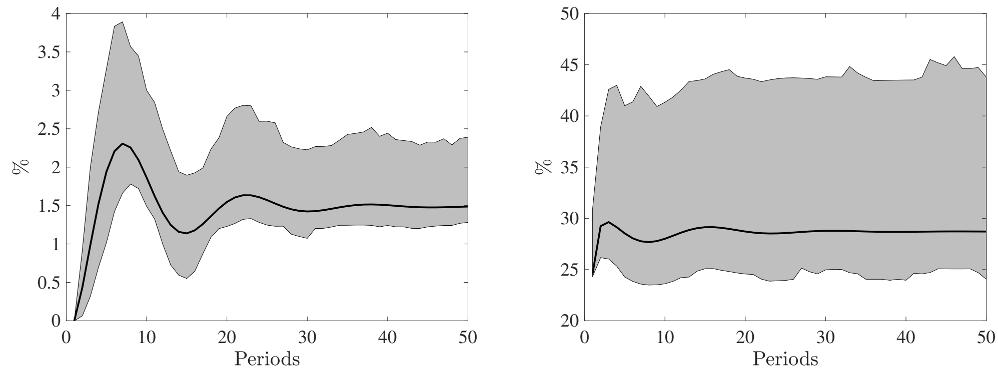
I further show that, for the aggregate Spanish economy, ϵ_2 and $\tilde{\epsilon_1}$, obtained from the bivariate identification schemes are highly correlated, and induce nearly identical dynamic responses of ISTC and stock prices. An important result for my analysis that would support the news driven fluctuations, is that the correlation between the two disturbances for the Spanish economy is very high, 0.97, indicating almost a perfect co-linearity.

The resulting impulse responses on (ISTC, SP) associated with the ε_2 and $\tilde{\varepsilon}_1$ shock for the Spanish economy are displayed in the figures 7.9 and 4.2. A first striking observation is that those responses appear very similar when comparing one orthogonalization to another. The figure 7.9 shows the dynamics associated with the ε_2 shock, the short-run restriction, which seems to affect slightly ISTC on impact and then gradually decreasing towards zero. This shock has a strong immediate effect on stock prices, reaching the maximum effect over the next twenty years. These results suggest that ε_2 contains information about future stock prices reflected in instantaneously positively growth. The dynamics associated with the $\tilde{\varepsilon}_1$ shock - which by construction should have a permanent effect on ISTC - has essentially the same immediate light positive impact effect on ISTC, followed by a gradually decrease towards zero. The effect on SP is substantial with a permanent increase after a period of twenty years as stock markets anticipate future profits.

The following graphs 7.9 and 4.2 presents the impulse response functions (IRF) of ISTC corresponding to the ε_2 shock (from short-run identification) and the $\tilde{\varepsilon}_1$ shock (from long-run identification).

Figure 4.1: IRF Short-run restrictions 2-VAR: ISTC IBEX 35

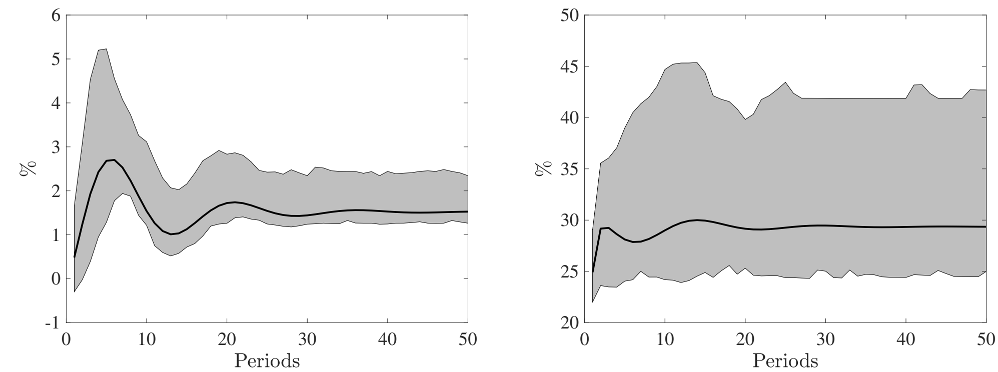
(a) IRF ISTC short run (b) IRF IBEX 35 short run



Note: The solid black lines represent the IRF of the ISTC and IBEX 35 to a unit aggregate news shock when is imposed the short-run restriction. The grey area represents the $5\% - 95\%$ confidence intervals. IRF of ISTC to a unit aggregate news shock are given in the left panel; IRF of IBEX 35 are given in the right panel.

Figure 4.2: IRF Long-run restrictions 2-VAR: ISTC IBEX 35

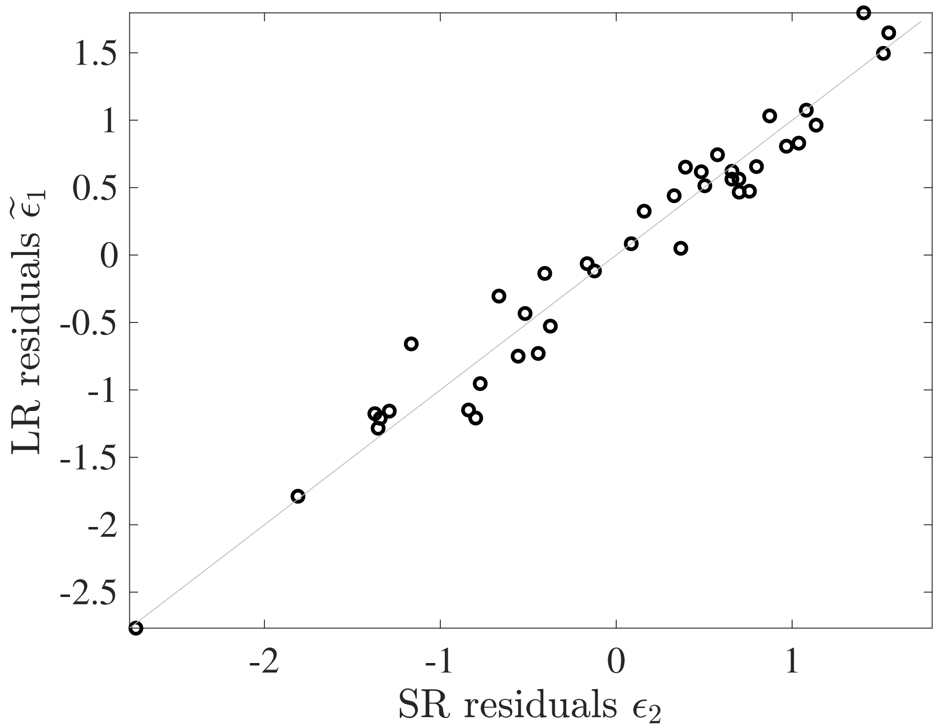
(a) IRF ISTC long run (b) IRF IBEX 35 long run



Note: The solid black lines represent the IRF of the ISTC and IBEX 35 to a unit aggregate news shock when is imposed the long-run restriction. The grey area represents the $5\% - 95\%$ confidence intervals. IRF of ISTC to a unit aggregate news shock are given in the left panel; IRF of IBEX 35 are given in the right panel.

The scatter plots of ε_2 and $\tilde{\varepsilon}_1$are shown in figure 4.3. As can be seen from the figure, the ε_2 and $\tilde{\varepsilon}_1$ line is up on the 45 degrees line, which also supports the very high correlation between these shocks. These two orthogonalization techniques recover essentially the same shock.

Figure 4.3: Identified structural residuals correlation 2-VAR: ISTC IBEX 35



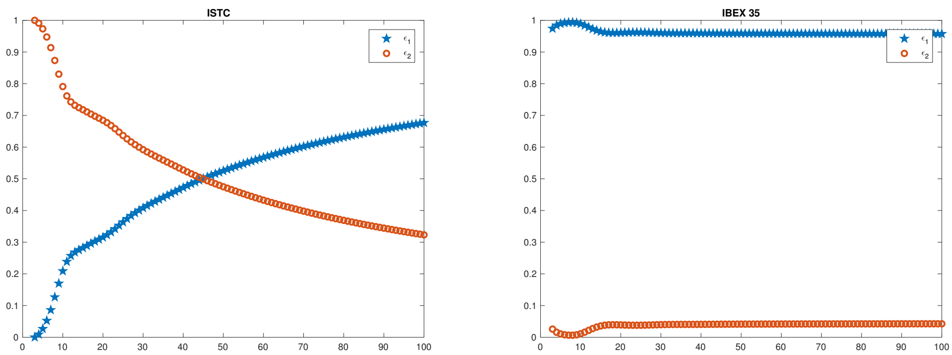
Note: Figure 4.3 displays the two shocks, the ε_2 and $\tilde{\varepsilon}_1$. The coefficient of correlation between these two series is 0.97 (with a standard deviation of 0.018); Both shocks are obtained from the baseline specification: one lag and cointegrating relation.The straight line is the 45-degree line.

Figures 4.4 and 4.5 display the fraction of the FEV of the ISTC (left panel) and IBEX 35 (right panel) explained by a ISTC news shock. Looking at the impact on the IST, left panel on figures 4.4 and 4.5, the news shock explain almost none of the movement in ISTC on impact but reaches up to 90% of ISTC variations after 40 periods. This news shock explains over

90% of the FEV of IBEX 35 on impact, decreasing fast after 15 periods. Looking at the impact on the IBEX 35, right panel on figures 4.4 and 4.5, the TFP news shock explain almost all of the movement in IBEX 35 at all horizons, while the IBEX 35 shock on IBEX 35 have practically no effect at all horizons. The two figures imply that news shock is sufficient to describe the majority of ISTC and IBEX 35 movements.

Figure 4.4: FEV Short run restrictions 2-VAR: ISTC IBEX 35

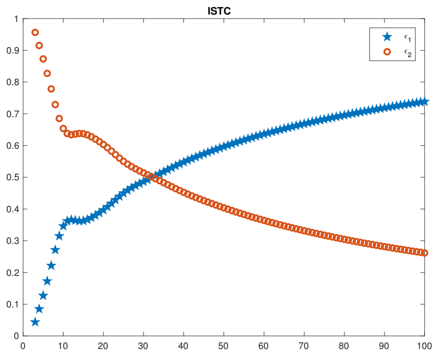
(a) FEV ISTC short run (b) FEV IBEX 35 short run



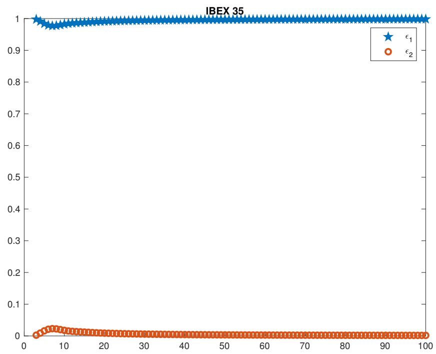
Note: Forecast error decomposition of the ISTC and IBEX 35 Index to a unit aggregate news shock. Impulse responses of ISTC to a unit aggregate news shock are given in the left panel; the responses of stock prices indices are given in the right panel.

Figure 4.5: FEV Long run restrictions 2-VAR: ISTC IBEX 35

(a) FEV ISTC long run



(b) FEV IBEX 35 long run



Note: Forecast error decomposition of the ISTC and IBEX 35 Index to a unit aggregate news shock. Impulse responses of ISTC to a unit aggregate news shock are given in the left panel; the responses of stock prices indices are given in the right panel.

The results from the IRF of the bivariate vector autoregression model of ISTC and IBEX 35 by employing two different orthogonalization schemes indicate that the BP methodology has recovered a single shock. Practically, the short- and long-run restrictions capture the empirical evidence of the Spanish news shocks ISTC. This large and significant response of IBEX 35 to a news shock suggests that the behavior of stock prices might carry relevant information for understanding the propagation of news shocks. The forecast error variance decomposition (FEV)[3] confirms the importance of this

[3]FEV is an alternative way to represent impulse response functions. In a linear model with multiple exogenous driving forces, the fraction of the forecast error variance of an endogenous variable due to a particular shock equals the sum of squared impulse response functions to that shock up to a given forecast horizon divided by the sum of squared impulse response functions to all shocks up to the same forecast horizon. As the forecast horizon tends towards infinity, the variance decomposition is often said to be unconditional in that it shows the fraction of the unconditional variance of an endogenous variable attributable to each shock. Variance decompositions are frequently employed to asses the relative importance of different exogenous shocks in accounting for business cycles.

identified shock.

4.1.2 Bivariate VECM: ISTC and macroeconomic forward looking variables

In this section I present the identified structural residuals correlation of the system in which - in addition to the ISTC - consumption (C), aggregate investment (I), hours (H), GDP, residential investment and equipment investment are alternatively introduced. The corresponding IRF short- and long-run restrictions on each system are presented in the Appendix I.

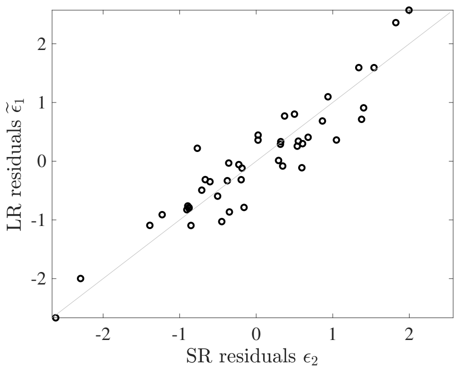
In the figure 4.6 the shocks series are highly correlated and they induce similar dynamics as the system ISTC and IBEX 35. This result suggests that, regardless of the macroeconomic variables used in the 2-VAR setting, the BP methodology prove to be an important mechanism to identify news shocks. Overall, the high coefficient of correlation presented in the table 4.1 indicate that the variables chosen seem to be relevant for understanding the news shocks, and could be considered that represent important driving forces behind economic fluctuations.

Table 4.1: Coefficient of correlation

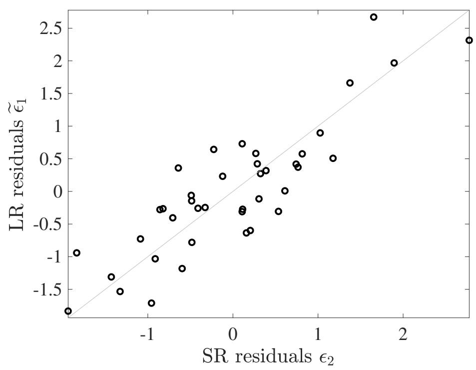
	C	I	Hours	GDP	Residential Invest.	Equipment Invest.
ISTC	0.93	0.87	0.97	0.81	0.99	0.89

Figure 4.6: Spain: Identified structural residuals correlation: bivariate SVAR analysis

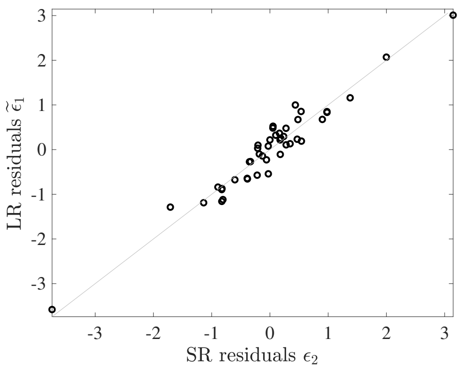
(a) Residuals corr.: ISTC C



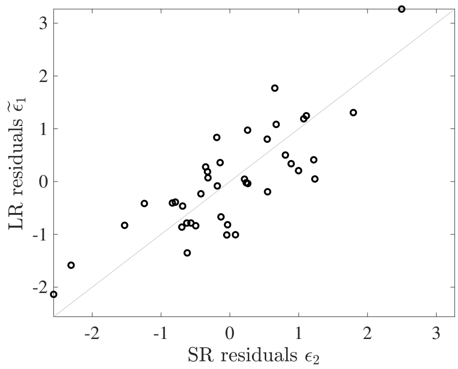
(b) Residuals corr.: ISTC I



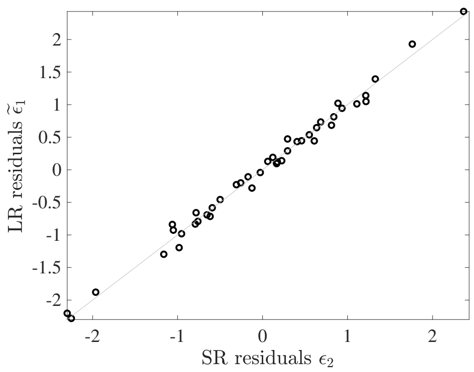
(c) Residuals corr.: ISTC Hours



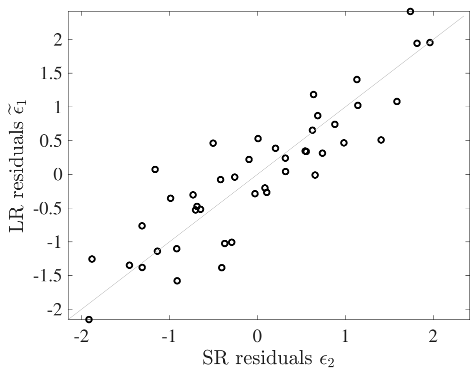
(d) Residuals corr.: ISTC GDP



(e) Residuals corr.: ISTC Residential Investment



(f) Residuals corr.: ISTC Equipment Investment



Note: Figure 4.6 displays the two shocks, the ε_2 and $\tilde{\varepsilon}_1$. The coefficient of correlation between each VAR specification series appears in table 2.1 ; The shocks are obtained from the baseline specification: one lag and cointegrating relation.The straight line is the 45-degree line.

4.2 Evidence from 3-variables VECM

The BP methodology results found relevance of a news shock in a bivariate setting. In order to assess the relevance of a news shock for macroeconomic fluctuations, I examine whether these observations exist in higher dimensional systems. The comovement of different macroeconomic variables is an important feature for the business cycles. The comovement patterns may include the significant clues about the mechanisms and shocks that generate business fluctuations. Hence, investigating the comovement of these macro variables to news shocks is very important to study the business cycle fluctuations.

As I review the different identifying assumptions, I begin focusing on the following simple approach to identifying news shocks. In order to see how the approach can be applied to systems with many variables, I consider a vector of macroeconomic times series of dimension n, whose Wold representation is as follows:

$$\begin{bmatrix} \Delta X_{1t} \\ \Delta X_{2t} \\ . \\ . \\ . \\ \Delta X_{nt} \end{bmatrix} = C(L) \begin{bmatrix} \mu_{1,t} \\ \mu_{2,t} \\ . \\ . \\ . \\ \mu_{n,t} \end{bmatrix}. \tag{4.1}$$

Where the two first variables in the system are always ISTC and stock prices, $X_{1t} = ISTC_t$ and $X_{2t} = SP_t$, while the $n-2$ other variables can be different from one system to another. We aim at identifying some of the structural shocks from the following alternative representation with orthogonal innovations:

$$\begin{bmatrix} \Delta X_{1t} \\ \Delta X_{2t} \\ . \\ . \\ . \\ \Delta X_{nt} \end{bmatrix} = \Gamma(L) \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ . \\ . \\ . \\ \varepsilon_{n,t} \end{bmatrix}. \tag{4.2}$$

To fully identify the n structural innovations, we need $n(n-1)/2$ restrictions. As we aim at identifying news shocks about future productivity, we can consider a subset of restrictions that will allow us to identify only the news shock and a surprise investment specific technical change shock. To do this, we first assume that only two shocks can permanently affect ISTC in the long run. This amounts to imposing $n-2$ zeros for the last $n-2$ columns of the first line of the long run matrix $\Gamma(1)$. We then need to separate those two technology shocks: this is done by assuming that the surprise technology shock is the only shock that affects ISTC on impact, which implies that the only non-zero term in the first row of the impact matrix Γ_0 is the $(1,1)$ term. These $2n-3$ restrictions allows for a unique identification of the news shock ε_2 and the surprise technology shock ε_1.

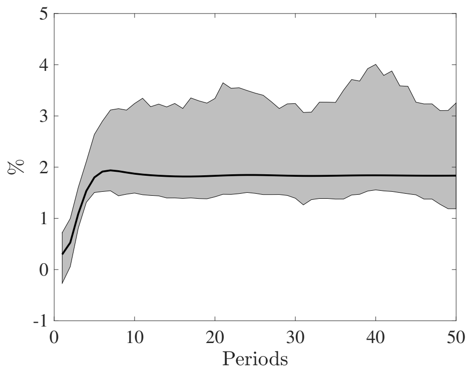
In what follows, I present the evidence from a three-variable VAR. I consider a larger VAR to know how other variables respond to news shocks, as there are likely more than two types of shocks that drive macro-fluctuations. I extend the system to a trivariate setting in which the third variable is one of the main macro aggregates, consumption, investment, output, hours and residential investment alternatively in addition to ISTC and IBEX 35. As I have discussed before, increasing the information set reduces the likelihood of non-fundamentalness problems. However, Beaudry and Portier (2006) findings to higher dimension VARs are questioned. On one hand, Kurmann and Mertens (2014) and Lucke (2010) show that some of the BP identification schemes used for larger systems may be problematic in the case of long run restrictions and when the system is not estimated in levels. On other hand, drawback or difficulty with a larger system is that it requires more identification assumptions.

Figure 4.7 displays the responses of ISTC and stock prices to the expected news shock, ε_2, estimated using a trivariate system where the third variable is varied. The black lines correspond to the median IRF in the six three-variable VARs in which the third variable is alternatively (C, I, H, GDP, Residential Investment, Equipment Investment), ie, per capita values of consumption, investment, output, hours worked, residential capital investment and equipment investment. Confidence bands are the ones obtained for each system, while all estimations are in levels. I first checked the cointegration properties of such systems. Running trivariate Johansen tests with lags indicated by the Schwarz Criterion I found evidence of two cointegrating vectors if it was added output, investment, consumption or hours as a third variable. Hence, I treat all trivariate systems as having two cointegrating vectors.

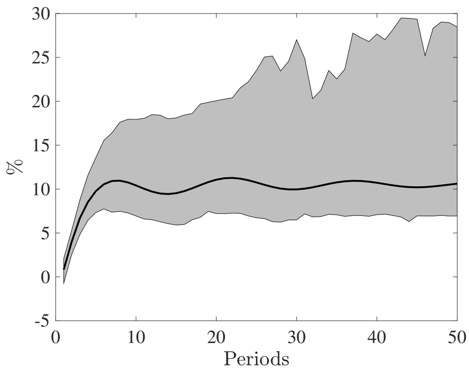
Two main conclusions can be drawn from theses responses: first, the responses are significative when we change the third variable in the system with the exception of Hours and Equipment Investment which are not significant; second, the responses suggest 3-VAR system would allow to investigate effects of aggregate news shocks.

Figure 4.7: IRF 3 variables VAR

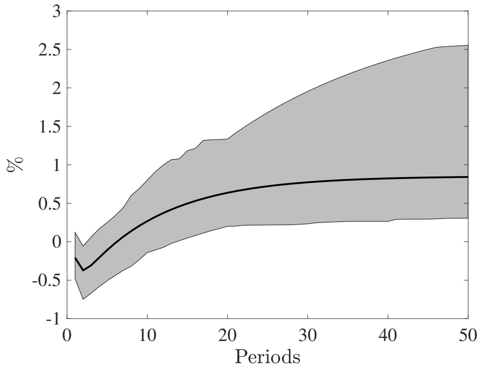
(a) IRF ISTC IBEX 35 C



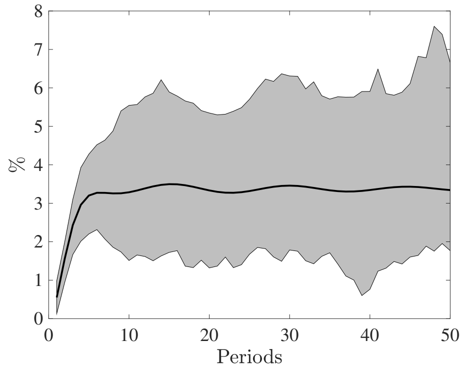
(b) IRF ISTC IBEX 35 I



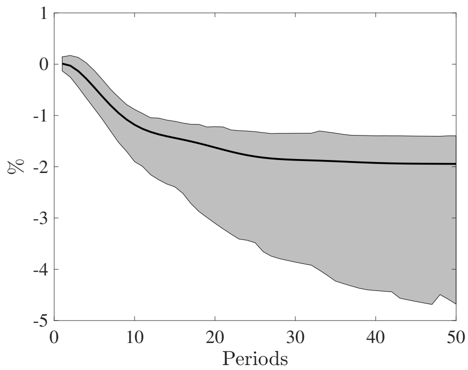
(c) IRF ISTC IBEX 35 H



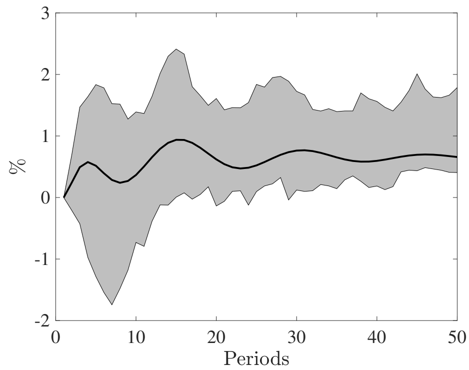
(d) IRF ISTC IBEX 35 GDP



(e) IRF ISTC IBEX 35 Residential cap.



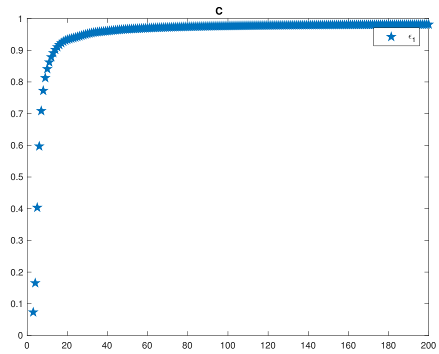
(f) IRF ISTC IBEX 35 Equipment cap.



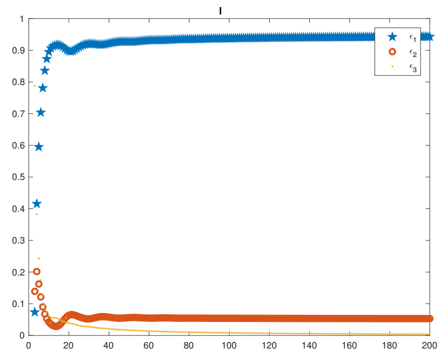
Note: The impulse response of Consumption, Investment, Hours, GDP, Residential Investment and Equipment Investment when successively added into a trivariate VAR system where the first two variables are ISTC and IBEX 35. The solid black lines represent the impulse responses functions of the ISTC to a unit aggregate news shock. The grey area represents the $5\% - 95\%$ confidence intervals. The VECM is estimated with one lag and two cointegrating relations.

Figure 4.8: FEV 3 variables VAR

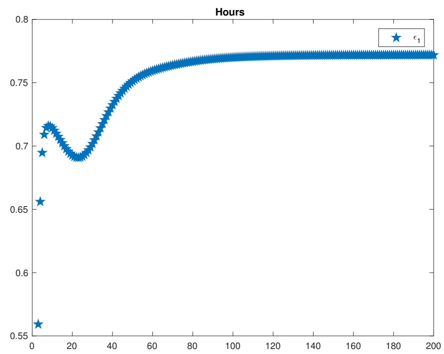
(a) FEV ISTC IBEX 35 C



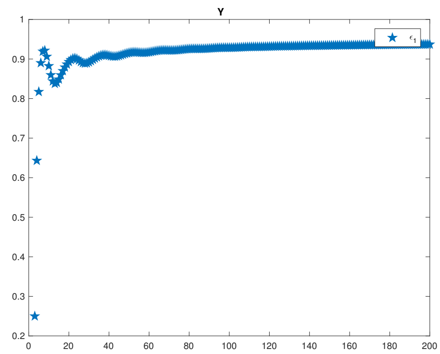
(b) FEV ISTC IBEX 35 I



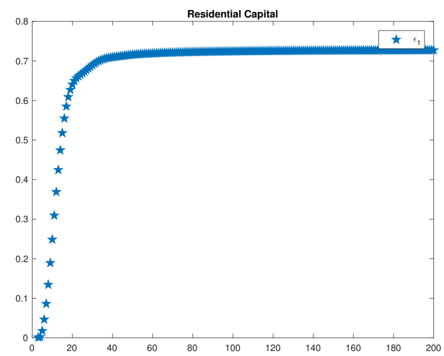
(c) FEV ISTC IBEX 35 H



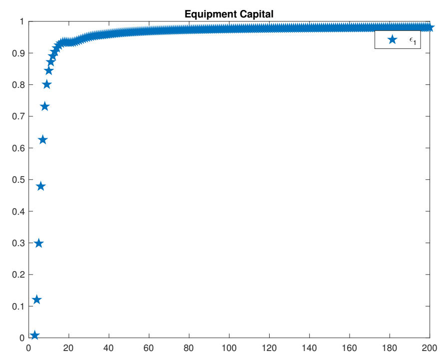
(d) FEV ISTC IBEX 35 GDP



(e) FEV ISTC IBEX 35 Residential Invest.



(f) FEV ISTC IBEX 35 Equipment Invest.



Note: The FEV of news shock that explain the variation of Consumption, Investment, Hours, GDP, Residential Investment and Equipment Investment when successively added into a trivariate VAR system where the first two variables are ISTC and IBEX 35. The VECM is estimated with one lag and two cointegrating relations.

The variance decompositions in figure 4.8 indicate that $\tilde{\varepsilon}_1$ (shown in the figure), and similarly ε_2 (not shown[4]), explain a substantial fraction of fluctuations at business cycle frequencies. In effect, given the interpretation of this shock as reflecting news about ISTC innovations, the variance decomposition results suggest that news shocks may be a major source of business cycle fluctuations.

4.3 Evidence from 4-variables VECM

The BP methodology results found relevance of a news shock in a bivariate and trivariate setting. The focus here is to examine whether in a higher dimensional system, the BP methodology can still recover the transmission mechanism of an news shock. In order to assess the relevance of a news shock for macroeconomic fluctuations, I examine whether the comovement of different macroeconomic variables are identified in a 4-VAR setting.

4.3.1 VECM: IST, IBEX 35, C, and I

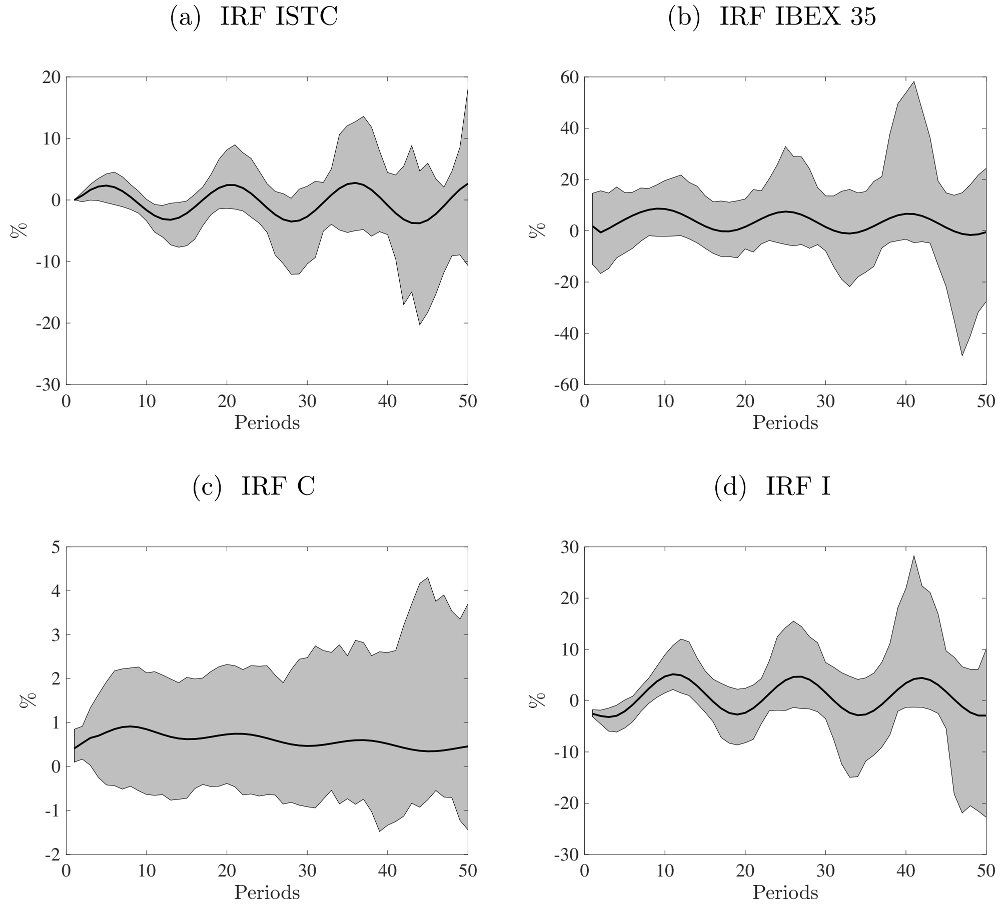
By contrast with the 2 and 3-VAR, in a 4-VAR setting the BP methodology's results are not conclusive in identifying news shocks. As it can be seen in the figure 4.9, the analysis suggests that a favorable aggregate news shock does not generate comovement among macroeconomic variables. In a 4-VAR setting, the BP methodology does not shed light on the transmission mechanism of a news shock on macroeconomic dynamics. The comovement patterns and the mechanisms that generate business fluctuations are absent. Hence, the identification of news shocks proposed by Beaudry and Portier (2006) in a 4-VAR setting does not seem relevant for understanding the business cycle fluctuations.

[4] $\tilde{\varepsilon}_1$ is not shown in the figure because the two shocks are very similar and do not bring new information; $\tilde{\varepsilon}_1$ explains a substantial fraction of fluctuations at business cycle frequencies.

As a robustness check, in the Appendix J there are presented the IRF (figure J.1) and FEV (figure J.2) of an alternative 4-VAR: ISTC, GDP, C, Hours.

Figure 4.9 displays the IRF to news shock in a 4-variables VAR: ISTC, IBEX 35, C, I.

Figure 4.9: IRF 4 variables VAR: ISTC, IBEX 35, Consumption, and Investment

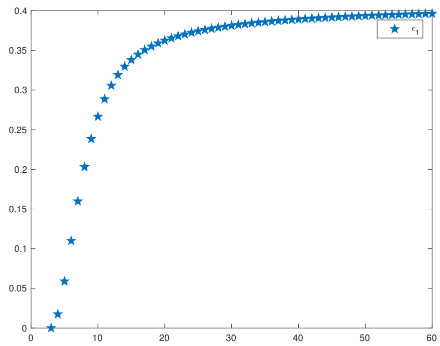


Note: The impulse response of the IST, IBEX 35, consumption, investment. The solid black lines represent the impulse responses functions of the ISTC to a unit aggregate news shock. The grey area represents the 16%−84% confidence intervals. The VECM is estimated with one lag and four cointegrating relations.

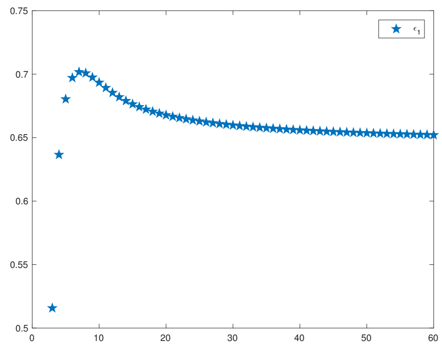
Figure 4.10 displays the FEV to news shock in a 4-variables VAR: ISTC, IBEX 35, C, I.

Figure 4.10: FEV 4 variables VAR: ISTC, IBEX 35, Consumption, and Investment

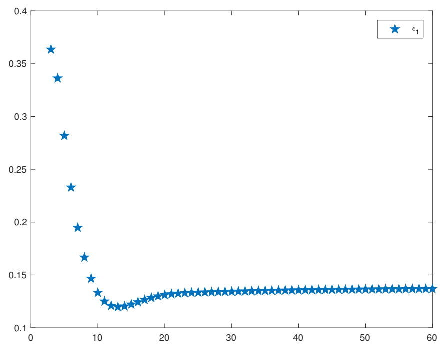
(a) FEV ISTC



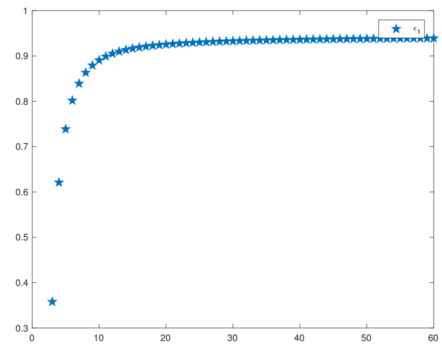
(b) FEV IBEX 35



(c) FEV C



(d) FEV I



Note: The FEV of the ISTC, IBEX 35, consumption, investment to a unit aggregate news shock. The VECM is estimated with one lag and four cointegrating relations.

Chapter 5

Maximum Forecast Error Variance Methodology

The maximum forecast error variance (MFEV) methodology to identify news shocks is used in Barsky and Sims (2011). They identify the news shock as the combination of VAR prediction errors that has zero contemporaneous impact on productivity but accounts for the maximum share of the forecast error variance (FEV) of productivity over a ten year horizon. BS methodology uses an agnostic VAR identification with a medium-sized VAR. This identification strategy that is an application of principal components, considers all shocks that are orthogonal to the innovation in current productivity. Following Uhlig (2004a), it chooses the shock that maximally explains a weighted average of future levels of productivity. In Barsky and Sims (2011) the news shock is identified as the linear combination of reduced form innovations orthogonal to the TFP innovation which maximizes the sum of contributions to TFP's forecast error variance not only at a given horizon but also at all horizons up to a truncation horizon.

The results of theirs methodology are in striking contrast with those of Beaudry and Portier (2006). While consumption increases following a news shock, output, investment, and hours fall slightly. This finding that is consistent with the results of standard neoclassical models, holds across different

VAR specifications in their paper.

5.1 MFEV Advantages

One important fact is that relative to the estimation and specification of a fully-developed DSGE model, this identification methodology that uses medium sized VAR imposes a minimum of theoretical restrictions and allows the data to speak for itself. At the same time, the max-share approach has a central conceptual advantage: the shock identified is only required to be the main source, as opposed to the only source, of long-run productivity. As such, the max-share approach affords the possibility that other shocks (e.g. a surprise productivity shock) exert long-lasting effects on adjusted TFP.

Barsky and Sims (2011) approach has several desirable features, especially in a small sample with annual data like the Spanish dataset. First, it allows but does not require that either the contemporaneous ISTC shock or the ISTC news shock or both have a permanent impact on ISTC. Second, because identification is not based on the zero frequency, one need not take an explicit stance on the order of integration of variables or on the cointegrating relationships among them. As such, the approach does not make any restriction about common trends in the different VAR variables. Third, because it is a partial identification method, the approach can be applied in small samples to VARs in many variables without imposing additional and potentially invalid assumptions about other shocks.

5.2 Empirical Strategy

This section explains the empirical strategy of identifying news shocks relying heavily on the notations in the original article of Barsky and Sims (2011). The BS identification method is based on the assumption that investment specific technical change is driven by only two shocks. One is a contemporaneous shock to ISTC that has immediate impact on the level of ISTC. The other one that they refer to as a news shock, is a shock that has no contemporaneous effect on ISTC, but leads to a change in ISTC in the future.

Assume that aggregate technology is described as following a stochastic process driven by two shocks. The first is the traditional surprise technology shock of the real business cycle literature, which affects the level of technology contemporaneously, in the same period in which agents observe it. The second is identified as news shock, which is distinguished from the first in that agents observe the news shock in advance. Both of those shocks effect all the variables contemporaneously.

Letting A_t denote technology, i.e. surprise investment specific technological change and news shock, this stochastic structure can be expressed in terms of the moving average (MA) representation:

$$lnA_t = [B_{11}(L) \quad B_{12}(L)] \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{5.1}$$

$\varepsilon_{1,t}$ is the conventional surprise technology shock while $\varepsilon_{2,t}$ is the news shock. The only restriction on the moving representation is that $B_{12}(0) = 0$, so that news shocks have no contemporaneous effect on technology. The following process is satisfying this assumption:

$$lnA_t = lnA_{t-1} + \varepsilon_{1,t} + \varepsilon_{2,t-j} \tag{5.2}$$

where ε_2 has no contemporaneous effect on the level of technology but foretells a change in investment specific technical change j periods into the future. In a univariate context, it would not be possible to separately identify ε_1 and ε_2. The identification of news shocks must come from surprise movements in variables other than investment specific technical change. In this setting, the estimation of a vector autoregression (VAR) seems sensible. In a system featuring an empirical measure of ISTC and several forward-looking variables, I identify the surprise investment specific technical change shock as the reduced-form innovation in ISTC. The news shock is then identified as the shock that best explains future movements in ISTC not accounted for by its own innovation. The identification follows directly from the assumption that two shocks characterize the stochastic process for technology.[1]

5.2.1 Identifying News Shocks

Let $\mathbf{y}_t$ be a $k \times 1$ vector of observables of length T. It can be represented in reduced form moving average representation in the levels[2] of the observables either by estimating a stationary vector error correction model (VECM) or an unrestricted VAR in levels:

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t \tag{5.3}$$

Assume there exists a linear mapping between innovations and structural shocks:

$$\mathbf{u}_t = \mathbf{A}_0 \varepsilon_t \tag{5.4}$$

This implies the following structural moving average representation:

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\varepsilon_t \tag{5.5}$$

[1] In practice, identification strategy involves finding the linear combination of VAR innovations contemporaneously uncorrelated with technology innovations which maximally contributes to investment specific technological change future forecast error variance. This identification strategy is closely related to Francis et al. (2010) maximum forecast error variance approach, which builds on Faust (1998) and Uhlig (2004a,b) .

[2] In recent years, estimating VARs in levels has become standard practice in the macroeconomic literature (Barsky and Sims (2011) or Kurmann and Otrok (2013)). Estimation of a VAR in levels will produce consistent estimates of the VAR impulse responses and is robust to cointegration of unknown form. Besides, the estimation in levels allows us to include polynomial (linear and quadratic) trends to capture non-stationary components of the data as an alternative to the cointegration assumption.

where $\mathbf{C} = \mathbf{B}(\mathbf{L})\mathbf{A}_0$ and $\varepsilon_t = \mathbf{A}_0^{-1}\mathbf{u}_t$.

The impact matrix must satisfy $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$, where $\mathbf{\Sigma}$ is the variance-covariance matrix of reduced-form innovations. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, $\tilde{A}$ (it can be choosen the convenient Choleski decomposition), the entire space of permissible impact matrices can be written as $\tilde{A}_0 D$, where D is a orthonormal matrix ($D' = D^{-1}$ and $DD' = I$, where I is the identity matrix).

The h horizon-ahead forecast can be written as follows:

$$\mathbf{y}_{t+h} - E_{t-1}\mathbf{y}_{t+h} = \sum\nolimits_{\tau=0}^{h} \mathbf{B}_\tau \tilde{\mathbf{A}}_0 \mathbf{D} \varepsilon_{t+h-\tau} \tag{5.6}$$

where $\mathbf{B}\tau$ is the matrix of moving average coefficients at horizon τ.

The contribution to the forecast error variance of variable i attributable to structural shock j at horizon h is then:

$$\Omega_{i,j}(h) = \frac{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \tilde{\mathbf{A}}_0 \mathbf{D} \mathbf{e}_j \mathbf{e}_j' \mathbf{D}' \tilde{\mathbf{A}}_0' \mathbf{B}_\tau{}' \right) \mathbf{e}_i}{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \mathbf{\Sigma} \mathbf{B}_\tau' \right) \mathbf{e}_i} = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \tilde{\mathbf{A}}_0 \gamma \gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{i,\tau}'}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \mathbf{\Sigma} \mathbf{B}_{i,\tau}'} \tag{5.7}$$

The $\mathbf{e}_i$ denote selection vectors with one in the ith place and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the jth column of $\mathbf{D}$, which will be denoted by γ. $\tilde{\mathbf{A}}_0\gamma$ is $k \times 1$ is a vector corresponding to the jth column of a possible orthogonalization and has the interpretation as an impulse vector. The selection vectors outside the parentheses in both numerator and denominator pick out the ith row of the matrix of moving average coefficients, which is denoted by $\mathbf{B}_{i,\tau}$.

Let q_t^i occupy the first position in the system, and let the unanticipated shock be indexed by 1 and the news shock by 2. The identifying assumption implies that these two shocks account for all variation of q_t^i at all horizons:

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \quad \forall h \tag{5.8}$$

It is general not possible to force this restriction to hold at all horizons. Instead, following BS, I propose picking parts of the impact matrix to come as close as possible to making this expression hold over a finite subset of horizons. With the surprise shock identified as the innovation in observed technology, $\Omega_{1,1}(h)$ will be invariant at all h to alternative identifications of the other $k-1$ structural shocks. As such, choosing elements of A_0 to come as close as possible to making the above expression hold is equivalent to choosing the impact matrix to maximize contributions to $\Omega_{1,2}(h)$ over h.

Since the contribution to the forecast error variance depends only on a single column of the impact matrix, this suggests choosing the second column of the impact matrix to solve the following optimization problem:

$$\gamma* = \arg\max \sum_{\mathbf{h=0}}^{\mathbf{H}} \Omega_{1,2}(h) = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \tilde{\mathbf{A}}_0 \gamma\gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{i,\tau}'}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \mathbf{\Sigma} \mathbf{B}_{i,\tau}'} \tag{5.9}$$

s.t.

$$\tilde{\mathbf{A}}_0(1,j) = 0 \quad \forall j > 1$$

$$\gamma(1,1) = 0 \tag{5.10}$$

$$\gamma'\gamma = 1 \tag{5.11}$$

So as to ensure that the resulting identification belongs to the space of possible orthogonalizations of the reduced form, the problem is expressed in terms of choosing γ conditional on an arbitrary orthogonalization, $\tilde{A}_0$. H represents the finite truncation horizon[3]. The first two constraints impose that the news shock has no contemporaneous effect on the level of q_t^i. The third restriction (that γ have unit length) ensures that γ is a column vector

[3] The finite truncation horizon in this paper is 10 years.

belonging to an orthonormal matrix. According to Uhlig (2004a), this maximization issue can be written in quadratic form, where the nonzero part of y is an eigenvector related to the maximum eigenvalue of the weighted sum of the lower submatrices $(k-1) \times (k-1)$ pertaining to $\left(\mathbf{B}_{i,\tau}\tilde{\mathbf{A}}_0\right)'\left(\mathbf{B}_{i,\tau}\tilde{\mathbf{A}}_0\right)$ over τ. Through this process news shock is identified as the first principal component of observed IST orthogonal to its own innovation.

Chapter 6

MFEV Methodology Results

This section presents the empirical results of the MFEV identification methodology used in Barsky and Sims (2011). I use the same real data series for the Spanish economy from 1970 to 2015 downloaded from the EU KLEMS data base, the 2017 release.

6.1 Evidence from 2-variables VAR

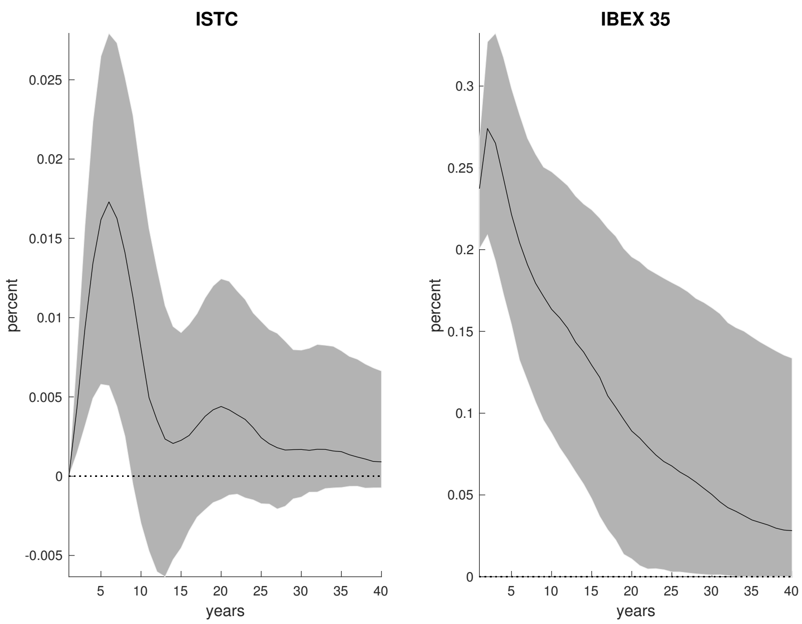
In order to facilitate the comparison with the BS identification results presented in chapter 4, I use the same VAR setting. The first variable in the bivariate framework is the ISTC as a measure of productivity. While the second one, is the same forward looking variable that was alternatively used in the the BP setting. News about ISTC shocks can have an impact on second variable, but it may need some time to actually affect ISTC because of an implementation lag. Looking at the behavior of forward-looking variables, including stock prices, GDP, consumption, investment, residential investment and equipment investment, is key to our ability to identify an important role for predictable fluctuations in the level of future ISTC. All systems are estimated in log levels of all variables, while the number of lags are been selected using information criteria, likelihood ratio test statistic, and Akaikes information criterion. To improve precision the VAR is estimated via Bayesian methods subject to a Minnesota prior on the estimation while the error bands are computed by drawing from the posterior.

6.1.1 2-variables VAR: ISTC and IBEX 35

In a bivariate SVAR approach the variables are the investment-specific technical change (ISTC) as the measure of productivity denoted by IST, and the IBEX 35 as stock prices. According to a likelihood ratio test one lag is chosen for this estimation.

The figure 6.1 presents the impulse response of a news shock on ISTC and IBEX 35. In the left panel we observe the impulse response of ISTC which by construction has no reaction on impact, becoming significant for ten period after the first period. In the right panel, the IBEX 35 reacts strongly, increasing on impact; it remains positive for more than 25 periods. There is virtually no discrepancy in this setting between the responses to a news shock identified with the the BS or BP methodology (figure 7.9 and 4.2), with the exception that the increase in IBEX 35 is permanent in the BP methodology.

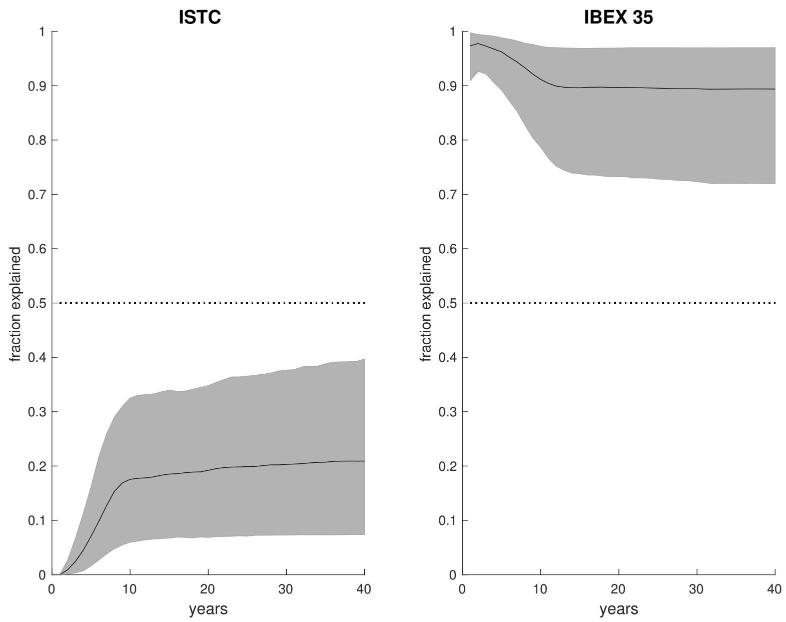
Figure 6.1: IRF 2-VAR: ISTC IBEX 35



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and IBEX 35 to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the 16%−84% confidence intervals.

The figure 6.2 displays the fraction of the FEV of the ISTC and IBEX 35 explained by the news shock. The solid lines correspond to the posterior median estimates, while the grey bands display the 16%-84% posterior coverage intervals. As the right panel shows (IBEX 35 FEV), the news shock explains more than 85% of IBEX 35 increase over the entire 0 to 40 periods forecast horizon. This result indicates that stock prices are to a large part driven by investment-specific technology news shocks.

Figure 6.2: FEV 2-VAR: ISTC IBEX 35



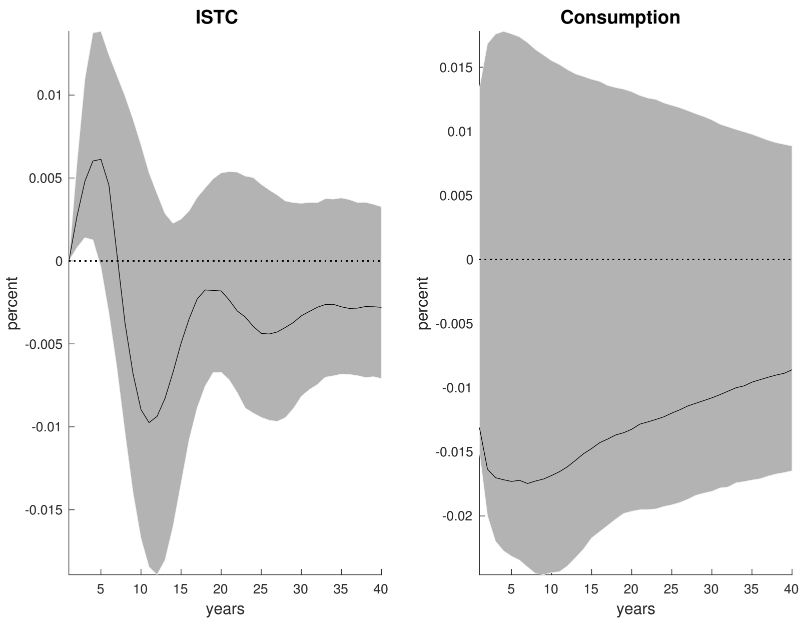
Note: The solid black lines represent the estimated median FEV of the ISTC and IBEX 35 to a unit aggregate news shock obtained using the BS identification. The grey area represents the $16\% - 84\%$ confidence intervals obtained by drawing from the posterior.

6.1.2 2-variables VAR: ISTC and C

Next I present the bivariate SVAR where the variables are the ISTC and the Consumption as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

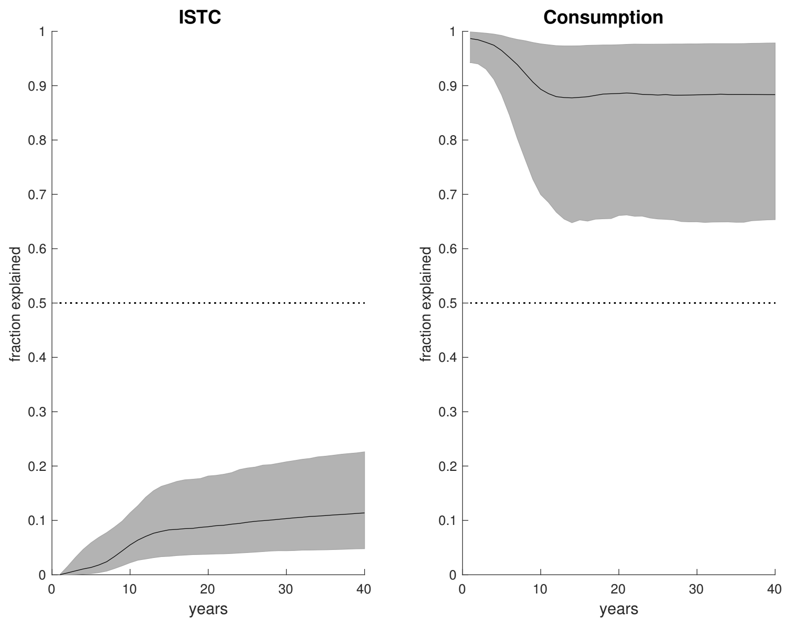
The figure 6.3 presents the impulse response of a news shock on ISTC and Consumption. Contrary to the BP identification, the consumption in the BS identification remains roughly insignificant.

Figure 6.3: IRF 2-var: ISTC C



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and Consumption to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure 6.4: FEV 2-var: ISTC C



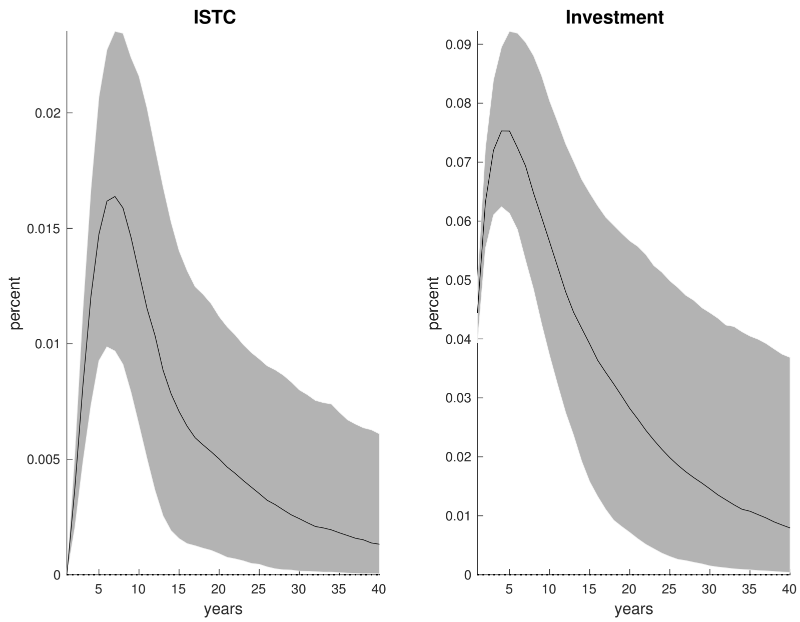
Note: The solid black lines represent the estimated median FEV of the ISTC and Consumption to a unit aggregate news shock obtained using the BS identification. The grey area represents the $16\% - 84\%$ confidence intervals obtained by drawing from the posterior.

6.1.3 2-variables VAR: ISTC and I

In the next bivariate SVAR setting, the variables are the ISTC and the Investment as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

The figure 6.5 presents the impulse response of a news shock on ISTC and Investment. The Investment jumps up about 5% on impact of the shock, remaining significant for 25 periods. The strong reaction of the Investment is therefore largely driven by the ISTC news shock, which has no effect on impact on the ISTC (by construction), but within 2 periods of the shock, the ISTC starts to increase remaining significant for 10 periods..

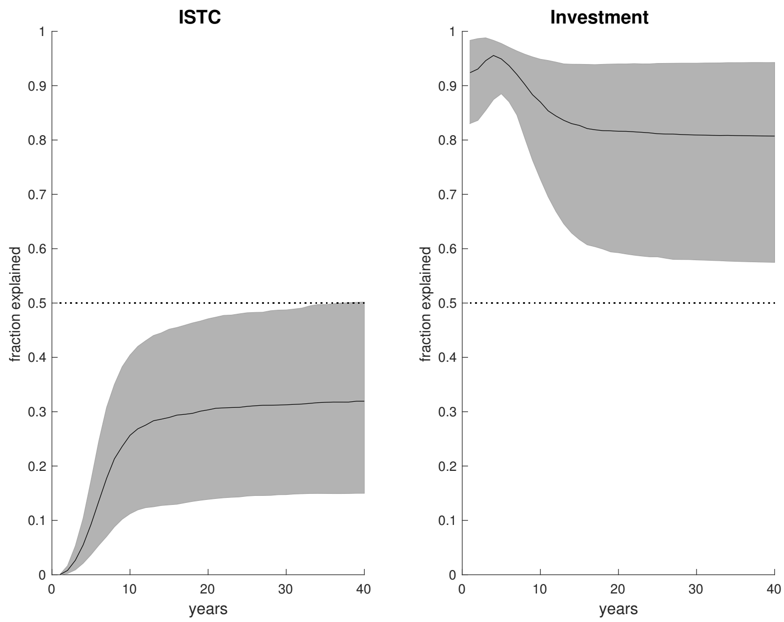
Figure 6.5: IRF 2-VAR: ISTC I



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and Investment to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure 6.6 displays the fraction of the FEV of the variables in the (ISTC, Investment) VAR explained by a ISTC news shock. As I found for the IBEX 35, the ISTC news shock explains almost all of the movements in Investment on impact, and up to 90% of variations after 10 quarters. The news shock explains about 50% of ISTC variations after 8 periods.

Figure 6.6: FEV 2-VAR: ISTC I



Note: The solid black lines represent the median FEV of the ISTC and Investment to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

In Appendix K I represent the IRF and FEV of alternative SVAR estimations as a measure of robustness.

6.2 Evidence from 3-variables VAR

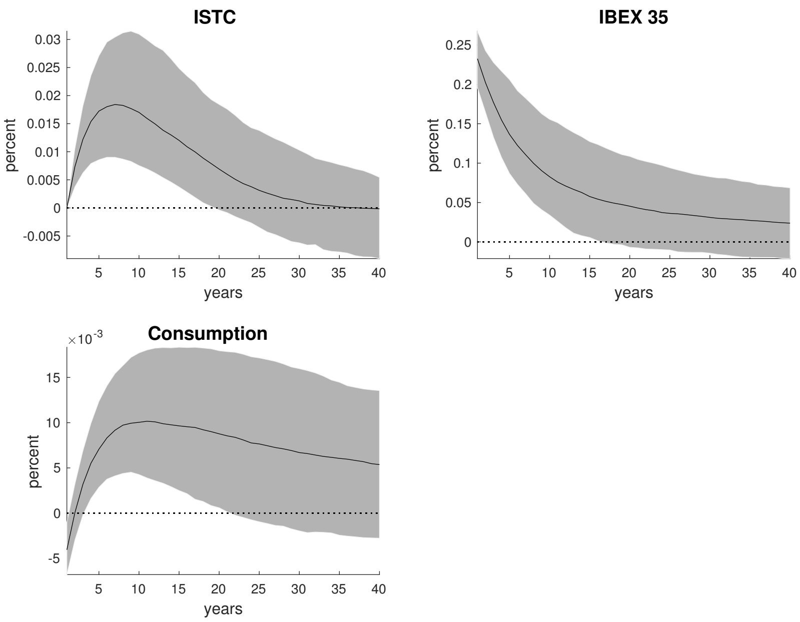
In a trivariate SVAR BS identification approach the variables are the ISTC as the measure of productivity and IBEX 35, followed by an extra variable.

6.2.1 3-variables VAR: ISTC, IBEX 35 and C

In this estimation I use a trivariate SVAR: the variables are ISTC, IBEX 35, and Consumption; according to a likelihood ratio test one lag is chosen for this estimation.

The figure 6.7 displays the impulse response of a news shock on ISTC, IBEX 35 and Consumption to a 1% innovation in the news shock. The IBEX 35 jumps up about 25% on impact of the shock, while the Consumption remains roughly zero on impact before becoming slightly positive for about 15 periods. Interestingly, the strong reaction of the IBEX 35 is therefore largely driven by the ISTC news shock, while for Consumption there is a mild response to news shock. The insignificant reaction of Consumption on impact and its gradual increase to a higher level thereafter suggests that the identification methodology captures a slow diffusion process of ISTC that is anticipated by economic actors.

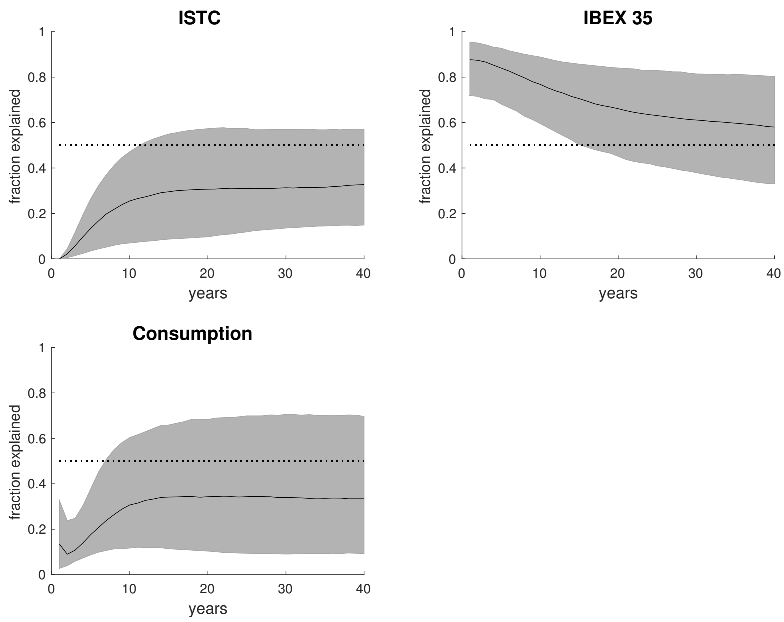
Figure 6.7: IRF 3-VAR: ISTC IBEX 35 C



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC, IBEX 35 and Consumption to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure 6.8 displays the fraction of the FEV of the variables in this VAR setting explained by a ISTC news shock. On impact, it explains almost 90% of the movement in IBEX 35, but almost nothing of Consumption variation; after15 periods it explains about 40% of Consumption. However, the ISTC news shocks accounts for a relatively important fraction of variations in the long end of IBEX 35. In other words, the ISTC news shock seems to be a major determinant of movements in IBEX 35 in this setting, but very little determinant of the Consumption.

Figure 6.8: FEV 3-VAR: ISTC IBEX 35 C



Note: The solid black lines represent the median FEV of the ISTC, IBEX 35 and Consumption to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

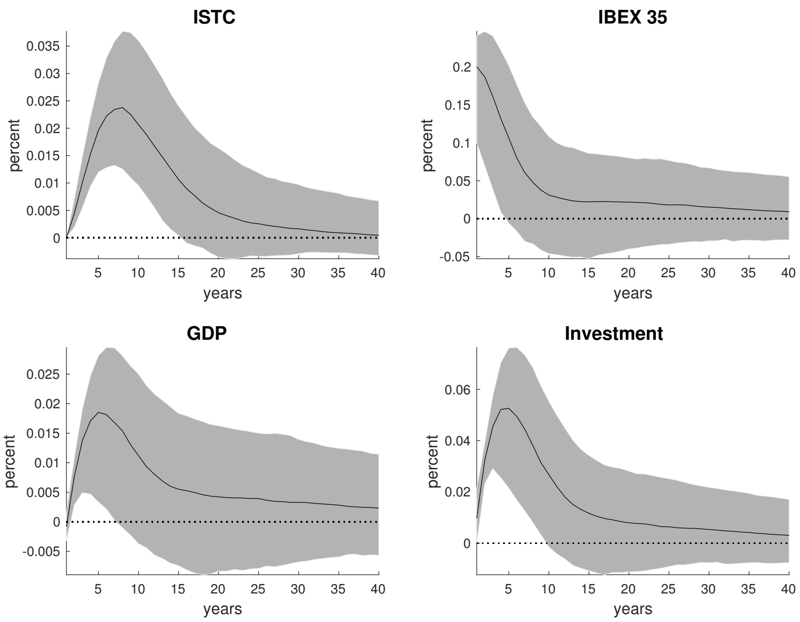
In Appendix K I represent the IRF and FEV of alternative 3-SVAR estimations as a measure of robustness.

6.3 4-variables VAR: ISTC, IBEX 35, GDP, and I

In a four SVAR approach the variables are: ISTC, IBEX 35, GDP, and Investment; according to a likelihood ratio test one lag is chosen for Spanish data.

The figure 6.9 reports the IRF of a news shock on a 4-VAR: ISTC IBEX 35 GDP, and Investment. Compared with the BP methodology in a 4-VAR, the results are striking. The IRF are all four significant at different periods horizons: ISTC increases gradually from zero (by construction for the news shock identification) to a higher level, being significant for 15 periods; IBEX 35 jumps up significantly on impact and then returns back to its pre-shock value after 5 periods; GDP increases slightly (but insignificantly) on impact and then gradually increases to a higher level for 7 periods; Investment increases on impact, remaining higher their initial value for more than 10 periods. In particular, the increase in IBEX 35 is larger than increase in Investment, implying it contains information about a future increase in ISTC and implicitly in Investment and GDP.

Figure 6.9: IRF 4-VAR: ISTC IBEX 35 GDP I

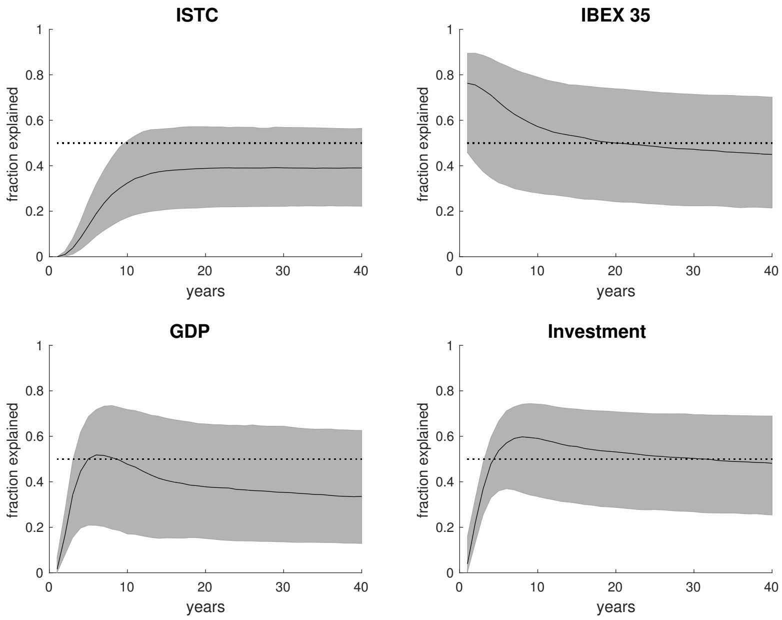


Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC, IBEX 35, GDP, and Investment to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the $16\% - 84\%$ confidence intervals.

The FEV presented in figure 6.10 confirms the conclusion from the four-variable VAR that the news shock is an important factor for macroeconomic fluctuations. Indeed, the shock accounts for an important fraction of the FEV of real macroeconomic aggregates; the shock explains more than 50% of the variation of these variables at medium horizon, confirming that is likely to be a main driver of business cycle dynamics. All of these results suggest that the BP methodology has identified a news shock in a 4-VAR setting contrary to the BS methodology.

Hence, there are indeed news about future ISTC innovations that are a main driver of the macroeconomic variables.

Figure 6.10: FEV 4-VAR: ISTC IBEX 35 GDP I



Note: The solid black lines represent the median FEV of the ISTC, IBEX 35 GDP, and Investment to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

In Appendix K I represent the IRF and FEV of alternative 4-SVAR estimations as a measure of robustness. The alternative 4-VAR: ISTC, GDP, Hours and Residential Investment.

Chapter 7

Stationary VAR analysis and conclusion

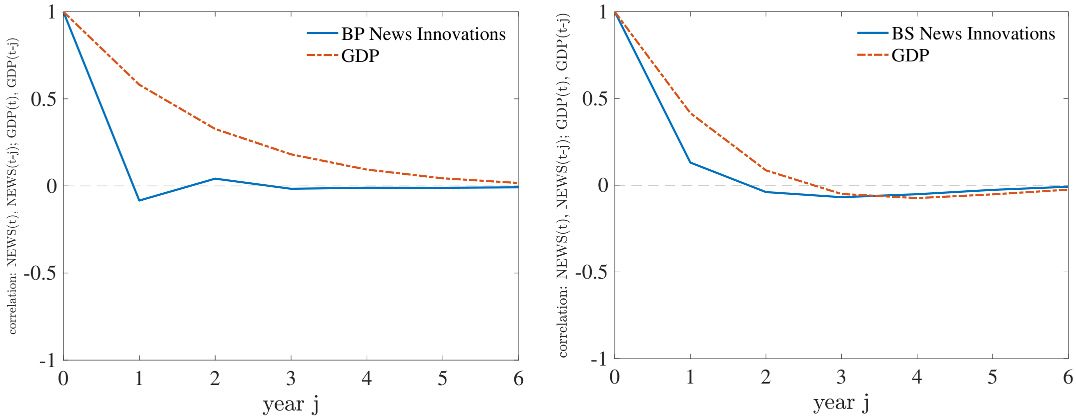
In this concluding chapter I complete the analysis by estimating a stationary VAR(1). It includes on one hand the news shocks from the bivariate SVAR, TFP and IBEX 35 identified with the BP and BS methodologies, and on other hand some macroeconomic variables (for example, output, consumption, and investment). I look to the dynamic properties of these variables and how do these variables interact with the news shocks by computing the comovements between pairs of variables (lead and lags) and, in particular, determine the number of periods that news shocks anticipate the different macro variables. In order to achieve stationarity for the macro variables, I use log difference for the VAR with the BP news shock, as this methodology identify the news shocks with the variables in the first difference. In the BP methodology case, as the news shocks are identified with the variables in levels, in order to obtain stationarity, I HP-filtered the variables.

7.0.1 Autocorrelations

The next figures present the autocorrelations of the variables used in the VAR.

Figure 7.1: Autocorrelations: News shock, GDP

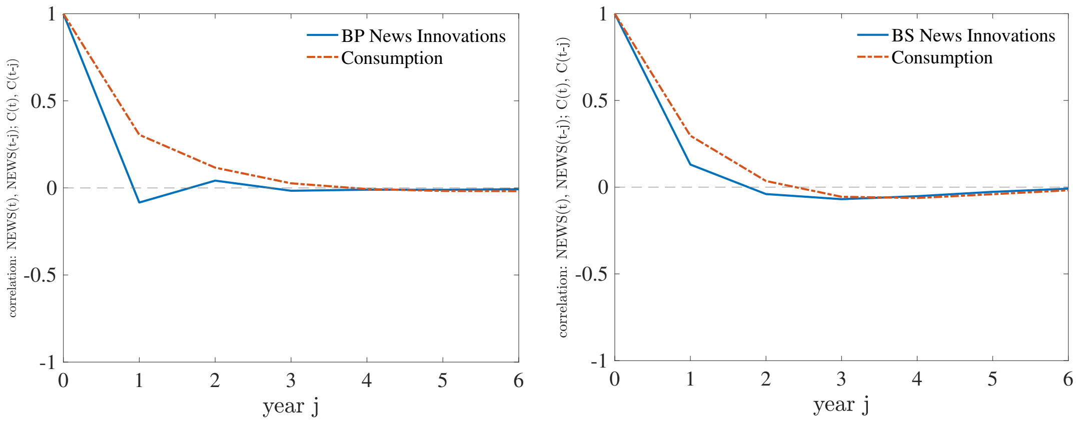
(a) Autocorr BP-News shock GDP (b) Autocorr BS-News shock GDP



The figure 7.1 indicates that the BS identified news shock (right panel) has an important contribution to the GDP persistence, much more than the BP identified news shock (left panel).

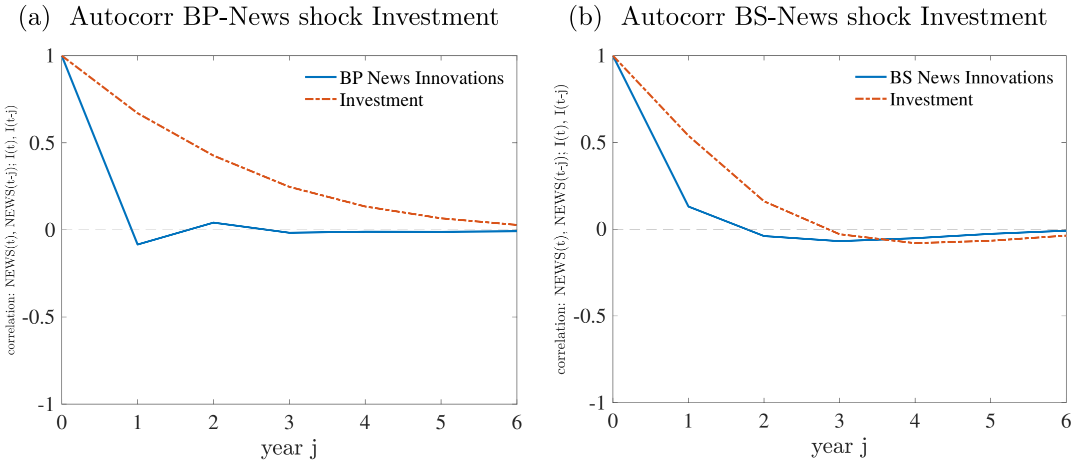
Figure 7.2: Autocorrelations: News shock, Consumption

(a) Autocorr BP-News shock Consumption (b) Autocorr BS-News shock Consumption



The figure 7.2 shows that the news shock has a high contribution to the Consumption persistence, especially the BS methodology identified news shock (right panel).

Figure 7.3: Autocorrelations: News shock, Investment



The figure 7.3 shows that the BS methodology identified news (right panel) has a more important contribution to the Investment persistence than the BP news identified shock.

7.0.2 Correlations

The next figures present the correlations of the variables used in the VAR.

Figure 7.4: Correlations with BP-methodology news shocks

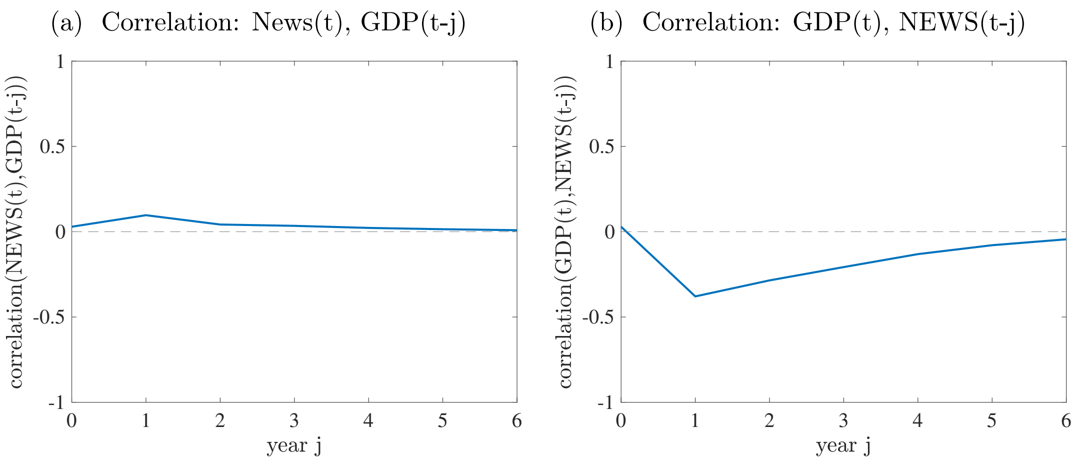


Figure 7.5: Correlations with BS-methodology news shocks

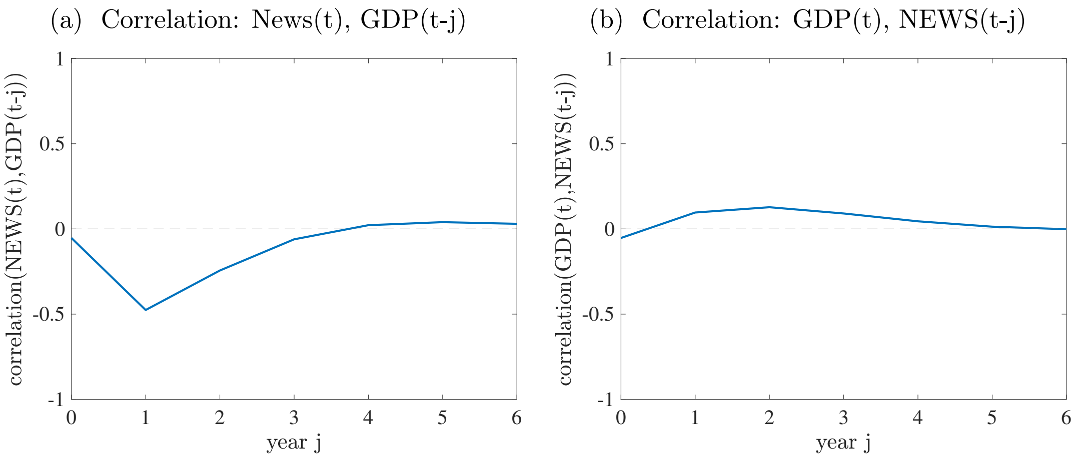


Figure 7.6: Correlations with BP-methodology news shocks

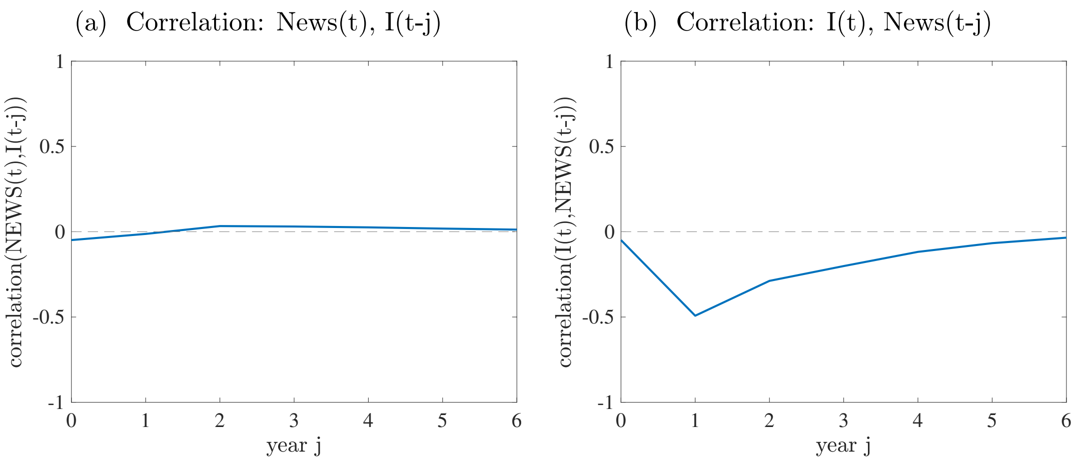


Figure 7.7: Correlations with BS-methodology news shocks

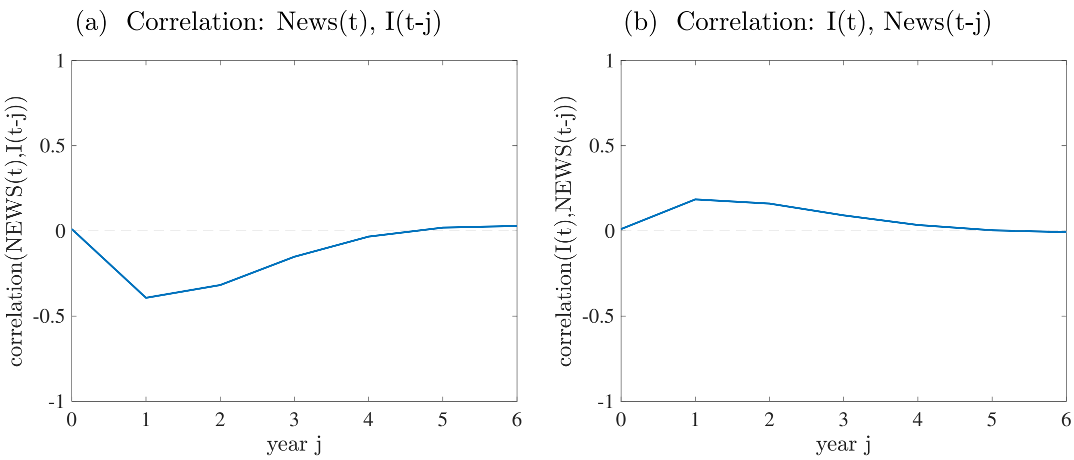


Figure 7.8: Correlations with BP-methodology news shocks

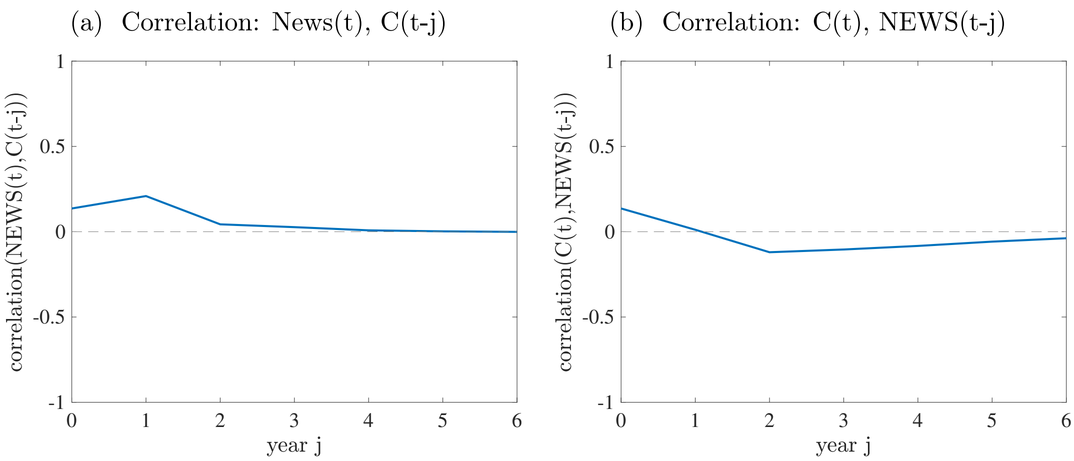
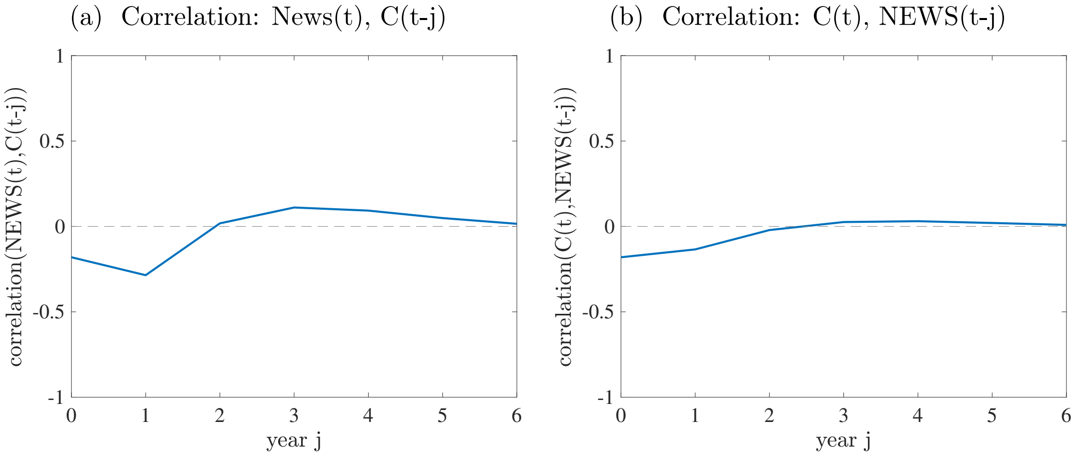


Figure 7.9: Correlations with BS-methodology news shocks



In this part I have used two alternative strategies widely accepted in the literature in order to identify news shocks: the Beaudry and Portier (2006) and Barsky and Sims (2011). Both methodologies, BP and BS, are based on the assumption that news shocks impact productivity only with a delay.

I applied this assumption to a measure of productivity, the investment-specific technology, ISTC in different SVARs of 2, 3 and 4 variables. I used IBEX 35 as a measure of stock prices and a battery of macroeconomic forward-looking variables in order to observe if news shocks generate co-movement among consumption, investment, output, hours and residential investment after a positive aggregate news shock.

When applied to Spanish data from 1970 to 2015, I find results that are consistent with the news interpretation. In a 2-VAR setting, the ISTC increases gradually with a significant lag whereas forward-looking variables jump on impact independently on the methodology used.

Contrary to the BP identification, when the BS identification strategy is used in a 4-VAR setting, the ISTC news shock accounts for a big part of fluctuations in real aggregates at medium- and long horizons, generating strong impact responses on IBEX 35 and macroeconomic variables.

My conclusion is that shocks identified via two restrictions schemes along the lines of Beaudry and Portier (2006) play a important role in a two-variables VECM. In particular, the news shock explains high fractions of main macroeconomic series' variance, predicting permanent changes on them.

The alternative identification strategy in the spirit of Barsky and Sims (2011) overcomes the criticisms of the BP identification mentioned in the chapter 1, especially in three- and four-variables VAR. The impact responses of all variables are larger when BS identification is used.

By comparing the results from these two identification methods, this part of the dissertation reassesses the empirical evidence in favor of the news driven business cycle in the Spanish economy. Furthermore, they appear to be strongly associated with long-run movements in ISTC suggesting the link between news-driven fluctuations and future ISTC.

Part IV

NEWS-DRIVEN HOUSING BOOMS? SPAIN VS GERMANY

Motivated by the Spanish residential investment boom episode of the 2000s, this part examines the empirical significance of news shocks on business cycle fluctuations in the Spanish and German economies. Specifically, in the context of structural vector autoregressions (SVARs), I investigate if news shocks on investment-specific technical change (ISTC) drove the residential investment for the Spanish economy, and business structures and equipment for the German economy. The findings for Spain are that the news shocks on residential ISTC explain a high variance of output, aggregate investment, and residential investment. In contrast, for Germany, the news shocks on business structures and equipment explain a higher fraction of the variance of output, consumption and non-residential investment. Then, I propose a two-sector RBC model to interpret the propagation mechanisms described in the SVAR. I simulate the model first as a closed economy for Spain and for Germany, and then I compare the results obtained in this setting with a small open economy for Spain. In both settings, the identified news shocks in Spain stimulate investment in residential structures, whereas in Germany the news enhances investment in equipment and structures. While the results suggest news shocks contribution to aggregate fluctuations is relatively more important in Spain than in Germany, I provide evidence that news shocks propagation mechanism is consistent with the housing boom in Spain.

Chapter 1

Introduction

The Spanish recent economic expansion has been characterized by sustained growth of residential investment (Díaz and Franjo (2016)[1], Aspachs-Bracons and Rabanal (2009)). In Spain, the housing accounts for a large fraction of households wealth[2] and investment in housing accounts for a large fraction of overall economic activity. The important sheer size of its housing sector affect macroeconomic outcomes as well as all other asset prices. In fact, Spain is just one of the many other European countries that experienced a housing boom in the early/mid-2000s. In contrast, Germany, a peer Euro Zone economy, had an economic performance very different from that of Spain; even during years of expansion did not experience a housing boom, while in the last three decades, the German housing prices have been more stable than elsewhere in Europe (Fernández-Villaverde and Ohanian (2010), OECD (2014)). In fact, looking at the residential investment sector, Spain and Germany present fundamental differences.[3] The empirical evidence illustrates that investment

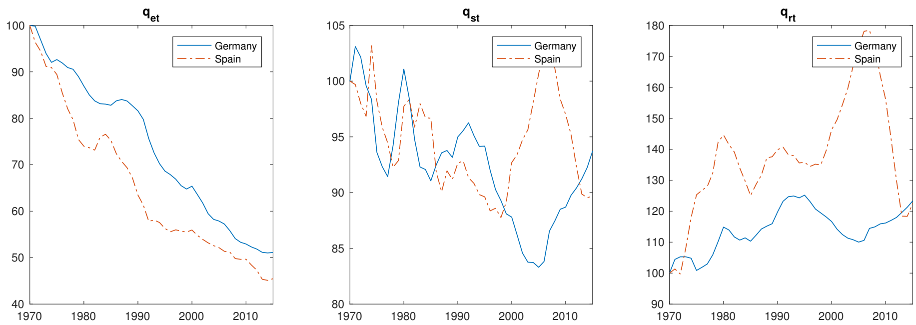
[1]Díaz and Franjo (2016) documented that Spain grow in spite of stagnant TFP due to an inefficient high investment rate in subsidized residential structures.

[2]In Spain the house ownership is at 86.28% (2005) as in "Encuesta continua de presupuestos familiares. Base 1997. Resultados anuales 2005". http://www.ine.es/jaxi/Datos.htm?path=/t25/e437/p02/a2005/l0/&file=04001.px

[3]In Germany the house ownership is at 48% (2008) as in "Sample survey of income and expenditure (EVS)". https://www.destatis.de/EN/FactsFigures/

has undergone large shifts since 1970. Figure 1.1 depicts some data that are indicative of this period. The figure plot the residential, business structures and equipment relative prices of investment (RPIs) for Spain and Germany from 1970 to 2015[4]. It is evident that until 1998 all three factor prices of both countries shared a common tendency. From that point on, that coincides with the "1998 Spanish Land Law"[5], the residential and business structures RPI diverge in the two economies. On those Spanish and German RPI a wide gap opens until 2012.

Figure 1.1: **Relative Prices of Investment: Spain vs. Germany**



Note: q_{et} represents the relative price of equipment, q_{st} represents the relative price of structures, while q_{ht} represents the relative price of residential investment.

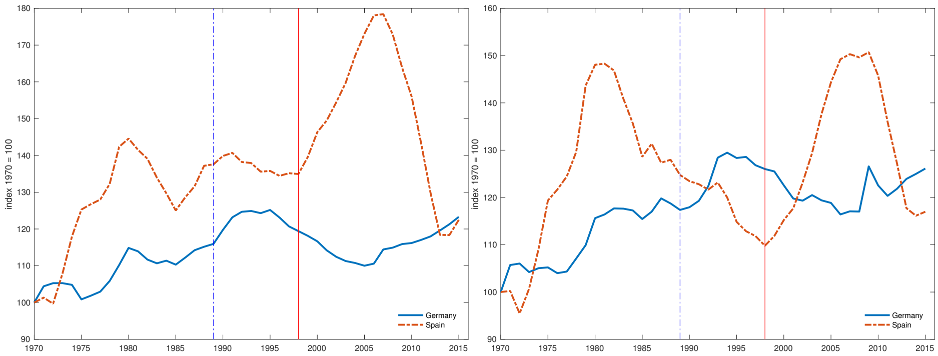
SocietyState/IncomeConsumptionLivingConditions/AssetsDebts/Tables/HouseholdOwningRealProberty_EVS.html

[4]Annual data from the *EU KLEMS* the 2017 release is presented in appendix M

[5]Actually, there were 2 laws; the first one, the Law 7/1997 was setting liberalizing measures on land: to guarantee access to housing, and in order to make the land cheaper, it proposed measures aimed at increasing the supply of land available for development. For this purpose, it eliminated the distinction between programmed and non-scheduled developable land, making all of it developable. At the same time, it also simplified procedures by shortening deadlines. With the second one, the Land Law of 1998, the Spanish state invaded part of the competences of the Autonomous Communities and the Town Councils generating an absolute monopoly on land development. The Law 6/1998 on soil regime and valuations confirmed the liberalizing measures on soil already fixed in law 7/1997. https://es.wikipedia.org/wiki/Ley_del_Suelo_de_Espa~na

Figure 1.2: SPAIN vs GERMANY

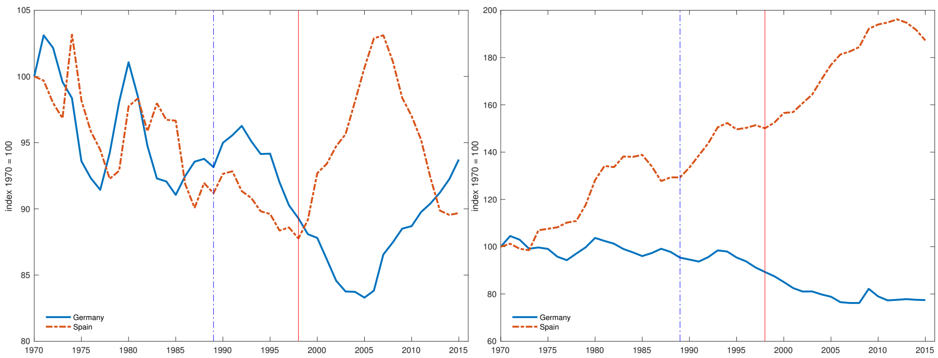
(a) Relative Price of Residential Investment (b) Residential Structures Capital/GDP



Note: The blue dotted vertical line marks the 1989 German unification; the red line marks "1998 Spanish Land Law"; the relative price of investment is in units of non durable consumption goods and services; normalized so that 1970 is the base year.

Figure 1.3: SPAIN vs GERMANY

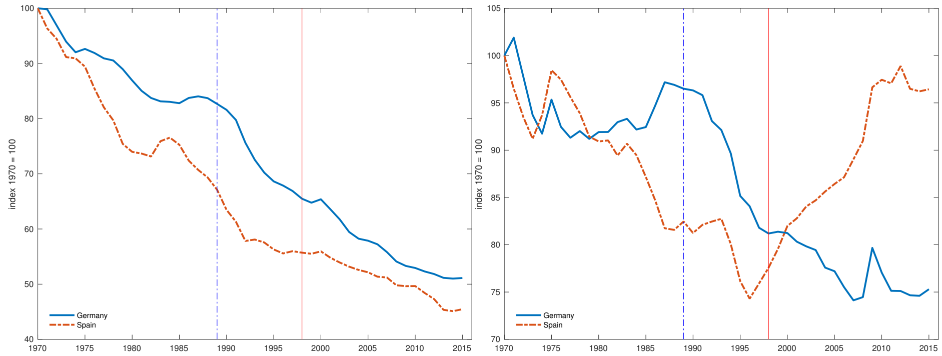
(a) Relative Price of Structures Investment (b) Non-Residential Structures Capital/GDP



Note: The blue dotted vertical line marks the 1989 German unification; the red line marks "1998 Spanish Land Law"; the relative price of investment is in units of non durable consumption goods and services; normalized so that 1970 is the base year.

Figure 1.4: SPAIN vs GERMANY

(a) Relative Price of Equipment Investment (b) Equipment Capital/GDP



Note: The blue dotted vertical line marks the 1989 German unification; the red line marks "1998 Spanish Land Law"; the relative price of investment is in units of non durable consumption goods and services; normalized so that 1970 is the base year.

Analyzing further the empirical evidence, this paper aims at providing an answer to the following question: why do some countries experience housing booms and other do not?

In this paper, I argue that IST news shocks might explain most of the investment differences between countries. Specifically, I extract news about future investment decisions in Spain and Germany from the observed movements of the RPIs. I follow Fisher (2006) and Canova et al. (2007) assuming that investment-specific shocks are the sole driver of long-run movements in the RPI. As such, the identification framework implies that two shocks drive the long-run variation in RPIs, one being the traditional unanticipated IST shock and the other being the IST news shock, where the news shock has no effect on current IST but rather foretells future changes in it.

I start from the hypothesis that the extent to which news shocks contribute to housing booms, depends on the household's willingness to substitute consumption for investment in the residential structures, business structures or equipment. Spain and Germany are natural candidates to prove the interrelation between news shocks and short-run investment dynamics. They both are Euro Zone economies that share the same institutional framework. Consequently, as the propagation mechanism is different due to technology and preferences, I show that news shocks effects on short-run investment dynamics in the two countries are important, but qualitatively and quantitatively different.

The contribution of this paper is the introduction of news shocks to RPIs: news shocks to relative prices of residential investment, business structures, and equipment.

First, I identify news shocks using structural vector autoregression (SVAR). I start the empirical analysis by applying the identification strategy of news shocks proposed by Barsky and Sims (2011). This approach imposes minimum of theoretical restrictions. Basically, I estimate the model and identify the news shock as the shock that best anticipates the relative prices of investment in the long-run and does not move it on impact. Then, I quantify how the news shocks propagate into the macroeconomic variables, and how it affect households investment decisions.

The findings for the Spanish economy are that news shocks to relative prices of residential investment account for 59% of the forecast-error variance of output, and 65% of aggregate investment. Additionally, the news shocks to relative prices of residential investment explain 80% of the housing investment. On impact, output, aggregate investment, consumption and hours worked have a statistically significant positive response, confirming the role for news shocks as a source of cyclical fluctuations. Such effects are essentially similar to those obtained by Beaudry and Portier (2004) who find shock-induced aggregate comovement.

In contrast, for Germany, the effects are reversed. The news shocks to relative prices of business structures and equipment are those that explain the highest fraction of the variance of output, consumption and investment in business structures and equipment, even though, the shares are much smaller compared with Spanish economy.

Second, I propose a model to interpret the propagation mechanism of news shocks. For that reason, I write a stylized version of Díaz and Franjo (2016) two-sectors model economy. The utility function employs Jaimovich and Rebelo (2009) preferences augmented with home production in the line of Benhabib et al. (1991), Greenwood and Hercowitz (1991) and McGrattan et al. (1997). In the standard macro model, agents can substitute between leisure and labor and between consumption and investment. Rather, following the home production literature, in my model households can substitute between leisure and working in the market or working at home, and between consumption and investment in market capital or residential capital. The home production sector reallocates labor and capital between market and non-market activity. In addition, households, optimally decide how much to invest and to accumulate from the three types of capital: either equipment and business structures or residential structures.

Finally, I include news shocks that impact on individuals' expectations in each country. The news shocks on the relative prices of investment allow to distinguish how agents adapt their willingness to substitute current consumption for future investment in housing, structures or equipment. Therefore, the news shocks effects on each country depend critically on the parameters that control the elasticities of substitution, between household and market variables in utility and production functions, and those that control the labour supply elasticity set in the Jaimovich and Rebelo (2009) preferences specification. Indeed, in this setting, the model will generate two important forms of comovement in response to news shocks to relative prices of residential investment. The first one is the aggregate variables comovement: output, consumption, aggregate investment, and hours worked rise and fall together. The other is the sectoral comovement: output, employment, investment and capital accumulation rise and fall together on each of the two sectors of the model economy.

From the two-sectors model several interesting findings emerge. The wealth effect in Spain translates into increased residential investment. At the same time, if the elasticity of intertemporal substitution is high enough, then the substitution effect dominates the wealth effect which in Germany translates into investment in equipment and business structures.

This paper is linked with three literatures. First, it is related to empirical literature suggesting news about the future might be an important driver of the business cycle.[6] Many macroeconomists have recognized the importance of the news impact on the economic fluctuations after Beaudry and Portier (2006) called the attention toward news-driven business cycles. [7] The empirical part of this literature relies on reduced form time series techniques, while the other part uses dynamic stochastic general equilibrium (DSGE) models. In the context of vector autoregressive (VAR) methodologies, Beaudry and Portier (2006) and Beaudry and Lucke (2010) find that total factor productivity (TFP) news shocks are important drivers of the US business cycles, while Barsky and Sims (2011) and Forni et al. (2014a) find they are not. The estimated DSGE methodology (Fujiwara et al. (2011), Khan and Tsoukalas (2012), Schmitt-Grohé and Uribe (2012)), find them to be negligible sources of fluctuations.

Second, I have many points of contact with the literature that studies investment-specific technology (IST). Greenwood et al. (1988) were the first to suggest that investment shocks could be a viable alternative to neutral technology shocks as sources of business cycles in a general equilibrium environment and consider IST's relevance for growth, business cycles, and asset prices. Greenwood et al. (1997) show that investment-specific technological progress is responsible for the major share of growth in the post-war U.S. More recently, Fisher (2006) identifies in a structural VARs framework that unanticipated IST shocks have accounted for over two-thirds of business cycle

[6] Pigou (1927) was one of the first authors to propose that agents' expectations about the future are an important source of business cycle fluctuations.

[7] Recent papers document the importance of news shocks Beaudry and Portier (2004, 2006, 2014); Schmitt-Grohé and Uribe (2012); Jaimovich and Rebelo (2009); Christiano et al. (2008); Fujiwara et al. (2011); Barsky and Sims (2011); Kurmann and Otrok (2013); Forni et al. (2014b)

fluctuations in output over the 1982-2000 period.

Closely related to my research it is Ben Zeev and Khan (2015) and Ben Zeev (2018). They identified IST news shocks using a VAR methodology and determined theirs relative importance. Ben Zeev and Khan (2015) do provide strong support for IST news shocks when investigating the role of news in driving U.S. business cycles. Although in this paper my focus is on specific news shocks on the relative price of residential investment, they find similar variance decomposition for the aggregate variables in the US with the one that I present for the Spanish economy; in the US, the news shocks account for 70% of the business cycle variation in output, hours, and consumption, and 60% of the variation in investment.

Third, this paper is related to the home production models that starts with Benhabib et al. (1991) and Greenwood and Hercowitz (1991). They show that home production models match key business-cycle moments better than models without home production.

My results provide evidence that residential IST news shocks constitute a significant force behind Spanish economic business cycles. Even though the news shocks affect in less measure the German economic business cycles, do seem to explain the investment and capital accumulation increase in equipment and business structures. An important conclusion of the paper is that the news shocks are consistent with the housing boom in the Spanish economy. My paper suggests that news shocks may help explain on one hand the increase of investment in residential structures, and on other hand the economic growth of the Spanish economy in the period 1970 - 2015.

The rest of this paper is structured as follows. Chapter 2 reviews the news shocks identification scheme. Chapter 3 reports the empirical evidence. Chapter 4 outlines the baseline theoretical model and describes the calibration. Chapter 5 reports the results of the theoretical model. Chapter 6 presents the small open economy setting. Chapter 7 concludes.

Chapter 2

Empirical Approach

The central insight for the purpose of this paper is to show that the news about RPIs might lead to predictable changes in investment decisions. To prove my case, I focus on three RPI[1], q_{it}. In terms of notation in this paper, I call residential RPI, q_{rt}, business structures RPI, q_{st}, and equipment RPI, q_{et}.

To proceed, I estimate a vector autoregression (VAR) model on Spanish and German annual data[2] in the period 1970 - 2015. I follow Barsky and Sims (2011) methodology[3] to identify the news shock as the combination of VAR prediction errors that has zero contemporaneous impact on RPIs but accounts for the maximum share of the forecast error variance (MFEV) of RPIs over a ten year horizon. Specifically, Barsky and Sims (2011) apply the strategy proposed by Uhlig (2004a) for the purpose of identifying news shock.

Although in the literature are proposed other news shocks identification

[1]The graphs for the RPI are shown in figure 1.1

[2]The data is presented in appendix M

[3]Barsky and Sims (2011) methodology that is presented in appendix N is based on the FEV maximization approach of Uhlig (2004a) who chooses the shock that maximally explains a weighted average of future levels of productivity. In this paper I attach equal weights to the various horizons over which news shocks are to be explained.

strategies (i.e. Beaudry and Portier (2006)[4]), in this paper I consider the maximum forecast error variance (FEV) identification approach for several advantages given my data sample. First, the approach allows but does not require that either the contemporaneous shock or the news shock or both have a permanent impact on RPIs. Second, the approach does not make any restriction about common trends in the different VAR variables. Third, because it is a partial identification method, the approach can be applied to VARs in many variables without imposing additional assumptions about other shocks.

2.1 Identification Strategy

Since Barsky and Sims (2011) approach already exists in the literature, in this section I describe the basics of the methodology and relegate the details to the appendix N.

I assume that the RPIs follows a stochastic process driven by two shocks. First, an unanticipated shock which impacts investment prices level in the same period in which agents observe it. I refer to this as the unanticipated shock. Second, a shock which the agents observe in advance but it impacts the level of investment prices in the future. I refer to this as the RPIs news shock, q_{it}.

This identifying assumption can be expressed in terms of the univariate moving average representation:

[4] Beaudry and Portier using bivariate VAR, imposed two identifying restrictions: first, that one shock has no long-run effects on TFP and label the orthogonal shock as the news shock; second, that one shock has zero short-run effect and label that shock as the news shock. As it turns out, the two restrictions lead to similar results. They find that the identified news shock leads to positive conditional comovement among macroeconomic aggregates on impact, that aggregate variables strongly anticipate movements in technology, and that news shocks account for a large fraction of the variance of aggregate variables at business cycle frequencies.

$$\ln\, q_{it} = [B_{11}(L) \quad B_{12}(L)] \begin{bmatrix} \varepsilon_t \\ \nu_t^n \end{bmatrix} \tag{2.1}$$

ε_t - traditional surprise relative prices shock - that impacts it in the same period in which agents see it, while ν_t^n - news shock - which agents observe in advance.

The only restriction on the moving representation is that $B_{12}(0) = 0$, so that news shocks have no contemporaneous effect on relative prices. The following is an example process satisfying this assumption:

$$\ln\, q_{it} = g + \ln\, q_{it-1} + \varepsilon_t + \nu_{t-j}^n \tag{2.2}$$

Here log q_{it} follows a random walk with drift, with g describing the drift term.

ν_t^n, the news shock, has no immediate impact on the level of q_{it}, but in j periods into the future. ε_t is the conventional surprise q_{it} shock. Given the timing assumption, ν_t^n has no immediate impact on the level of q_{it} but portends a change in q_{it} some j periods into the future.

In a univariate context, it would not be possible to separately identify ε_t and ν_{t-j}^n.

The identification of news shocks must come from surprise movements in variables other than q_{it}. As such, estimation of a vector autoregression (VAR) seems sensible in this context. In a system featuring an empirical measure of q_{it} and macro variables, I identify the surprise shock as the reduced-form innovation in q_{it}. The news shock is then identified as the shock that best explains future movements in q_{it} not accounted for by its own innovation.

Chapter 3

News Shocks Empirical Evidence

In this chapter I present the main results of the VAR model for the economies of Spain and Germany. The benchmark VAR includes the logs of eight variables: RPI, q_{it}[1], total output, GDP_t, consumption, C_t, aggregate investment, X_t, hours worked, H_t, residential investment, X_{rt}, business structures investment, X_{st} and equipment investment, X_{et}. Although in this section I present results only for the q_{rt} news shock (i.e. one which portends future increase in residential RPI), in the the Appendix O there are shown the estimations of the news shocks on business structures and on equipment RPIs. In addition in the Appendix P, I estimate news shocks on an alternative VAR.[2]

The system is estimated in levels. The Akaike criteria, the Hannan-Quinn information and Schwartz criteria favor two lags. As a benchmark, I choose to estimate a VAR with two lags; the results are robust to using a different number of lags. I estimate a Bayesian VAR (BVAR) using the MATLAB main program routine provided by Kurmann and Otrok (2013).

In the figures representing the impulse response functions, (IRF), and the forecast error variance, (FEV), the solid lines correspond to the posterior

[1] i stands q_{rt}-residential investment, q_{st} - business structures, q_{et} - equipment investment

[2] The alternative VAR includes the logs of eight variables: relative price of investment, q_{it}, GDP, GDP_t, consumption, C_t, aggregate investment, X_t, equipment investment, X_{et}, business structures investment, X_{st}, residential investment, X_{rt}, and IBEX 35 for Spain, or DAX for Germany.

median estimates, while the grey bands display the 16%-84% posterior coverage intervals. These bands are constructed from a residual based bootstrap procedure repeated 1000 times.

As described in Section 2.1, I extract the shocks that maximize the fraction of the FEV of q_{it} explained by the news shocks over the forecast horizon of 10 periods[3], weighting the importance of each of the forecasts equally. This choice is motivated by the fact that I want to capture short- and medium-run movements of q_{it} while providing at the same time reliable estimates at the long end of the forecasting horizon.

3.1 Forecast Error Variance and Impulse Response Functions

Figure O.3 and O.4 in Appendix O display the fraction of the FEV of the benchmark VAR explained by the relative prices of residential investment shock for the Spanish and German economy. Figures O.1 and O.2 in Appendix O display the IRF of the benchmark VAR explained by the q_{rt} shock for the Spanish and German economy. I consider that a positive realization of the news shock means an expected future increase in residential RPI.

3.1.1 q_{rt} News Shocks Effects on Aggregate Variables

The figures O.3 and O.4 in Appendix O depict the contribution to forecast error variance at all horizons up to the 10 year. It is evident that favorable news shock on the residential RPI, q_{rt}, increase significantly on impact all the real aggregates and display persistent dynamics, even though they are different for Spain than for Germany.

[3]When using the method of Barsky and Sims (2011) to identify future q_{it} news shocks, I find that the results are not sensitive to the choice of forecast horizons (i.e. the results are very similar regardless of the forecast horizons used).

For the Spanish economy, the news shock[4] explains 61% of the variation of residential RPI, 59% of output, 65% of aggregate investment, and more then 40% of hours worked, on witch all the effect is on impact. On output, aggregate investment and consumption, the hump-shaped effect of the news shocks variance decomposition suggests that the news effect is accumulating in time. The residential RPI news shock explain very little of the consumption, only 15%.

The fraction of variation explained by German news shock shows a very different picture than the Spanish one. The news shock[5] explains less of the variation of output compared with the Spanish economy, 51% for Germany against 59% for Spain. Even less for the aggregate investment and hours: 39% and 11% respectively. Contrary to the Spanish economy, the highest fraction of variation is explained for the consumption, 48%, which effect is on impact.

Figures O.1 and O.2 in Appendix O show the estimated IRF of the Spanish and German variables to a positive one standard deviation residential RPI news shock from the benchmark VAR. Following a positive realization of the news shock, the housing prices do not change on impact by construction, after which they grow gradually and peak after 6 years.

The Spanish output, investment, consumption, and hours worked jump on impact, with highly statistically significative responses. Output, consumption, investment reach their peak after three periods. Hours worked, after the initial jump is decreasing and become insignificant after 5 periods. Output and aggregate investment, are particularly persistent, with hump-shaped effects.

For Germany, the output, consumption, investment and hours worked jump on impact with statistically significative responses. After the initial jump, all four variables exhibit low persistence, decaying rapidly and becom-

[4]Table O.1 shows the median impact percentile and the forecast horizon period in which that is achieved for Spain

[5]Table O.2 in Appendix O shows the median impact percentile and the forecast horizon period in which that is achieved for Germany

ing insignificant after 4-5 periods. Contrary to Spain, the German hours worked are statistically significant just for the first period.

3.1.2 q_{rt} News Shocks Effects on Investment Categories

Figures O.1 and O.2 in Appendix O show the estimated impulse responses of the Spanish and German variables to a positive one standard deviation q_{rt} news shock from the benchmark VAR. The news shock effects of a residential RPI on different investment categories variables for the Spanish and German economies are the following: for Spain, the residential investment variance explained by the news shock is 80%, while the fraction of FEV for the equipment and business structures it is much lower, around 43% and 46% respectively. The picture of decomposed IRF of investment in residential structures, business structures and equipment shows that all three responses are statistically significant, all three jumping on impact. Residential investment is the one that presents the highest amplitude and persistence being significant even after 10 periods. It reaches the peak in the third period, at more than 6.5% higher than its pre-shock value. In contrast, although the equipment investment reaches the peak rapidly, it shows the lowest degree of amplitude and persistence.

For the German data, the residential investment is not statistically significant. The business structures and equipment IRF are statistically significant, both jump on impact and decay shortly after that. The business structures IRF shows the highest degree of persistence to a news shock.

3.2 Benchmark VAR Results Interpretation

The key result of this section is that a positive residential RPI (q_{rt}) news shock implies positive comovement among macroeconomic aggregates in line with the positive unconditional comovement of these series in the data. For both countries, a positive realization of the q_{rt} news shock (i.e. one which portends future increase in residential RPI) is associated an initial increase of output, investment, consumption, and hours worked. Compared with the German responses, the Spanish ones exhibit a much higher persistency and amplitude. The results match closely the findings in Beaudry and Portier (2006) who find comovement following a TFP news shock. According to Beaudry and Portier (2006), an initial comovement of output, investment, consumption, and hours is consistent with a favorable interpretation of the news-driven business cycle hypothesis. In the same time my results contradict Barsky and Sims (2011)) who do not find the aggregate comovement following to a TFP news shock. For Barsky and Sims (2011), the news shocks constitute a main driver of business cycles when a positive news shock leads to comovement in consumption and hours on impact.

A number of interesting results emerge from the analysis. From the IRF and FEV decomposition analysis between Spain and Germany, I conclude the q_{rt} news is a driver of the business cycle, with a strong reaction for Spain, and a softer reaction for Germany. There is an important difference of the effects of a q_{rt} news shock at the investment categories level. In Spain an q_{rt} news shocks beside increasing all aggregate variables, it is increasing very strong the residential investment, confirming the recent economic growth of the Spanish economy due to housing sector. At this point, it appears that a news shock on the residential RPI has the effect of increasing on one hand the residential investment, and on the other hand, its complements: business structures and equipment.

In Germany, on contrary, the same news shock it propagates itself stimulating equipment and business structures investment with an effect that seems to indicates that might be a substitution effect: the residential investment is substituted by investment in business structures and especially in equipment.

All those findings hold across different VAR specifications in my paper. Included in the Appendix O are the FEV and IRF of the news shocks estimated on q_{st} and q_{et} that are enforcing my results. As well, inthe Appendix

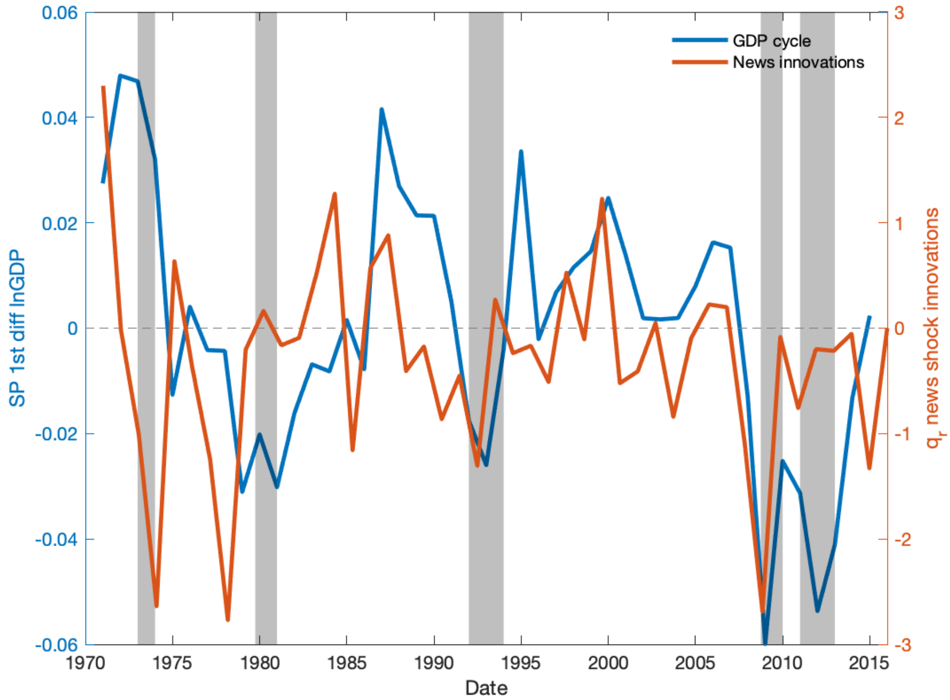
P there is an alternative VAR estimation, where I include a forward-looking variable, the IBEX 35 for Spain, and DAX for Germany. The alternative VAR specification also confirms the benchmark VAR results.

The next figure 3.1 represents the news shock from the empirical identification together with the first difference of the log of GDP. It can be seen that the news shock has predictability characteristics for the business cycle fluctuations. The contemporaneous correlation between news shock and the Spanish growth rate is 0.02, whereas the correlation at one lag is -0.18 while at two lags is -0.16. The negative correlation indicates that with a period of two years the news shock is anticipating a peak or a trough, and the change of GDP tendency. The Spanish crises in '92, '08 and '11 are anticipated by the news shock with one period.

Table 3.1: Correlation at lags and leads of GDP growth rate and the news shock

	Cross-Correlation of GDP growth rate:				
	-2	-1	0	1	2
News shock	- 0.16	-0.18	0.02	0.5	0.4

Figure 3.1: Spain: q_r news shock against 1st diff log GDP



Note: The shaded areas correspond to recession dates for Spain; The units of the left vertical axes is the log difference of GDP per capita.

Chapter 4

Two-Sector Model with Home Production and ISTC

This section describes the theoretical model proposed to interpret the news propagation mechanism of the empirical SVARs. The real business cycle model is based on a stylized version of Díaz and Franjo (2016) augmented with Jaimovich and Rebelo (2009) preferences, home production and news shocks. The model has two productive sectors: the market sector and the home production sector. The market production function distinguishes between two different capital categories, equipment and structures, and labour market hours, while in the home sector, consumers produce home goods with home labour and residential capital. Key assumptions for the model are that home production is not perfect substitute for market goods and services, and is not tradable in the market.

The driving forces in the business cycle model include country - specific stochastic stationary contemporaneous shocks and news shocks. The news shocks are hitting the residential, business structures, and equipment ISTC. In particular, as the empirical analysis suggests, the ISTC news shock has different long-run implications, but the contemporaneous effects are essentially zero. Therefore, the specification, through parameters ρ_i that are relative prices-specific, captures well news processes in response to the q_{it} shock; although this is a common shock, it propagates differently to the ISTC in each economy.

As is standard in growth and business cycle models, the decentralized competitive equilibrium can be characterized by the solution of a planning problem. The planner chooses the representative household's stochastic sequences of consumption and leisure to maximize the utility of the representative agent, subject to the technological constraints of the economy.

4.1 Preferences

There is a continuum of households indexed by $j \in (0,1)$. Each household consumes, supplies labour, makes investment and capital utilization decisions. The preferences are defined as followed:

$$E_t \sum_{t=0}^{\infty} \beta^t U \left[C_t \bigg(C_{mt}, C_{rt}(K_{rt}, N_{rt}) \bigg), N_{mt} + N_{rt}, \chi_t \right] \tag{4.1}$$

The total consumption, C_t, is a composite consumption of market goods and services, C_{mt}, and residential production for consumption, C_{rt}. It is assumed that total consumption is given by a CES function such as:

$$C_t = \left(\omega C_{mt}^{\eta} + (1-\omega) C_{rt}^{\eta}\right)^{1/\eta}, \quad \eta \in (-\infty, 1] \tag{4.2}$$

Note that ω is the proportion of each good in the total consumption, and η is the parameter measuring the willingness of agents to substitute between the market consumption and home production consumption. The parameter η is key for the relationship between the two activities since the elasticity of substitution between market goods and home production goods is defined as $\epsilon = 1/(1-\eta)$.

Following Jaimovich and Rebelo (2009) preferences, the presence of χ_t makes preferences non-time-separable in consumption and hours worked, allowing to parameterize the strength of short-run wealth effects on the labor supply:

$$\chi_t = C_t^{\gamma} \chi_{t-1}^{1-\gamma}; \quad \gamma \in [0,1] \tag{4.3}$$

Jaimovich and Rebelo (2009) preferences nest two of the most popular utility functions in the business cycle literature. When $\gamma = 1$ the preferences are those proposed by King et al. (1988), which I refer as KPR. In change, when $\gamma = 0$ the preferences are those proposed by Greenwood et al. (1988), which I refer as GHH. The characteristics of the GHH preferences are that the labor effort is determined independently of the intertemporal consumption-saving choice.

Therefore χ_t becomes:

$$\chi_t = \left(\omega C_{m,t}^{\eta} + (1-\omega) C_{r,t}^{\eta} \right)^{\frac{\gamma}{\eta}} \chi_{t-1}^{1-\gamma} \tag{4.4}$$

Each household supplies labour to labour market, N_{mt}, and to residential production, N_{rt}.

$$N_t = N_{mt} + N_{rt} \tag{4.5}$$

The household combines residential capital with hours according to the home production function:

$$C_{rt} = A_t K_{rt+1}^{1-\theta_r} N_{rt}^{\theta_r} \tag{4.6}$$

where A_t is the home production productivity, which is assumed to follow a stochastic process driven by a shock, ε_{At}, i.i.d. process with zero mean and standard deviation σ_{ε}.

$$ln\ A_t = (1-\rho_A)\ ln\ \bar{A} + \rho_A\ ln\ A_{t-1} + \varepsilon_{At}$$

K_{rt} represents residential structures. The parameter θ_r represents the labour share in the home production function. The constrain says that home consumption must be produced at home and cannot be bought or sold on the market.

I write the utility function as

$$U(C_t, N_t, \chi_{t-1}) = \frac{\left(C_t - \psi N_t^{\theta}\left(\omega C_{mt}^{\eta} + (1-\omega)C_{rt}^{\eta}\right)^{\frac{\gamma}{\eta}} \chi_{t-1}^{1-\gamma}\right)^{1-\sigma} - 1}{1-\sigma} \tag{4.7}$$

4.2 Technology

The production of final output, Y_t, requires of market labor, N_{mt}, and two types of capital, equipment and business structures. Production technology is described by:

$$Y_t = Z_t K_{et}^{\alpha_e} K_{st}^{\alpha_s} N_{mt}^{1-\alpha_e-\alpha_s}, \quad 0 < \alpha_e, \alpha_s;\ \alpha_e + \alpha_s < 1. \tag{4.8}$$

where Z_t is the total factor productivity (TFP). The technology is assumed to follow a stochastic process driven by a shock, ε_{Zt}, i.i.d. process with zero mean and standard deviation σ_ε: $ln\ Z_t = (1-\rho_Z)ln\bar{Z} + \rho_Z ln\ Z_{t-1} + \varepsilon_{Zt}$

The household owns the total capital, K_t, divided between capital used to produce market goods and services and home production capital as follow:

$$K_t = K_{et} + K_{st} + K_{rt}, \tag{4.9}$$

The capital for market goods and services K_{mt} is split between equipment, K_{et}, and business structures, K_{st}, while the share of capital used in the house production function includes residential structures, K_{rt}. The household's capital stock evolves according to the law of motion:

$$K_{it+1} = (1-\delta_i)K_{it} + \Theta_{it}X_{it}, \text{ where } 0 < \delta_i < 1, \tag{4.10}$$

where X_{it} is the investment, and i that stands for equipment, X_{et} , business structures, X_{et}, and residential structures, X_{rt}.

Θ_{it} represents the level of investment-specific technology. Following Greenwood et al. (1997), Θ_{it} determines the amount of capital that can be purchased for one unit of output, representing the current state of the technology to produce capital. Changes in Θ_{it} represent investment-specific technological change and we assume that it affects all types of capital. The higher Θ_{it}, greater the amount of capital that can be incorporated into the economy with an investment unit, reflecting the fact that the quality of capital has increased. A technological news shock that increases Θ_{it} is associated expectations of future reduction of the cost of producing investment capital with respect to the cost of producing consumption goods.

In equilibrium, the inverse of the investment-specific technology shock, $q_{it} = 1/\Theta_{it}$, could be thought of as the relative price of capital in terms of consumption.

Final output, Y_t, can be used for four purposes: market consumption, C_{mt}, investment in business structures, X_{st}, investment in equipment, X_{et} or residential investment, X_{rt}:

$$Y_t = C_{mt} + X_{et} + X_{st} + X_{rt} \tag{4.11}$$

This is a closed economy.

The household maximizes utility subject to the global constraint of resources :

$$C_{mt} + X_t = Z_t K_{et}^{\alpha_e} K_{st}^{\alpha_s} N_{mt}^{1-\alpha_e-\alpha_s} \tag{4.12}$$

where $X_t = X_{et} + X_{st} + X_{rt}$,

4.3 News shocks

In this setting I introduce the news shocks on q_{it} as follows:

$ln\ q_{et} = (1-\rho_{q_e})\bar{q}_e + \rho_{q_e} ln\ q_{et-1} + \varepsilon_{q_e t} + \varepsilon_{news,t-4}$, where q_{et} stands for the relative price of equipment.

$ln\ q_{st} = (1 - \rho_{q_s})\bar{q_s} + \rho_{q_s} ln\ q_{st-1} + \varepsilon_{q_s t} + \varepsilon_{news,t-4}$, where q_{st} stands for the relative price of business structures.

$ln\ q_{rt} = (1 - \rho_{q_r})\bar{q_r} + \rho_{q_r} ln\ q_{rt-1} + \varepsilon_{q_r t} + \varepsilon_{news,t-4}$, where q_{rt} stands for the relative price of residential investment.

The news shock hits the three relative prices, but not at the same time, having the same magnitude in all three cases. Although I report only results on the news shocks on the relative prices of residential investment, $\nu_{n_r t-4}$, I also consider contemporaneous i.i.d. shock, $\varepsilon_{q_i t}$ and news shocks on the relative prices on investment in business structures and equipment.

The news shocks hits as the economy is in the steady state. Agents receive news about one percent increase in the relative prices of investment in residential investment up four periods ahead: $\varepsilon_{news,t-4}$ is an innovation to the level of q_{rt} that materializes in period t, but that agents learn about in period $t - 4$.

4.4 Social Planner's Problem

The planner chooses $\{Y_t, C_t, N_m, N_r, X_t\}$ to maximize 4.7 subject to 4.8 - 4.12 given $K_{i,0}$.

I solve the first-order conditions of equilibrium around the non-stochastic steady state of the model and solve numerically the system of stochastic difference equations in DYNARE.

4.5 Calibration

This section explores the reasonable setting of the parameters to be useful in studying the news shocks propagation mechanism. I calibrate my model so that in steady state to match the average values in the Spanish and German annual data for the 1970 - 2015 sample. The stochastic structure that governs the evolution of the news shocks is taken from the time series properties in the *EU KLEMS*[1] data base 2017 release.

Table 4.1: Calibration - Spain vs Germany

Param.	Spain	Germany		Target
β	0.95	0.98	discount factor	$1/(1+r_t)$
α_e	0.13	0.14	equipment capital share	Díaz and Franjo (2016)
α_s	0.10	0.11	structures capital share	Díaz and Franjo (2016)
θ_r	0.20	0.18	capital share in residential production	Calibrated
δ_e	0.11	0.13	equipment depreciation	EU KLEMS
δ_s	0.03	0.04	structures depreciation	EU KLEMS
δ_r	0.02	0.02	residential depreciation	EU KLEMS
$\bar{Z}$	0.65	0.89	average TFP	Estimated
ρ_Z	0.85	0.95	autocorr.TFP process	Estimated
$\bar{A}$	0.81	0.71	average home productivity process	Calibrated
ρ_A	0.98	0.93	autocorr. home productivity process	Calibrated
$\bar{q}_e$	0.15	0.5	average relative price of equipment	Estimated
ρ_{q_e}	0.88	0.96	autocorr. rel. price of equipment process	Estimated
$\bar{q}_s$	0.35	0.42	average relative price of structures	Estimated
ρ_{q_s}	0.94	0.92	autocorr. rel. price of structures process	Estimated
$\bar{q}_r$	0.38	0.42	average relative price of residential	Estimated
ρ_{q_r}	0.78	0.94	autocorr. rel. price of residential process	Estimated

To compare the two economies I make them equal in certain dimensions equalizing the parameters that are not essential for my argument. First, I fix the intertemporal elasticity of substitution (IES) to be the same in both economies. In the literature, it is fairly common to implicitly set $\sigma = 1$ which corresponds to the case of logarithmic utility.

[1] Díaz and Franjo (2016) use the same data base for the Spanish economy in theirs paper

Then, it seems natural to set equal the following two parameters: $\omega = 0.54$, which is the utility function parameter that measures the weight of the market consumption, C_m, and the labour disutility scale parameter, $\psi = 0.45$.

Table 4.2: Common specification

Param.	Value		Target
σ	1	Intertemporal Elasticity of Substitution (IES)	Jaimovich and Rebelo (2009)
ω	0.54	measures the weight of C_m in the utility function	Calibrated
ψ	0.45	scale parameter	Working time 1/3 of time endowment

The news shocks propagation mechanism depends on γ, η, and θ. Help the model to capture main features of the data, in order to achieve the comovement (γ) and persistency (θ) observed in the empirical identification. The next three parameters are key to better understand the implications of news shocks reproducing the observed investment process. There are, the parameter that governs the short run wealth-effect, γ, the parameter η that governs the elasticity of substitution between C_m and C_h, and the intertemporal labor supply elasticity parameter, θ.

γ helps to mimic the individual characteristics of the two economies. In the same line as Jaimovich and Rebelo (2009), in order to obtain comovement, the short-run wealth effects should be somewhat weaker than those implied by KPR (< 0.6). For that reason, I consider intermediate values of γ for both countries. For Spain, I set weak short-run wealth effects, close to GHH preferences, $\gamma = 0.06$, while for Germany, $\gamma = 0.56$.

As η governs the elasticity of substitution between market and home production, the news effects become more important in the model under a low elasticity of substitution between market and home production. - the elasticity of substitution between C_m and C_h is defined as $\epsilon_h = 1/(1-\eta)$. The reason for employing those particular values for η is based on one hand on the fact that it should reflect the believes about the complementarity and sustituibility between the market activity and home activity in the two economies. On other hand, because there is a lack of consistent and long time time series on time use in the home production for the two countries in my data set.

Given the empirical market labour differences of the two economies, I set for Germany a much responsive labor supply ($\theta < 1.3$) than for Spain, for which I set it not very responsive ($\theta < 7.2$).

Table 4.3: Key parameters

	SPAIN	**GERMANY**	
γ	0.06	0.56	governs the short-run wealth effect on the labor supply
η	-1.31	0.85	$\epsilon_h = 1/(1-\eta)$ elasticity of substitution between C_m and C_h
θ	7.2	1.25	intertemporal labor supply elasticity

Chapter 5

Theoretical Model Results

Next, I inspect the theoretical impulse response functions of relative prices of investment in response to news shocks in our benchmark model. I start with news shocks on relative prices of residential investment, q_{rt}. In Appendix Q, I include the estimations of news shocks on relative prices of business structures, q_{st}, and on news shocks on relative prices of equipment investment, q_{et}.

For the purpose of analyzing a news shock propagation mechanism, there are various moments of interest: the variable movement on impact, meaning at $t = 1$, at the period t between $2 < t < 4$, at the time of the realization, $t = 4$, and after the shock.

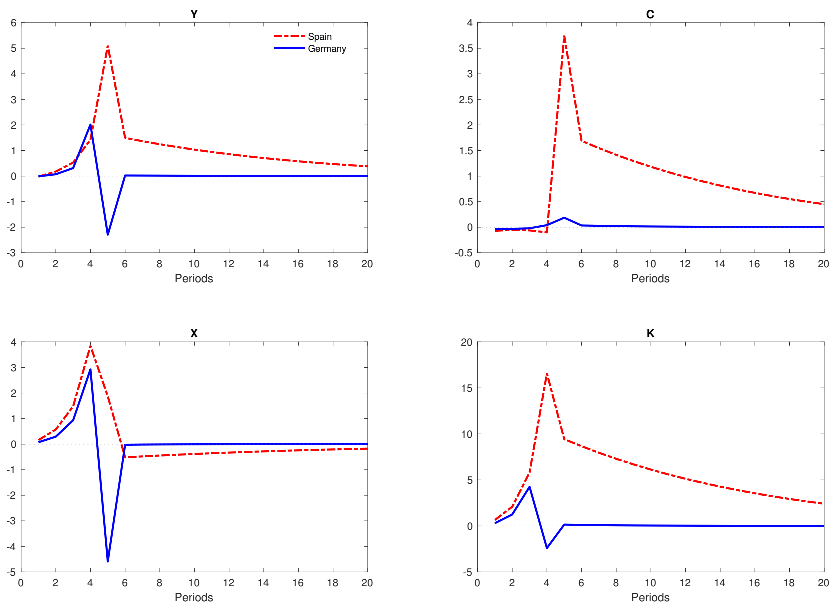
5.1 q_{rt} News Shocks

5.1.1 q_{rt} News Shock Effects on Aggregate Variables

Figure 5.1 shows the IRFs of aggregate model's variables following a news shock on the relative prices of residential investment increase of 1%.

On impact at time t the Spanish and German output, consumption, investment, and capital accumulation, do not move. For both economies, starting from the second period, the output, investment and capital accumulation

Figure 5.1: q_r news shock effect on aggregate variables



start increasing, though the positive shock only occurs in period four. The aggregate consumption does not react for either economy. The Spanish output, consumption and capital accumulation peak only after the realization of the news shock. That means, in the fifth period, when they reach the maximum after which persistently stay above the steady state for many periods. Starting with the sixth period, the Spanish aggregate investment falls slightly under the steady state where it stays for 15 periods. For Germany, most of the aggregate variables increase occurs between period two and four, when the news arrives, not in period four, when the q_{rt} shock materializes. After the forth period, the German output, investment and capital accumulation are falling, returning to the log run equilibrium already from the sixth period, while consumption response, even it is very small, it is positive.

The Spanish IRF output, consumption, and capital accumulation are positive and persistently above the steady state, indicating a long and persistent economic growth and capital accumulation already from the second period. For Germany, the initial increase of the variables is followed by a fall and a rapid return to the log run equilibrium after that.

At the aggregate level, if in the period before the shock realization the variables are positively correlated, after the shock materializes, effects are opposite for the two economies, with much stronger fluctuation for Spain, and less for Germany.

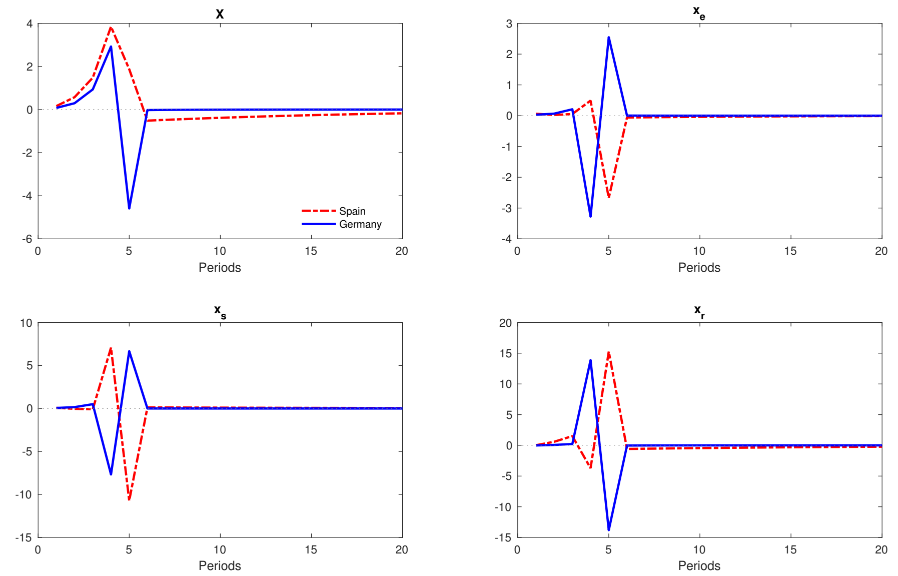
5.1.2 q_{rt} News Shock Effects on Investment Categories

Figure 5.2 shows the IRFs of investment categories following a news shock on the relative prices of residential investment increases of 1%. The first observation is that the model is able to mimic the negative correlation between the two countries found in the data, especially starting from the 2000s.

For the propagation mechanism, there are three moments of interest: the variable movement before, at the time of the realization, and after the shock.

For the Spanish economy, the equipment, X_e, and structures investment,

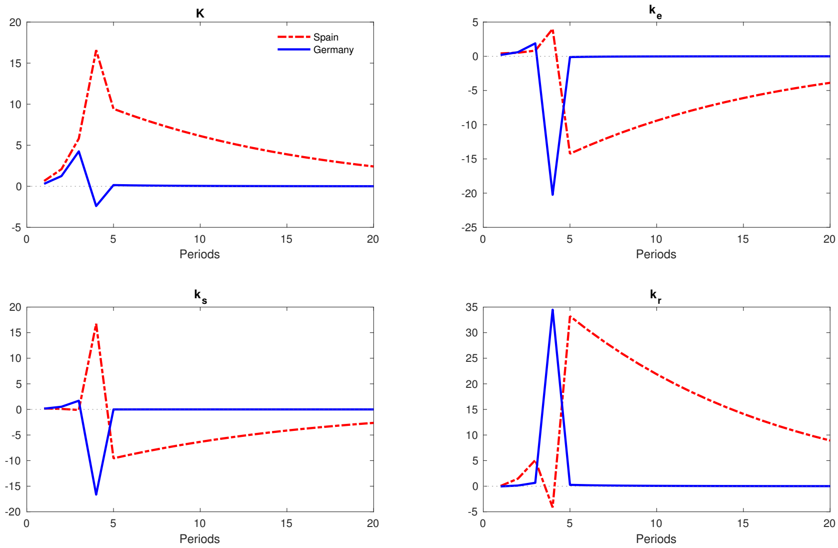
Figure 5.2: q_{rt} news shock effect on investment categories



X_s, are increasing on the realization of the shock, after which they both are falling. The initial increase in the structures investment is stronger than the equipment one, but also fall is deeper, even they are not persistent. The residential investment, X_r, is increasing strongly after the realization of the news shock, even thought in the period before the realization of the shock, there are two opposite very weak movements; one of a light increase starting from the second period, followed by a very short fall exactly on the realization of the shock.

For the German economy the movements are exactly opposite. Equipment and structures are decreasing on the shock realization, to increase in the following periods. The residential investment is increasing only on the realization of the shock after which is followed by a fall. For Germany, it appears that the news shock effect on the equipment and structural investment is positive, while seems to be negative for the residential investment.

Figure 5.3: q_{rt} news shock effects on capital categories



5.1.3 q_{rt} News Shock Effects on Capital Categories

Figure 5.3 shows the IRFs of capital categories model's variables following a news shock on the relative prices of residential investment decrease of 1%. Practically, the capital accumulation is negatively correlated for the two economies.

Again, I analyze the effects looking at the three moments of interest: the variable movement before, at the time of the realization, and after the chock. For the German economy, the capital accumulation is negative at the time of news shock realization for the equipment, k_e, and business structures, k_s, while is positive for the residential capital, k_r. None of the variable movement is persistent. On contrary, the Spanish variables are showing nice persistent movements; negative for the equipment and business structures, and positive and very persistent for the residential capital accumulation.

Chapter 6

Extension - a small open economy model

This section describes an extension of the theoretical model - news shocks in a small open economy. Based on the previous chapter model, I follow Schmitt-Grohé and Uribe (2003) and assume that the interest-rate faced by agents is increasing in the individual debt position, d_t. The small open economy model has two productive sectors: the market sector and the home production sector. The market production function distinguishes between two different capital categories, equipment and structures, and labour market hours, while in the home sector, consumers produce home goods with home labour and residential capital. As in the closed economy setting, key assumptions for the model are that home production is not perfect substitute for market goods and services, and is not tradable in the market.

The driving forces in the business cycle model include country - specific stochastic stationary contemporaneous shocks and news shocks. The news shock is hitting the residential investment ISTC. In particular, as the empirical analysis suggests, the ISTC news shock on has different long-run implications, but the contemporaneous effects are essentially zero.

As is standard in growth and business cycle models, the decentralized competitive equilibrium can be characterized by the solution of a planning problem. The planner chooses the representative household's stochastic sequences of consumption and leisure to maximize the utility of the representative agent, subject to the technological constraints of the economy.

6.1 Country-specific interest rate premium

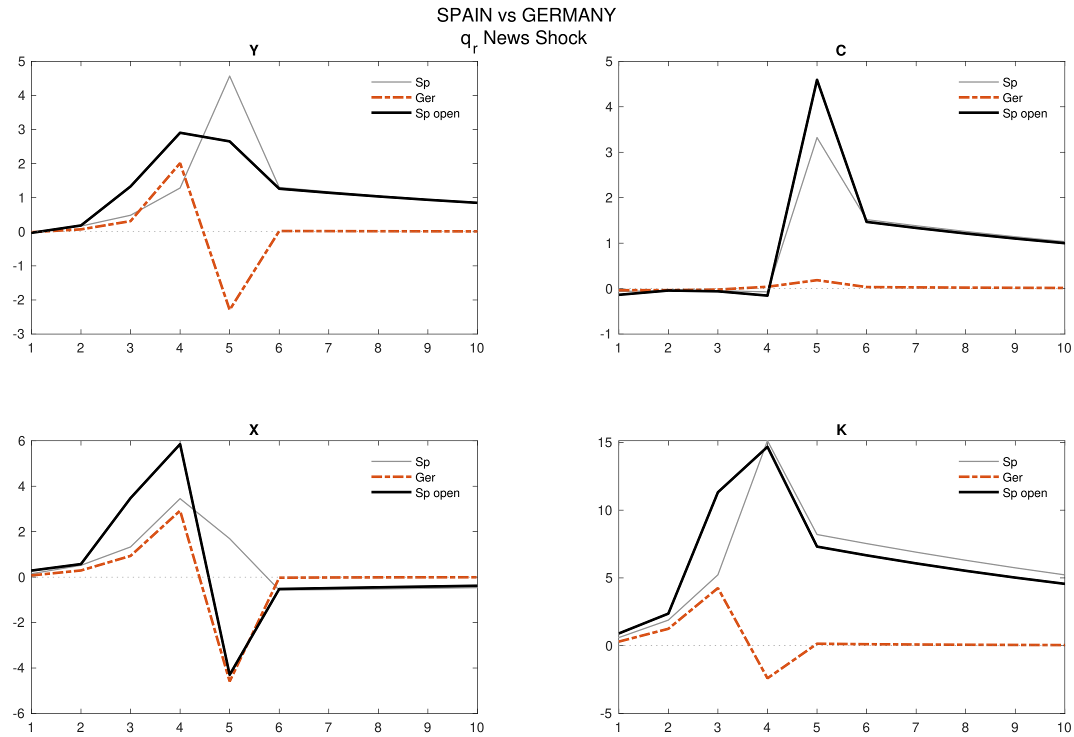
Households can borrow and lend in the international capital market at the exogenous international real interest rate, r_t. I assume that the domestic interest rate r_t is increasing in the aggregate stock of foreign debt, d_t. More precisely, I assume that r_t evolves according to:

$$r_t = r^* + p(\tilde{d}_t) \tag{6.1}$$

where r^* denotes the world interest rate and $p(\tilde{d}_t)$ is a country-specific interest rate premium. The function $p(\tilde{d}_t)$ is assumed to be strictly increasing. Following Schmitt-Grohé and Uribe (2003) I assume for the risk premium: $p(\tilde{d}_t) = \psi_d(e^{(d_t-\bar{d})} - 1)$, where $\psi_d > 0$ is a parameter and $\bar{d}$ is the level of debt in the steady state.

6.2 News shocks effects on aggregate variables

Figure 6.1: IRF Aggregate variables

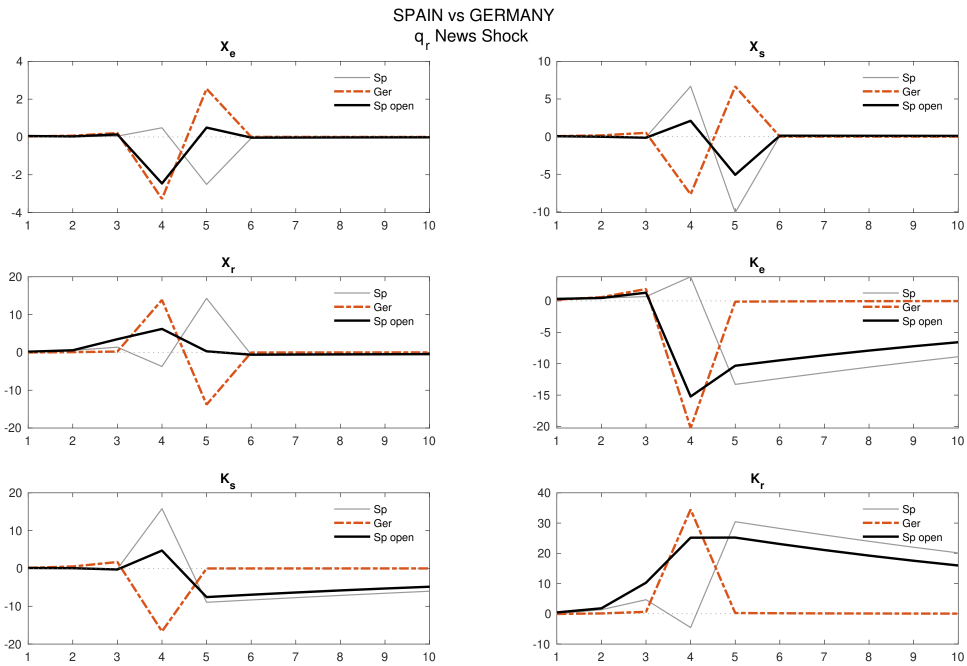


Note: The black line represents the Spanish economy in a small open economy setting; the dotted red line represents the German economy in the benchmark model, while the gray line represents the Spanish economy in the benchmark model.

In a small open economy the households can borrow and lend in international markets. In figure 6.1 we observe that the Spanish economy starts to increase a period earlier with respect to the closed economy. After the news shock hits, in period $t = 2$, as the Spanish household have the possibility to borrow in the international markets, the GDP, aggregate investment and capital accumulation starts to increase. Although the GDP increase is milder than the closed economy setting, the investment and the consumption increase is much stronger. As such, the model is able to replicate a well-known Spanish economic characteristic of a much volatile consumption than the GDP.

6.3 News shocks effects on Investment categories

Figure 6.2: IRF Investment categories



Note: The black line represents the Spanish economy in a small open economy setting; the dotted red line represents the German economy in the benchmark model, while the gray line represents the Spanish economy in the benchmark model.

The figure 6.2 represents the impulse response function of investment categories. The residential capital accumulation for the Spanish economy is starting to increase much earlier that in the closed economy setting. Although the increase is lower, the accumulated effect of the news shock is stronger.

Chapter 7

Conclusion

This part identifies news shocks using structural vector autoregressions. I found robust evidence that news shocks about future investment-specific technical change (ISTC) constitute a significant force behind Spanish and German economic business cycles in the period 1970 - 2015.

To obtain these results, I first applied the Barsky and Sims (2011) approach. The empirical impulse responses produce significant positive business cycle comovement in Spain. The news shocks that explain in a high measure the variation of output, investment and hours, are robust to different lag election and to an alternative VAR specification. A significant forecast error variance contributions (80%) of the residential investment in the Spanish economy is explained by news shocks on relative prices of residential investment. For the German economy, the news shocks explain the variance of the aggregate variables in a less measure.

Then, the theoretical RBC model of a closed economy that I propose to interpret the empirical results show that news shocks can be highly informative. In particular for Spain, the propagation mechanism of the ISTC news shock is consistent with the recent economic growth due to residential investment; it indeed justifies the contribution of the residential ISTC news shocks to the housing boom. The model simulations show that the news shocks on ISTC trigger a robust increase in output and stimulate investment and capital accumulation in residential structures. In contrast, for the German economy the news effects mainly enhance investment and capital accumulation in equipment and business structures. In addition, the percentage of the variance of output, investment, consumption and hours explained by investment-specific news shocks is larger for Spain than for Germany. The results in a small open economy confirms those findings.

The results suggest that news shocks contribution to business cycle fluctuation is relatively more important in Spain than in Germany. The paper shows that in the context of Spanish and German economy, the empirical methodology SVAR and DSGE provides strong support for the "news" view.

Part V

THESIS CONCLUSIONS

To the best of my knowledge, it is the first attempt to empirically identify the news shocks for Spain and its implications for the economic fluctuations. I analyzed the effect that news shocks can have on economic activity and have discussed the mechanisms behind the results obtained. Practically, this analysis explains economic fluctuations by essentially anticipated expectations in productivity which causes booms by stimulating residential investment. I argue that the expectations of a decrease in the total factor productivity for Spain was anticipated by the IBEX 35. The data shows business-cycle type comovements of output, consumption, investment, and hours following a news shock. I found that empirically news shocks can explain explain 59% of output's variance, 65% of aggregate investment, and 80% of residential investment. At the same time, when I studied the effects of news shocks on the Spanish and German economy. The results suggest news shocks contribution to aggregate fluctuations is relatively more important in Spain than in Germany. In addition, I provide evidence that news shocks propagation mechanism is consistent with the housing boom in Spain.

Second, in the context of news shocks, this dissertation proposes an exogenous source of productivity growth, the investment-specific technical change in the residential sector (ISTC) to explain the residential investment for the

Spanish economy.

Finally, this dissertation also contributes to the literature proposing theoretical DSGE models that contribute to the characterization of the housing booms due to the mechanisms of these shocks. However, I have abstracted from modeling the news shocks process in a situation of two countries that facing similar shocks encounter different propagation mechanism. The modeling of the characteristic determinants of that is an issue for future research and include housing markets, industrial sectorial composition, portfolio choice, institutional arguments, banking system and financial frictions. Thus, I hope my results are useful for designing and evaluating policies to overcome recessions and mitigate economic cycle fluctuations.

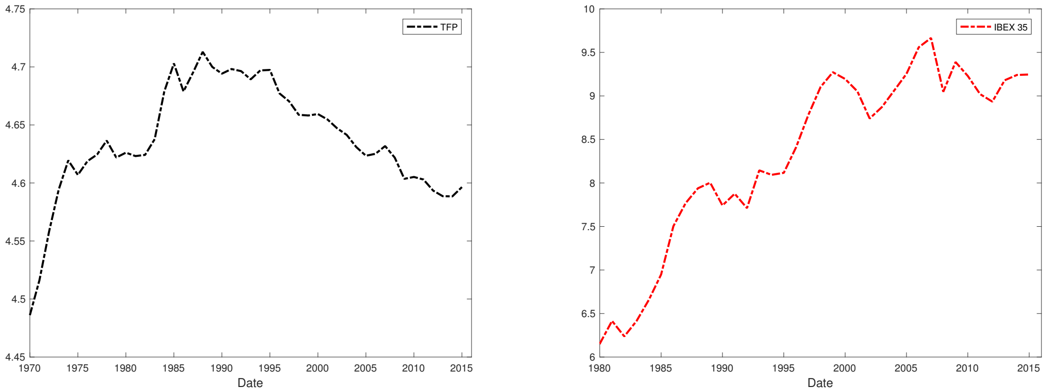
Appendix A

Data

A.1 Spanish TFP and IBEX 35

Figure A.1: SPAIN: TFP & IBEX 35

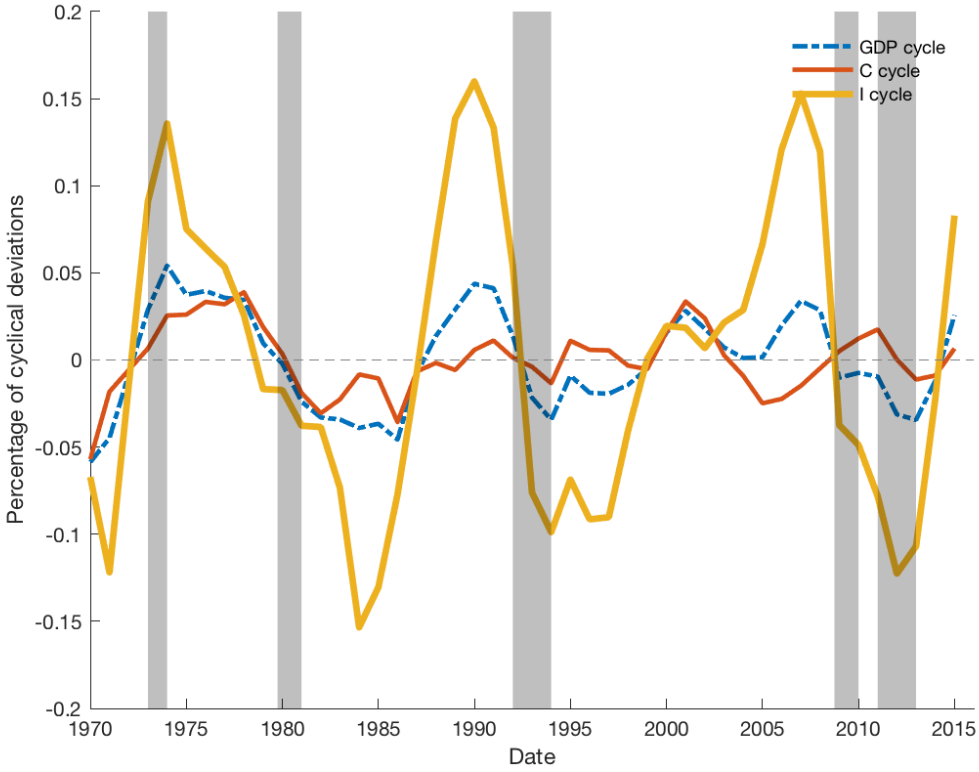
(a) TFP (b) IBEX 35



Note: **TFP** yearly series for the Spanish economy, 1970-2007 downloaded from EU KLEMS database; **IBEX 35** (1986-2015) downloaded from BLOOMBERG; the SP series deflated by the CPI, in per capita terms, deflated by the Spanish working population aged 16-64.

A.2 Spanish Macroeconomic Variables

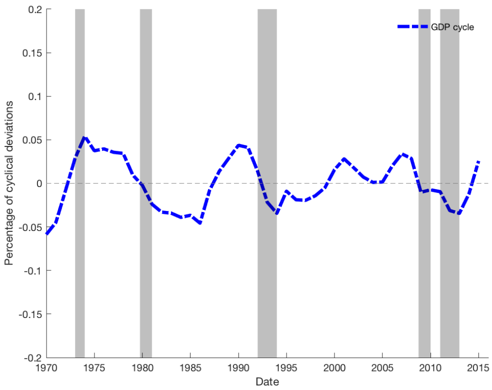
Figure A.2: Spanish GDP, C, I cycle



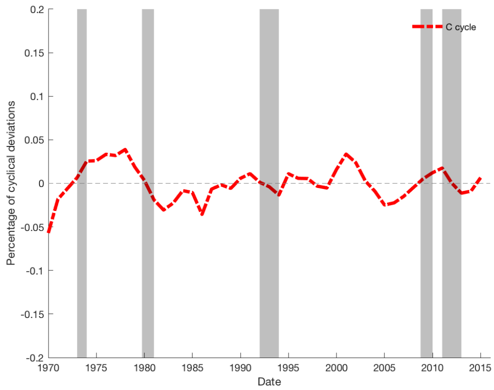
Note: **Spanish GDP, C, I cycle**: The Hodrick-Prescott cycle of the yearly GDP, C, I series for the Spanish economy, 1970-2015; the GDP, Consumption, and Investment data

Figure A.3: Macroeconomic variables cycle

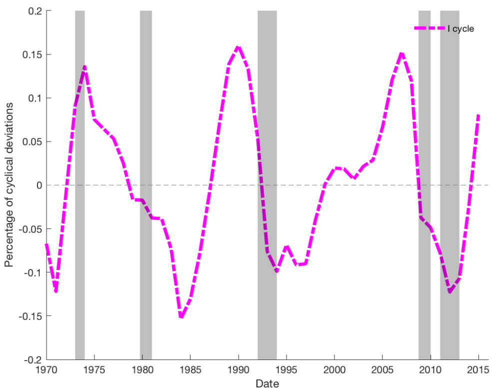
(a) GDP cycle



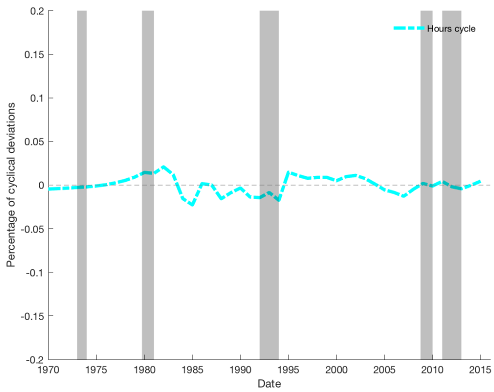
(b) Consumption cycle



(c) Investment cycle



(d) Hours cycle



Note: The Hodrick-Prescott cycle of the yearly GDP, Consumption, Investment, and Hours worked series for the Spanish economy, 1970-2015;

Appendix B

Estimation 3-variables VAR

B.1 Estimation 3-VAR: TFP, IBEX 35, GDP

Figure B.1: IRF 3-VAR: TFP, IBEX 35, GDP

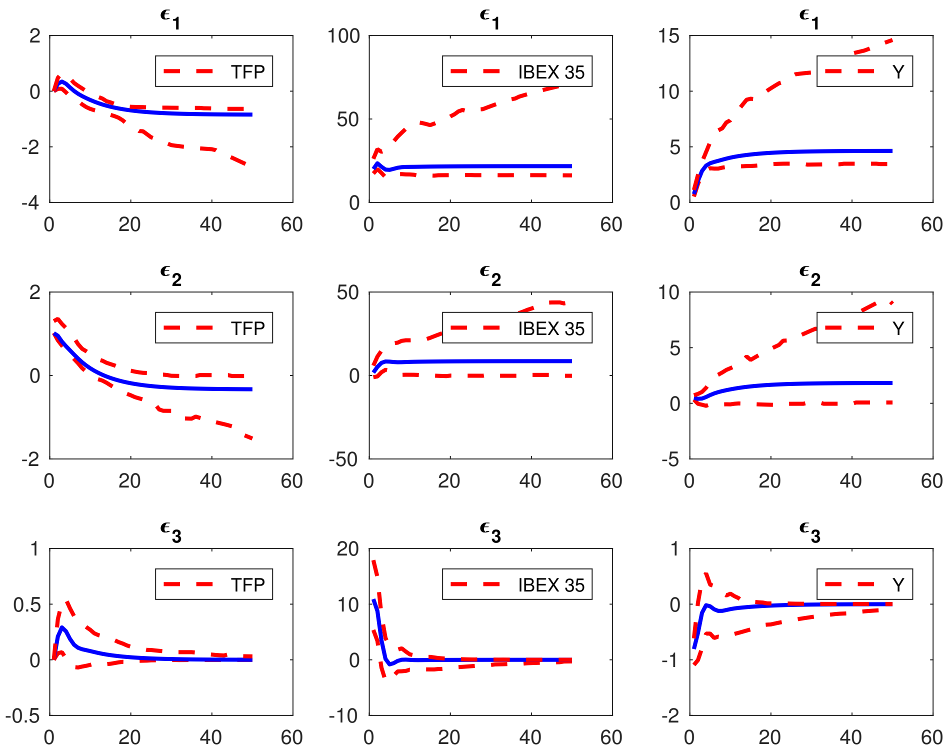
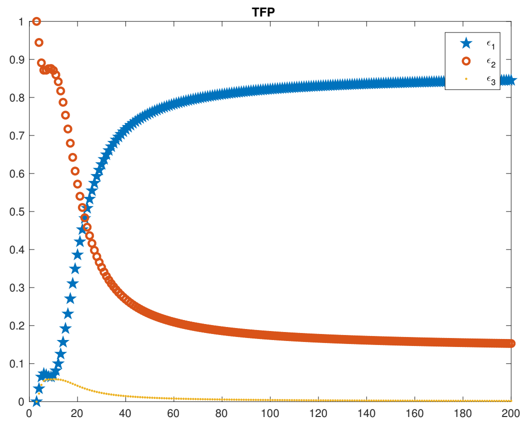
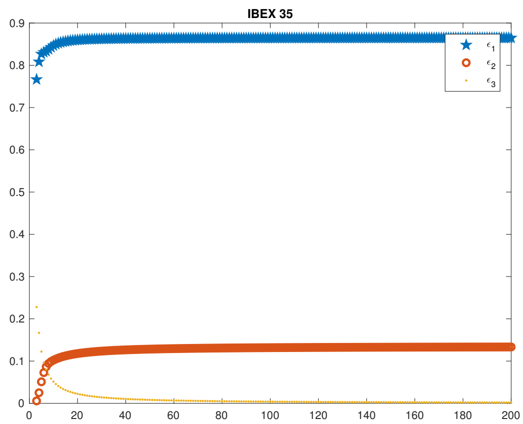


Figure B.2: FEV 3-VAR: TFP, IBEX 35, GDP

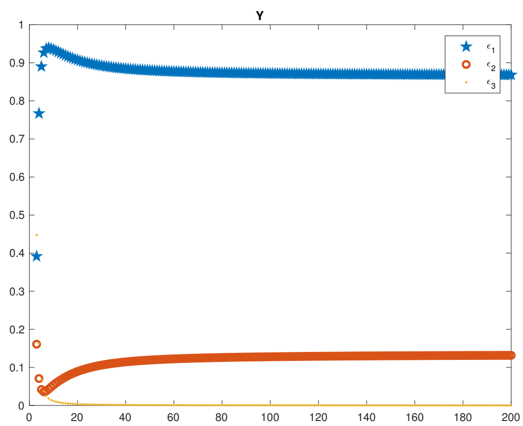
(a) FEV news shock on TFP



(b) FEV news shock on IBEX 35



(c) FEV news shock on GDP



B.2 Estimation 3-VAR: TFP, IBEX 35, Investment

Figure B.3: IRF 3-VAR: TFP, IBEX 35, Investment

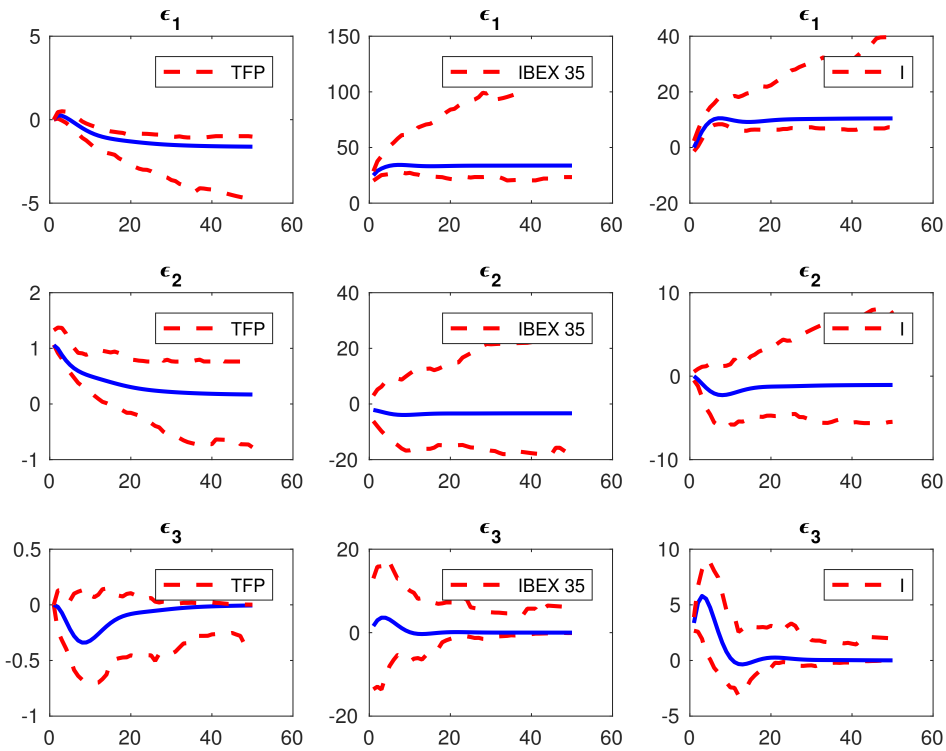
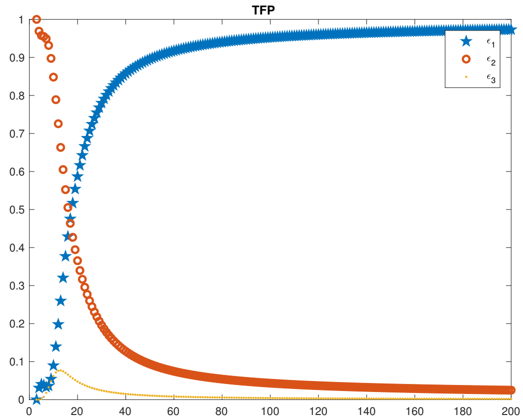
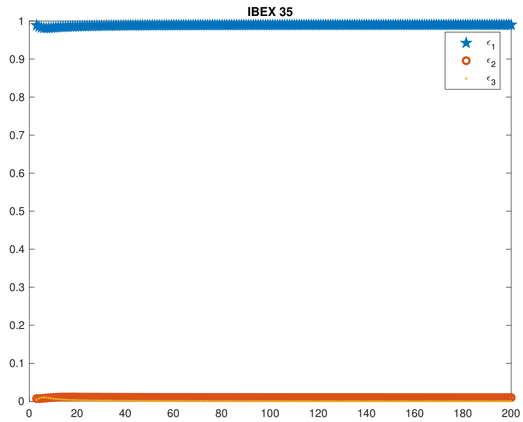


Figure B.4: FEV 3-VAR: TFP, IBEX 35, Investment

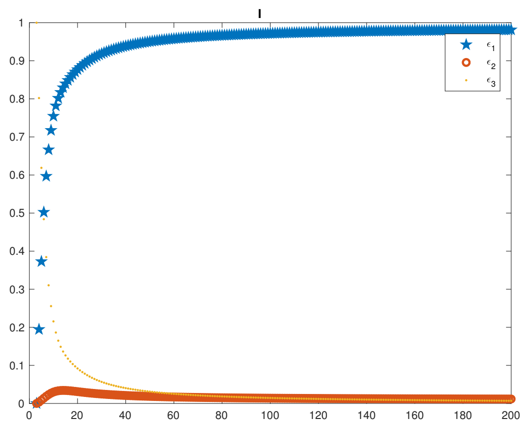
(a) FEV news shock on TFP



(b) FEV news shock on IBEX 35



(c) FEV news shock on I



B.3 Estimation 3-VAR: TFP, IBEX 35, Consumption

Figure B.5: IRF 3-VAR: TFP, IBEX 35, Consumption

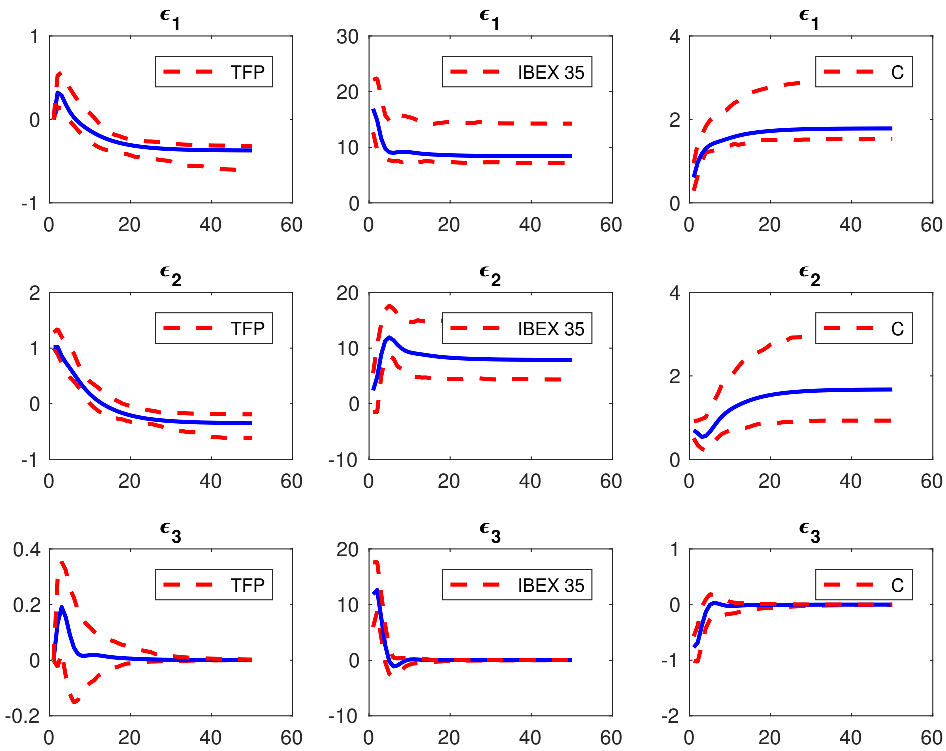
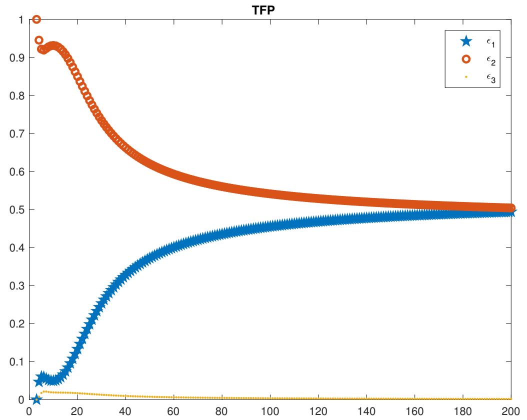
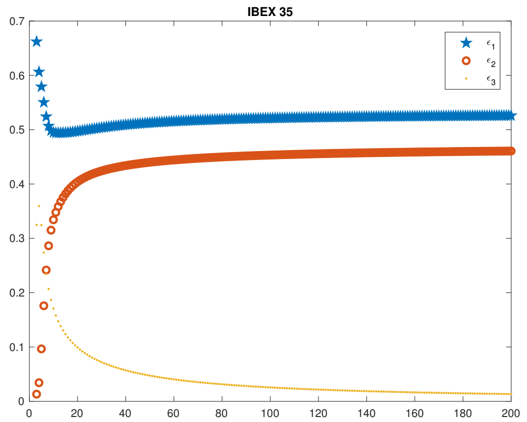


Figure B.6: FEV 3-VAR: TFP, IBEX 35, Consumption

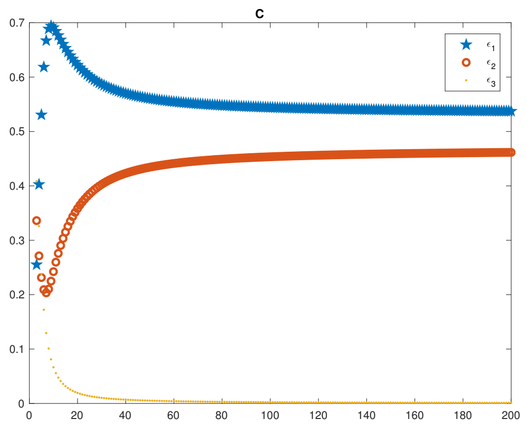
(a) FEV news shock on TFP



(b) FEV news shock on IBEX 35



(c) FEV news shock on C



B.4 Estimation 3-VAR: TFP, IBEX 35, Hours

Figure B.7: IRF 3-VAR: TFP, IBEX 35, Hours

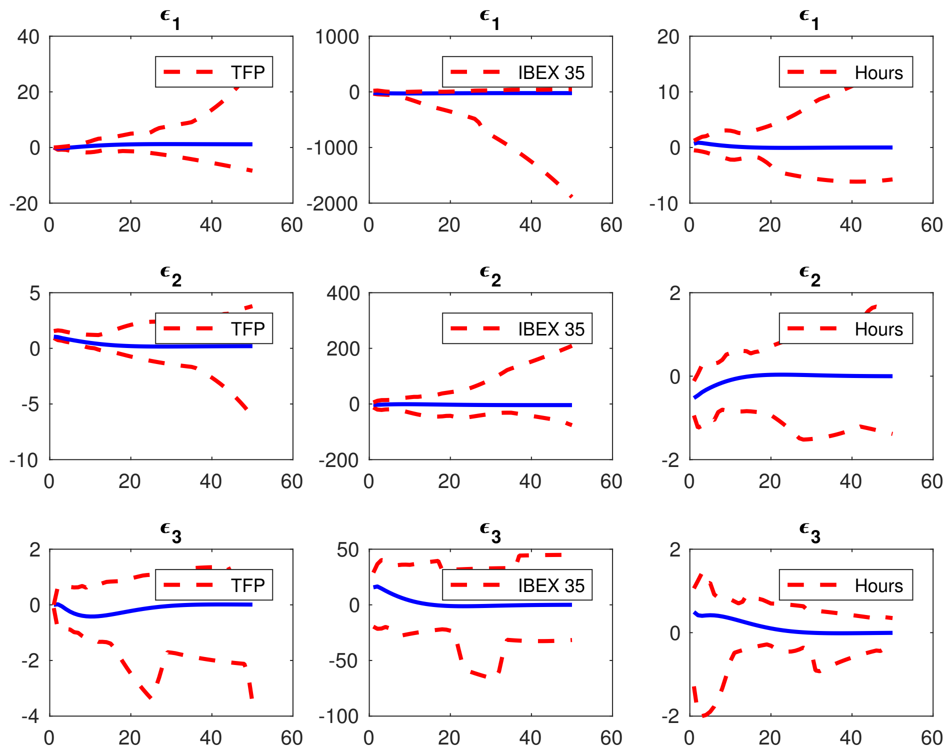
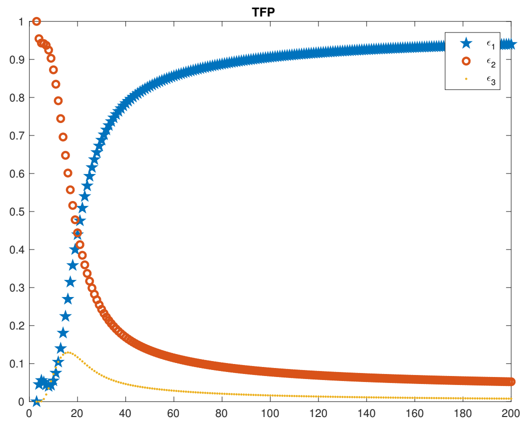
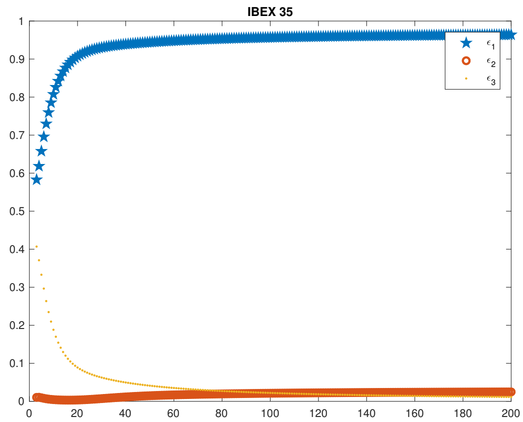


Figure B.8: FEV 3-VAR: TFP, IBEX 35, Hours

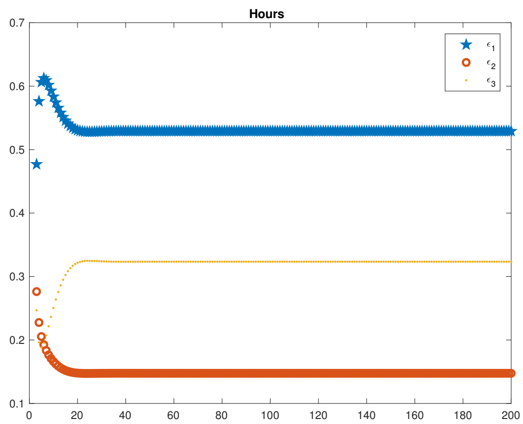
(a) FEV news shock on TFP



(b) FEV news shock on IBEX 35



(c) FEV news shock on C



B.5 Estimation 3-VAR: TFP, IBEX 35, Residential Investment

Figure B.9: IRF 3-VAR: TFP, IBEX 35, Residential Capital Investment

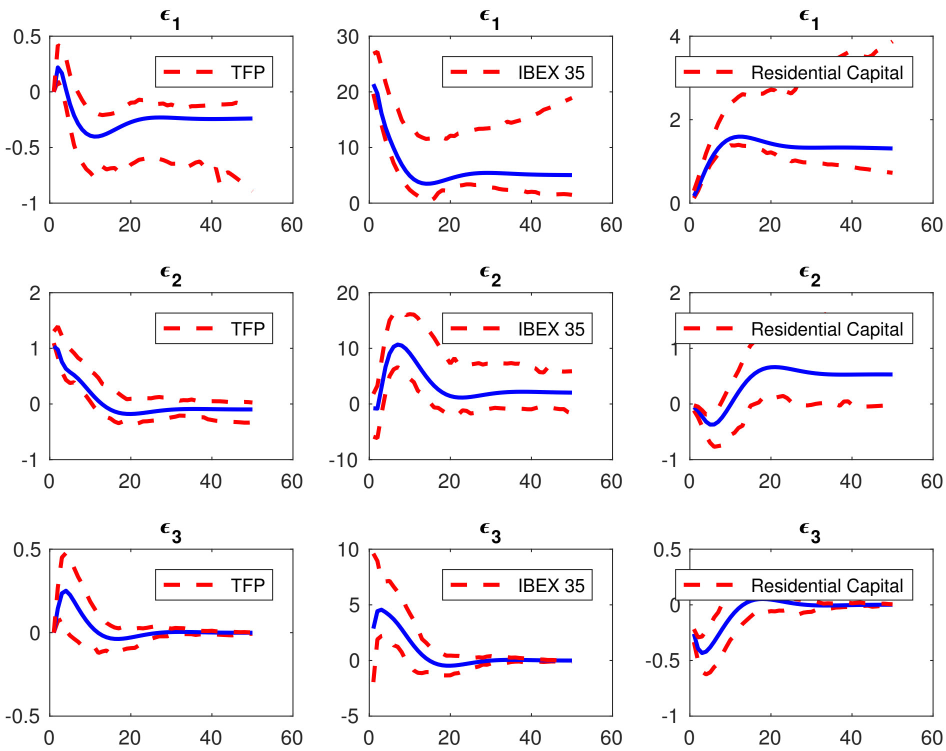
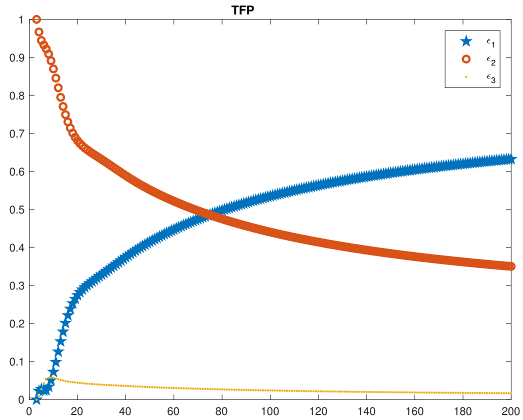
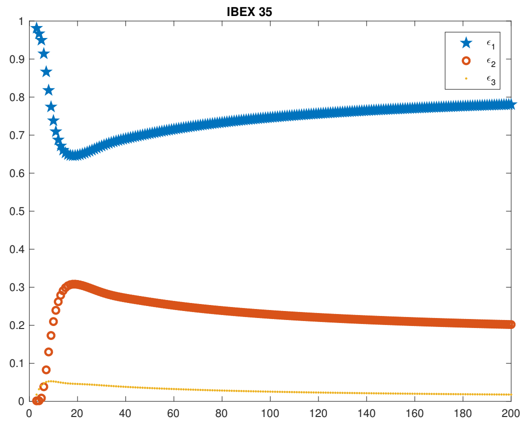


Figure B.10: FEV 3-VAR: TFP, IBEX 35, Residential Capital Investment

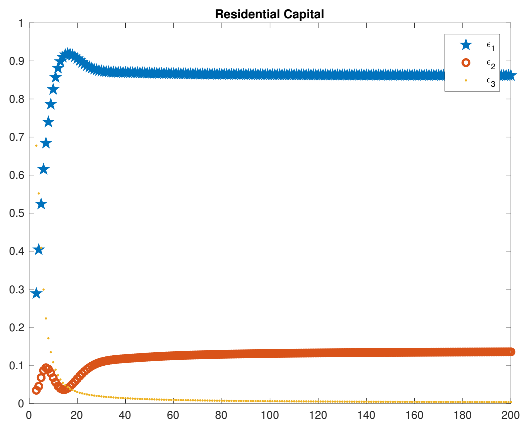
(a) FEV news shock on TFP



(b) FEV news shock on IBEX 35



(c) FEV news shock on Residential Capital Investment



Appendix C

Three-sector Model Economy

C.1 Social Planer Problem

The Lagrangian for this problem is:

$$
\begin{aligned}
&\mathcal{L}\left(\{C_t, l_{x,t}, l_{k,t}, K_{t+1}, \lambda_t, \mu_t\}\right) : \\
&\qquad E_0\left[\sum_{t=0}^{\infty} \beta^t \left\{log(C_t) + \nu_0(\bar{l} - l_{x,t} - l_{k,t})\right\}\right. \\
&\qquad - \lambda_t \left\{C_t - \left[\alpha\left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x}\right)^{\nu} + (1-\alpha)K_t^{\nu}\right]^{\frac{1}{\nu}}\right\} \\
&\qquad \left. - \mu_t \left\{K_{t+1} - (1-\delta)K_t - \theta_{k,t} l_{k,t}^{\alpha_k} \tilde{l}_k^{1-\alpha_k}\right\}\right]
\end{aligned}
\tag{C.1}
$$

FOC

$$
\frac{\partial \mathcal{L}}{\partial C_t} : \beta^t \frac{1}{C_t} - \beta^t \lambda_t = 0 \ \Rightarrow \lambda_t = \frac{1}{C_t} \tag{C.2}
$$

$$\frac{\partial \mathcal{L}}{\partial K_{t+1}} : -\beta^t \mu_t +$$
$$+\beta^{t+1} E_t \left(\mu_{t+1}(1-\delta) + \lambda_{t+1} \left[\alpha \left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \right)^{\nu} + (1-\alpha) K_{t+1}^{\nu} \right]^{\frac{1-\nu}{\nu}} (1-\alpha) K_{t+1}^{\nu-1} \right) = 0$$
$$\Rightarrow \mu_t = \beta E_t \left\{ (\mu_{t+1}(1-\delta) + \lambda_{t+1} \left[(1-\alpha) K_{t+1}^{\nu-1} \left[\alpha \left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \right)^{\nu} + (1-\alpha) K_{t+1}^{\nu} \right]^{\frac{1-\nu}{\nu}} \right] \right\} \tag{C.3}$$

$$\frac{\partial \mathcal{L}}{\partial l_x} : \nu_0 = \lambda_t \frac{\alpha \alpha_x \left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \right)^{\nu}}{l_{x,t}} \left[\alpha \left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \right)^{\nu} + (1-\alpha) K_t^{\nu} \right]^{\frac{1-\nu}{\nu-1}} \tag{C.4}$$

$$\frac{\partial \mathcal{L}}{\partial l_x} : \mu_t = \nu_0 \frac{l_{x,t}}{\alpha_x \theta_{k,t} l_{k,t}^{\alpha_k} \tilde{l}_k^{1-\alpha_k}} \tag{C.5}$$

$$\mu_t = \beta E_t \Big[\mu_{t+1}(1-\delta) + \lambda_{t+1} H_t \Big] \tag{C.6}$$

$$H_t = (1-\alpha) K_{t+1}^{\nu-1} \left[\alpha \left(\theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \right)^{\nu} + (1-\alpha) K_{t+1}^{\nu} \right]^{\frac{1-\nu}{\nu}} \tag{C.7}$$

$$C_t = \Big[\alpha N_t^{\nu} + (1-\alpha) K_t^{\nu} \Big]^{\frac{1}{\nu}} \tag{C.8}$$

$$K_{t+1} = (1-\delta) K_t + D_t \tag{C.9}$$

$$N_t = \theta_{x,t} l_{x,t}^{\alpha_x} \tilde{l}_x^{1-\alpha_x} \tag{C.10}$$

$$D_t = \theta_{k,t} l_{k,t}^{\alpha_k} \tilde{l}_k^{1-\alpha_k} \tag{C.11}$$

C.2 Steady State

At this point, the next step towards a numerical solution of the model is obtaining the steady state from the FOC. According to BP a number of additional requirements are assumed to hold in the steady state:

- $\nu_0 = 1$;
- $\tilde{l} = \tilde{l}_x + \tilde{l}_k = 2$ is the total time amount of household;
- $(\tilde{l}_x + \tilde{l}_k)/3$ is the working time in the steady state;
- $\theta_{x,ss} = 1$;
- $\theta_{k,ss} = 1$ (arbitrarily normalized);

$$C_{ss} = \frac{\alpha\alpha_x N_{ss}^{\nu}}{l_{x,ss}} \left[\alpha N_{ss}^{\nu} + (1-\alpha)K_{ss}^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{C.12}$$

$$\mu_{ss} = \frac{l_{k,ss}}{\alpha_k D_{ss}} \tag{C.13}$$

$$\frac{l_{k,ss}}{\alpha_k D_{ss}} = \beta \frac{H_{ss}}{C_{ss}(1-\beta(1-\delta))} \tag{C.14}$$

$$K_{ss} = \frac{D_{ss}}{\delta} \tag{C.15}$$

$$N_{ss} = l_{x,ss}^{\alpha_x} \tag{C.16}$$

$$D_{ss} = l_{k,ss}^{\alpha_k} \tag{C.17}$$

$$H_{ss} = (1-\alpha)K_{ss}^{\nu-1} \left[\alpha N_{ss}^{\nu} + (1-\alpha)K_{ss}^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{C.18}$$

Steady state equations for the determination of the investment price and for the return to investment are $p_{ss} = \mu_{ss} C_{ss}$ and $r_{ss} = \frac{H_{ss}}{p_{ss}} - \delta$.

From (C.14) and (C.17):

$$\frac{l_{k,ss}^{1-\alpha_k}(1-\beta(1-\delta))}{\alpha_k \beta} = \frac{H_{ss}}{C_{ss}} \tag{C.19}$$

From (C.12) and (C.17):

$$\frac{H_{ss}}{C_{ss}} = \frac{1-\alpha}{\alpha\alpha_x}\left(\frac{1}{\delta}\right)^{\nu-1} l_{k,ss}^{\alpha_k(\nu-1)}\left(\frac{2}{3} - l_{k,ss}\right)^{(1-\nu)\alpha_x} \tag{C.20}$$

Substituting in (C.19) we obtain:

$$\frac{\alpha}{1-\alpha}\frac{\alpha_x \delta^{\nu-1}(1-\beta(1-\delta))}{\alpha_k \beta} l_{k,ss}^{\alpha_k(\nu-1)}\left(\frac{2}{3} - l_{k,ss}\right)^{(1-\nu)\alpha_x} = 0 \tag{C.21}$$

C.3 Log-linearization

The log-linearized equations variables are indicated by $\hat{hat}$

I define:

$$\bar{\alpha}_k = \frac{(1-\alpha)K_{ss}^{\nu}}{\alpha N_{ss}^{\nu} + (1-\alpha)K_{ss}^{\nu}} \text{ and } \bar{\alpha}_n = \frac{\alpha N_{ss}^{\nu}}{\alpha N_{ss}^{\nu} + (1-\alpha)K_{ss}^{\nu}}$$

$$\nu \hat{N}_t - \hat{l}_{x,ss} + (1-\nu)\left[\bar{\alpha}_n \hat{N}_t + \bar{\alpha}_k \hat{K}_t\right] - \hat{C}_t = 0 \tag{C.22}$$

$$\hat{l}_{x,t} - \hat{D}_t - \hat{\mu}_t = 0 \tag{C.23}$$

$$\left[\bar{\alpha}_n \hat{N}_t + \bar{\alpha}_k \hat{K}_t\right] - \hat{C}_t = 0 \tag{C.24}$$

$$D_{ss}\hat{D}_t + (1-\delta)K_{ss}\hat{K}_t - K_{ss}\hat{K}_{t+1} = 0 \tag{C.25}$$

$$\alpha_x \hat{l}_{x,t} - \hat{N}_t = 0 \tag{C.26}$$

$$\alpha_k \hat{l}_{k,t} - \hat{D}_t = 0 \tag{C.27}$$

$$(\nu - 1)\hat{K}_t + (1-\nu)\left[\bar{\alpha}_n \hat{N}_t + \bar{\alpha}_k \hat{K}_t\right] - \hat{H}_t = 0 \tag{C.28}$$

$$C_{ss}\hat{C}_t + p_{ss}D_{ss}\hat{p}_t + p_{ss}D_{ss}\hat{D}_t - Y_{ss}\hat{Y}_t = 0 \tag{C.29}$$

$$\beta E_t\left[\frac{H_{ss}}{C_{ss}}\left(\hat{H}_{t+1} - \hat{C}_{t+1}\right) + (1-\delta)\mu_{ss}\hat{\mu}_{t+1}\right] - \mu_{ss}\hat{\mu}_t = 0 \tag{C.30}$$

The return to investment in log-linearized form is:

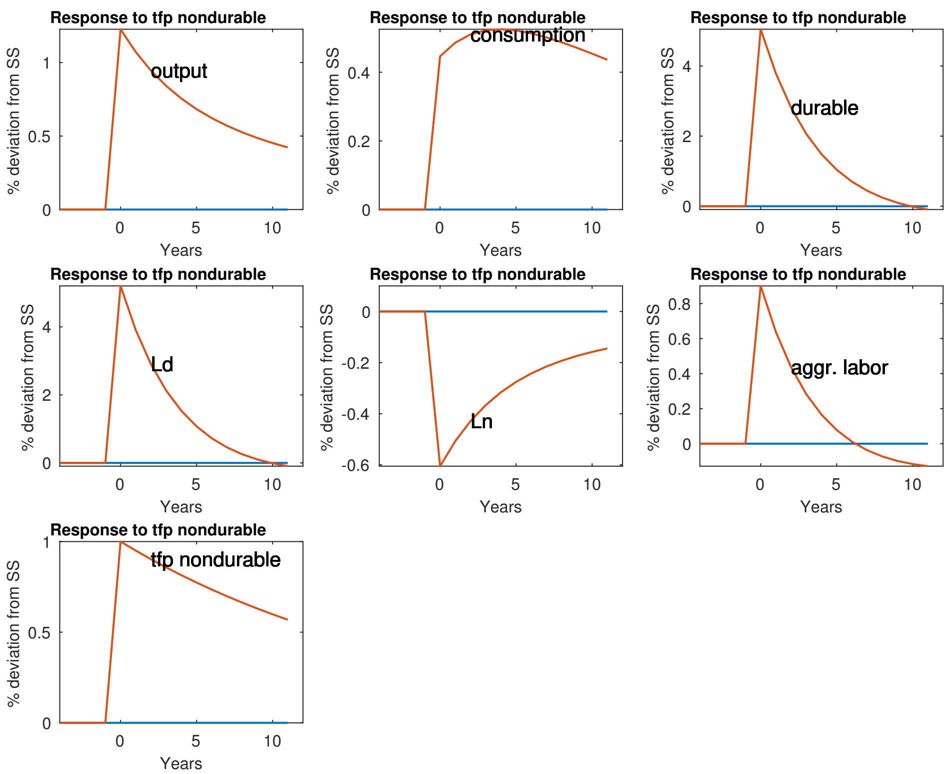
$$\frac{H_{ss}}{p_{ss}}\hat{H}_t + (1-\delta)\hat{p}_t - (1+r_{ss})\hat{p}_{t-1} - r_{ss}\hat{r}_t. \tag{C.31}$$

Appendix D

Three-sector Model Simulation

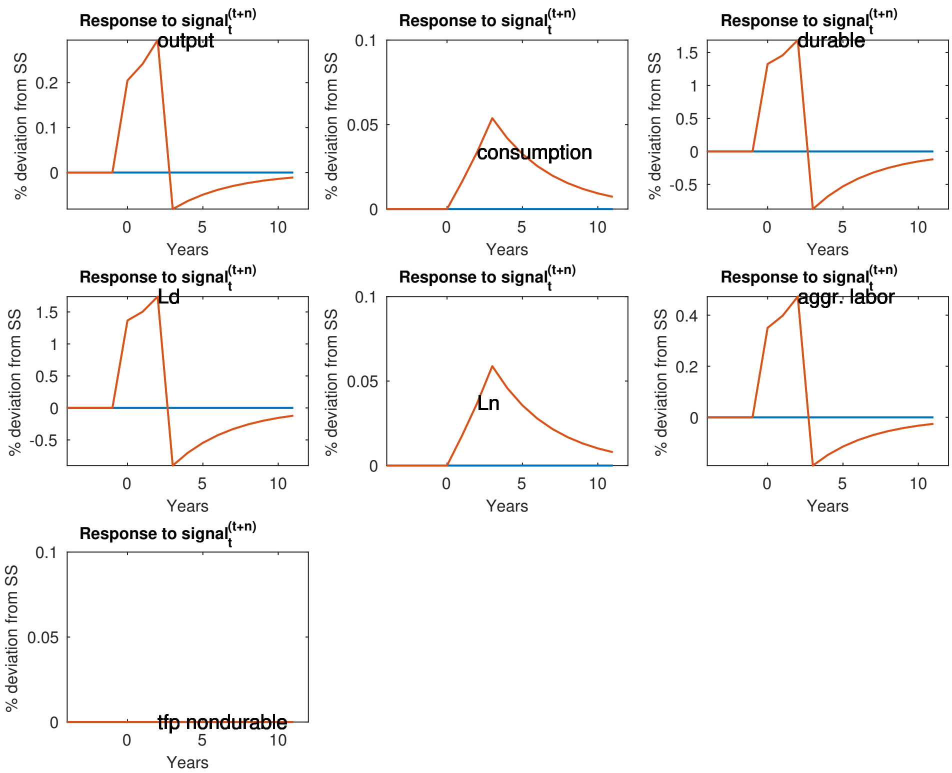
D.1 Model Simulation: Response to TFP Non Durable Shock

Figure D.1: MODEL SIMULATION: response to a TFP non durable shock



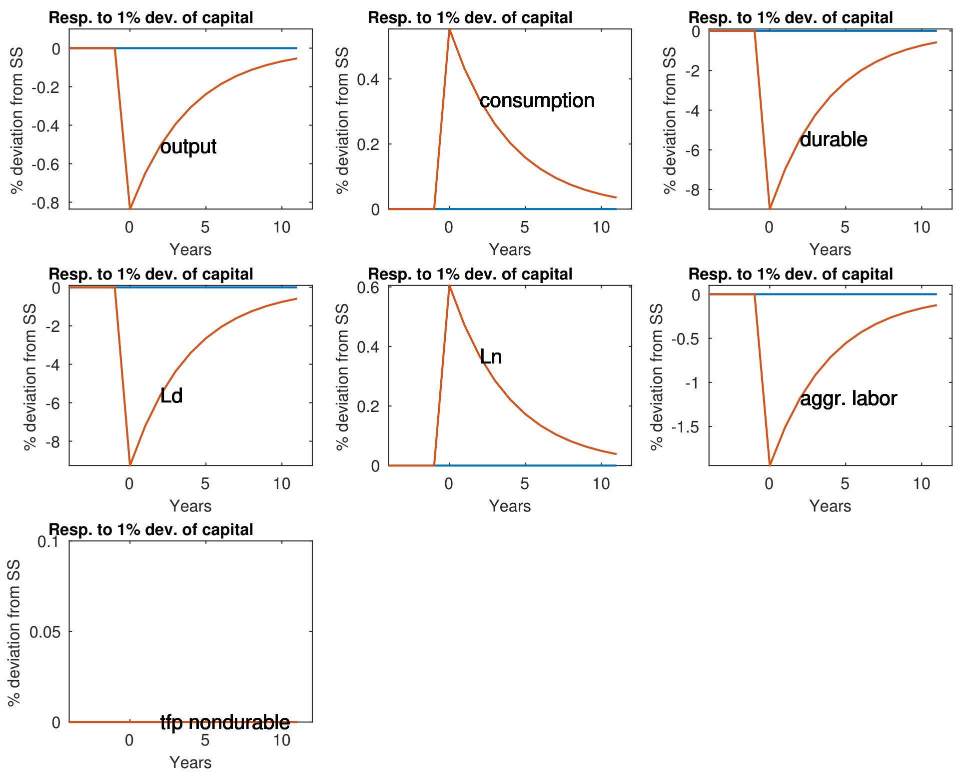
D.2 Model Simulation: Response to a 3 Periods Signal

Figure D.2: MODEL SIMULATION: response to a 3 periods signal



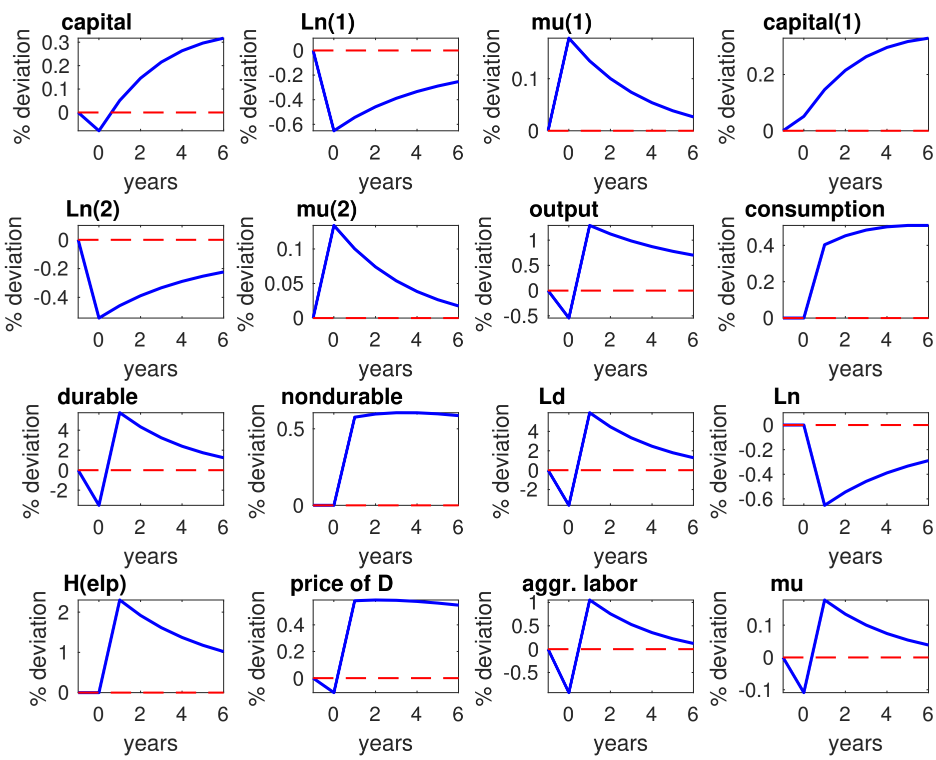
D.3 Model Simulation: Response to a Shock in Capital

Figure D.3: MODEL SIMULATION: response to a shock in capital



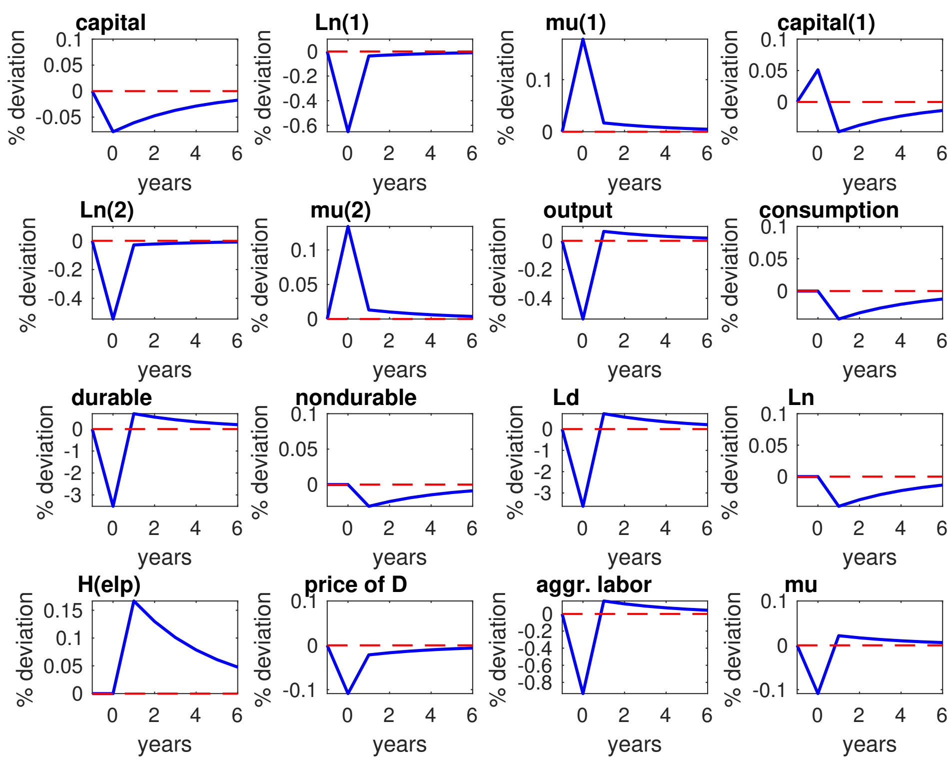
D.4 Model Simulation: Response to a Realized News Shock

Figure D.4: MODEL SIMULATION: response to a realized news shock



D.5 Model Simulation: Response to a Non-Realized News Shock

Figure D.5: MODEL SIMULATION: response to a non - realized news shock



Appendix E

Johansen Cointegration Test

Table E.1: Cointegration Johansen test for 2 - variables VAR: TFP, IBEX 35.

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	12.145	13.429	15.494	19.935
r <= 1	variable 2	0.894	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	11.251	12.297	14.264	18.520
r <= 1	variable 2	0.894	2.705	3.841	6.635

Table E.2: Cointegration Johansen test for 3 - variables VAR: TFP, IBEX 35, Y

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	35.802	27.067	29.796	35.463
r <= 1	variable 2	12.275	13.429	15.494	19.935
r <= 2	variable 3	0.875	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	23.527	18.893	21.131	25.865
r <= 1	variable 2	11.400	12.297	14.264	18.520
r <= 2	variable 3	0.875	2.705	3.841	6.635

Table E.3: Cointegration Johansen test for 3 - variables VAR: TFP, IBEX 35, I

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	38.076	27.067	29.796	35.463
r <= 1	variable 2	13.861	13.429	15.494	19.935
r <= 2	variable 3	2.927	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	24.215	18.893	21.131	25.865
r <= 1	variable 2	10.934	12.297	14.264	18.520
r <= 2	variable 3	2.927	2.705	3.841	6.635

Table E.4: Cointegration Johansen test for 3 - variables VAR: TFP, IBEX 35, C

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	46.114	27.067	29.796	35.463
r <= 1	variable 2	13.609	13.429	15.494	19.935
r <= 2	variable 3	2.226	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	32.506.527	18.893	21.131	25.865
r <= 1	variable 2	11.383	12.297	14.264	18.520
r <= 2	variable 3	2.226	2.705	3.841	6.635

Table E.5: Cointegration Johansen test for 3 - variables VAR: TFP, IBEX 35, Hours

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	28.725	27.067	29.796	35.463
r <= 1	variable 2	4.584	13.429	15.494	19.935
r <= 2	variable 3	0.179	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	22.873	18.893	21.131	25.865
r <= 1	variable 2	5.957	12.297	14.264	18.520
r <= 2	variable 3	0.179	2.705	3.841	6.635

Table E.6: Cointegration Johansen test for 3 - variables VAR: TFP, IBEX 35, Residential Investment

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	31.457	27.067	29.796	35.463
r <= 1	variable 2	6.704	13.429	15.494	19.935
r <= 2	variable 3	0.183	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	24.753	18.893	21.131	25.865
r <= 1	variable 2	6.520	12.297	14.264	18.520
r <= 2	variable 3	0.183	2.705	3.841	6.635

Appendix F

3-variables VAR BP Identification

Figure F.1: 3-VAR BP identification: ISTC IBEX 35 Consumption

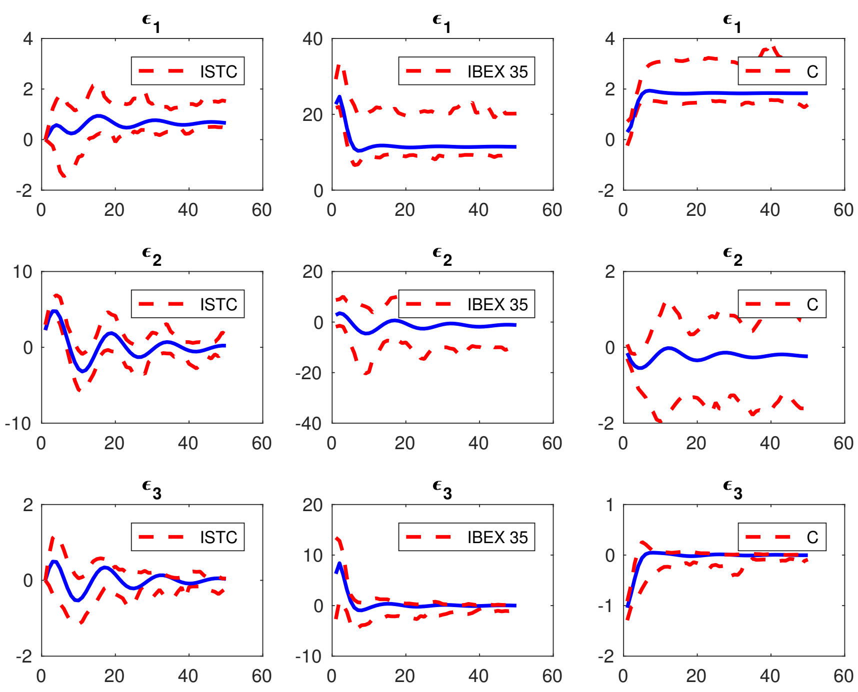


Figure F.2: 3-VAR BP identification: ISTC IBEX 35 Investment

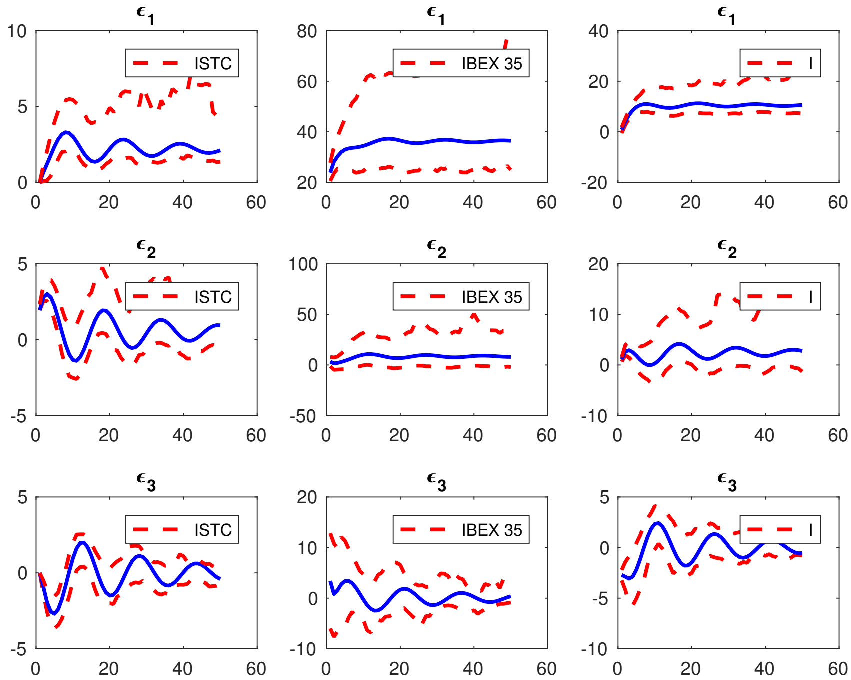


Figure F.3: 3-VAR BP identification: ISTC IBEX 35 GDP

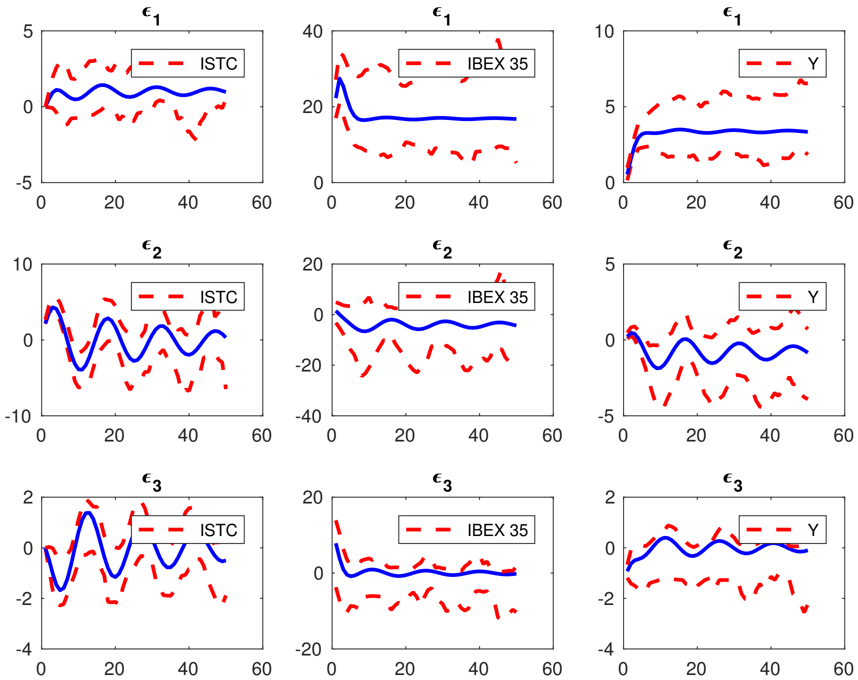


Figure F.4: 3-VAR BP identification: ISTC IBEX 35 Hours

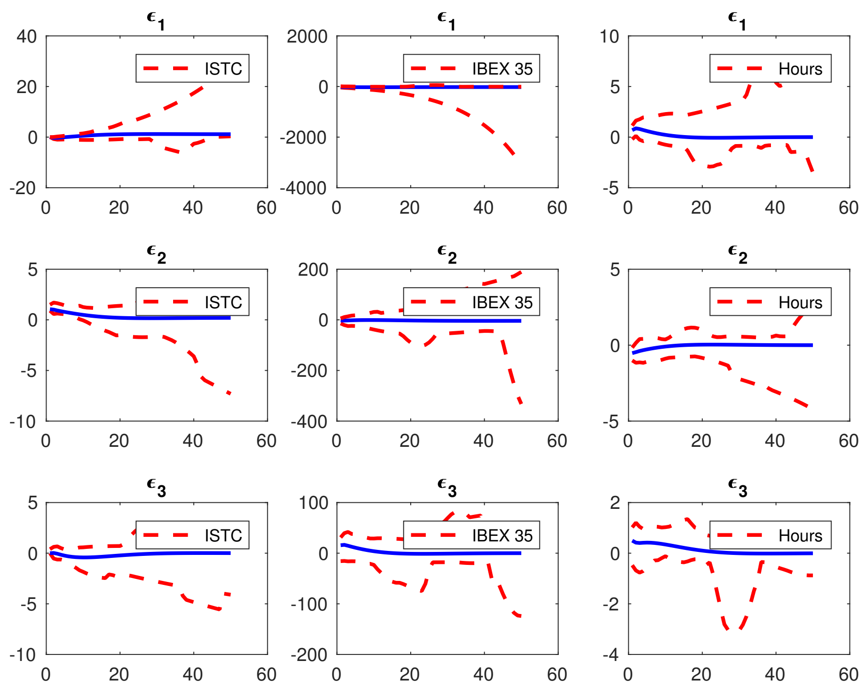
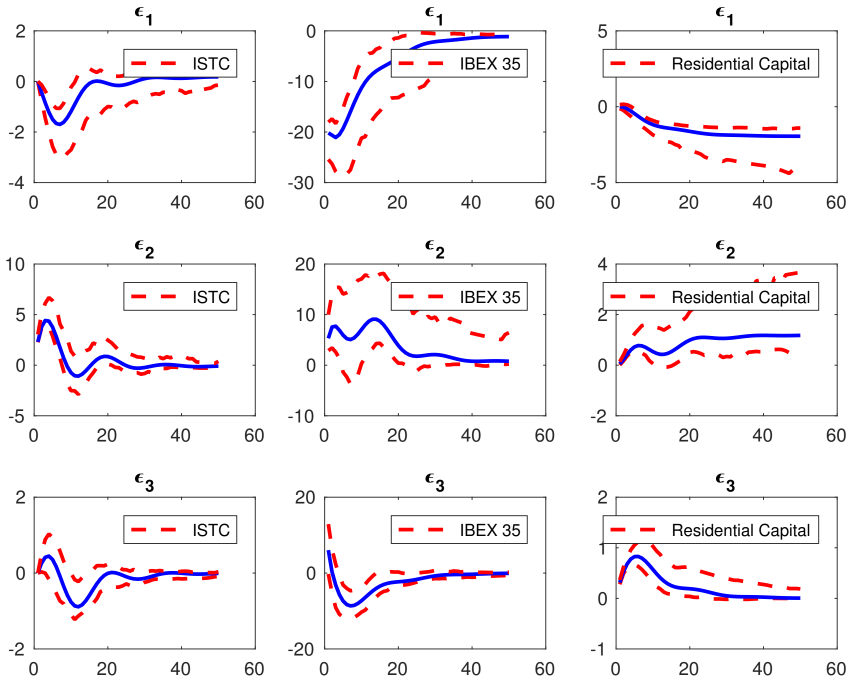


Figure F.5: 3-VAR BP identification: ISTC IBEX 35 Residential Investment



Appendix G

SVAR Identification Methodology

G.1 SVAR Identification Methodology

A VAR is given by:

$$Y_t = B_{(1)}Y_{t-1} + B_{(2)}Y_{t-2} + ... + B_{(l)}Y_{t-1} + u_t, t = 1, ..., T$$

where Y_t is an $m \times 1$ vector of data at date $t = 1 - l, ..., T$, $B_{(i)}$ are coefficient matrices of size $m \times m$ and u_t is the one-step ahead prediction error with variance-covariance matrix Σ. An intercept and perhaps a time trend is sometimes added.

Start by decomposing the prediction error u_t into economically meaningful or fundamental innovations. This is necessary because one is typically interested in examining the impulse responses to such fundamental innovations, given the estimated VAR.

Suppose that there are a total of m fundamental innovations, which are mutually independent and normalized to be of variance 1: they can therefore be written as a vector ε of size $m \times 1$ with $E[\varepsilon\varepsilon'] = I_m$. Independence of the fundamental innovations is an appealing assumption adopted in much of the VAR literature: if, instead, the fundamental innovations were correlated, then this would suggest some remaining, unexplained causal relationship between them. We therefore also adopt the independence assumption here. What is needed is to find a matrix A such that $u_t = A\varepsilon_t$.

G.1.1 Independence of Fundamental Innovations

Independence of the fundamental innovations is an appealing assumption adopted in much of the VAR literature: if, instead, the fundamental innovations were correlated, then this would suggest some remaining, unexplained causal relationship between them. We therefore also adopt the independence assumption here. What is needed is to find a matrix A such that $u_t = A\varepsilon_t$ The j-th column of A (or its negative) then represents the immediate impact on all variables of the j-th fundamental innovation, one standard error in size. The only restriction on A thus far emerges from the covariance structure:

$$\Sigma = E[u_t u_t'] = AE[\varepsilon_t \varepsilon_t']A' = AA'. \tag{G.1}$$

Simple accounting shows that there are $m(m-1)/2$ degrees of freedom in specifying A, and hence further restrictions are needed to achieve identification.

Usually, these restrictions come from one of three procedures:

1. choosing A to be a Cholesky factor of Σ and implying a recursive ordering of the variables as in Sims (1986),

2. from some structural relationships between the fundamental innovations $\varepsilon_{t,i},\ i = 1, ..., m$ and the one-step ahead prediction errors $u_{t,i}, i = 1, ..., m$ as in Bernanke (1986), Blanchard and Watson (1986) or Sims (1986), or

3. separating transitory from permanent components as in Blanchard and Quah (1989).

G.1.2 Infinite-Order Long-Run Identification

Start from the lineal model:

$$A(L)y_t = \varepsilon_t \tag{G.2}$$

where y_t is an $n \times 1$ vector of variables, $A(L) = \sum_{i=0}^{p} A_i L^i$ is a matrix polynomial in the lag operator, L, ε_t is a structural innovation, and $E(\varepsilon_t \varepsilon_t') = I$. To estimate this model using data, we begin with the reduced-form VAR:

$$B(L)y_t = \mu_t. \tag{G.3}$$

where $B(L) = \sum_{i=0}^{p} B_i L^i, B_0 = I$ and $E(\mu_t \mu_t') = \Omega$. The goal is to find a rotation of the moving-average representation of this VAR,

$$y_t = C(L)A_0^{-1}A_0\mu_t, \tag{G.4}$$

$C(L) = B(L)^{-1}$ which identifies the i.i.d. structural shocks of model:

$$\varepsilon_t = A_0\mu_t,$$

where A_0 is the contemporaneous parameter matrix. Identification is accomplished by imposing a sufficient number of restrictions on the system; $\frac{n(n-1)}{2}$ restrictions are required to fully identify the structural form (fewer restrictions are necessary to identify a single shock). Short-run restrictions often take the form of recursive or non-recursive zero restrictions on A_0. Long-run restrictions place constraints on the effect of the jth shock on the ith variable at an infinite horizon, given by $[C(1)A_0^{-1}]_{i,j}$, where neutrality implies the restriction $[C(1)A_0^{-1}]_{i,j} = 0$.

The key identifying assumption in Galí (1999) is that the technology shocks[1] are the only influence on long-run labor productivity. With produc-

[1] Start by assuming that for example, the log productivity x_t can be decomposed into two orthogonal components, technology, z_t, and non-technology, ε_t^{nt}, in the following manner:

$$x_t = z_t + \varepsilon_t^{nt}. \tag{G.5}$$

Assuming a stationary process for technology, the unit root in productivity must arise from z_t. This condition provides the foundation for both the standard long-run identification and our finite-horizon identification.

tivity entering in differences and ordered first in the VAR, this assumption is implemented by restricting the long-run responses to all non-technology shocks to be zero.

One important assumption is that the unit root in productivity is solely attributable to the technology shock z. That is,

$$[C(1)A_0^{-1}]_{i,j} \tag{G.6}$$

where $i = 1$ represents labor productivity ordered first and $j \neq i$ indicates all non-technology shocks.

One can similarly express the effect of the structural shocks on y at any horizon in terms of the h-step ahead forecast error for y:

$$y_{t+h} - \widehat{y_{t+h}} = \sum_{\tau=0}^{h-1} C_\tau A_0^{-1} \varepsilon_{t+h-\tau} \tag{G.7}$$

The h-step ahead forecast-error variance share for a particular variable i, attributable to a particular shock j is

$$\omega_{i,j}(h) = \frac{e_i' \left[\sum_{\tau=0}^{h-1} C_\tau A_0^{-1} e_j e_j' A_0^{-1'} C_\tau'\right] e_i}{e_i' \left[\sum_{\tau=0}^{h-1} C_\tau \Omega_\mu C_\tau'\right] e_i} \tag{G.8}$$

where e_i and e_j are, respectively, column vectors with the ith and jth elements equal to one and zero everywhere else. With this in mind, one can see that equation (G.8) implies the following:

Under the equation (G.6), for large enough h, the forecast-error variance share of productivity attributable to the identified technology shock is close to one. ($lim_{h\to\infty}\omega_{ij}(h) = 1$).

If productivity is ordered first, the assumption that the long-run response of labor productivity to all non-technology shocks are negligible drives, for $i > 1$, the numerator in equation (G.8) to zero for large h. In the following section, it is shown an alternative identification scheme based on equation (G.8) with a large, but finite, h.

G.1.3 Finite-Order Long-Run Identification

Galí (1999) aims at isolating technology shocks by their effect on productivity at horizons longer than business cycles. However, it differs from conventional long-run identification by relaxing the requirement that labor productivity has a unit root or that its unit root be fully characterized by the technology process. Instead, the technology shock is identified as belonging to the set of rotations that obtains the maximum forecast-error variance share in productivity at long horizons. The long-horizon restriction is imposed via methods first introduced in Faust (1998). Next subsection G.1.4 contains a more detailed exposition of the solution algorithm.

For a large, finite h such that the technology shock yields the maximum h-step ahead forecast error variance share for productivity is:

$$\max_{\alpha} \frac{e_i' \left[\sum_{\tau=0}^{h-1} \tilde{C}_\tau \alpha \alpha' \tilde{C}_\tau'\right] e_i}{e_i' \left[\sum_{\tau=0}^{h-1} C_\tau \Omega_\mu C_\tau'\right] e_i} \tag{G.9}$$

where α is an $n \times 1$ vector, and $\tilde{C}_\tau$ is obtained by post multiplying C_τ by any orthogonal decomposition of Ω_μ.

This identification is similar to that proposed in Uhlig (2004a) in that also focuses on the conditional variance in productivity at a finite (in Uhlig's case, medium term) forecast horizon. The primary differences are that allow the data to determine the value of the FEV share attributable to technology at a finite horizon and allow non-technology shocks to play a role at all horizons. Uhlig assumes that there is a finite horizon at which productivity is exclusively driven by technology.

Uhlig (2004a), Fisher (2006), and others argue that factors other than technology (e.g., capital tax shocks) can affect the long-run variance of productivity. By maximizing the forecast-error variance in productivity due to technology at a finite horizon, the approach implicitly accounts for these considerations, while not precluding a unit root in productivity.

While the MFEV approach has some advantages in small samples, the fact that the identification is data dependent may introduce an additional source of error. In small samples, regardless of whether or not the unit root assumption holds in the population, it is possible to attribute too much of the forecast-error variance in productivity to technology due to errors in estimating $C_\tau A_0^{-1}$.

G.1.4 MFEV Solution Algorithm

This section follows Faust (1998)

Start with the representation of a generic orthogonalized moving-average of the estimated reduced form VAR:

$$y_t = C(L)HH^{-1}\mu_t. \tag{G.10}$$

where $E(H^{-1}\mu_t)(H^{-1}\mu_t)' = I$. Next, consider the space of identifications, which can be expressed as linear rotations of (15), each formed according to an orthonormal matrix D:

$$y_t = \tilde{C}(L)DD'\tilde{\mu}_t. \tag{G.11}$$

where now $\tilde{C}(L) = C(L)H$ and $\tilde{\mu}_t = H^{-1}\mu_t$. We then denote dynamic response of y_t to the jth shock as $\tilde{C}(L)\alpha$, where α is the jth column of D. The jth shock is then $\alpha'\tilde{\mu}_t$.

Following Faust(1998), we identify α^* as the vector associated with the maximum forecast -error variance share for productivity due to the shock $\alpha^{*\prime}\tilde{\mu}_t$:

$$\begin{aligned} \alpha^* = \arg\max \frac{e_i'\left[\sum_{\tau=0}^{h-1}\tilde{C}_\tau\alpha\alpha'\tilde{C}_\tau'\right]e_i}{e_i'\left[\sum_{\tau=0}^{h-1}C_\tau\Omega_\mu C_\tau'\right]e_i} \\ \text{s.t.} \qquad \alpha'\alpha = 1 \end{aligned} \tag{G.12}$$

The restriction that α has unit length obtains the normalization of structural error variance to unity. In addition, we can easily incorporate linear sign and shape restrictions on the impulse responses by sujecting the optimization to restrictions of the form $\tilde{C}_\tau \alpha \geq 0$.

G.1.5 SVAR Setting

To identify and understand the implications of news shocks, I consider a four-variate SVAR setup where the first variable represents ISTC. The model the I call benchmark is formed by ISTC in the first positions and standard aggregate variables: GDP, Consumption, Investment, Hours worked and Inflation. The alternative model will integrate IBEX 35, a jump- variable which incorporate expectations as soon as they appear (as in Beaudry and Portier (2006). Barsky and Sims (2011, 2012) uses as the consumer confidence as jump variable.

I find that the identified news shock is associated with standard business cycle type phenomena in the sense that it generates a simultaneous boom in output, investment, consumption, and hours, with consumption leading the cycle. Moreover, I find that the news shocks generally accounts for over 42% of the forecast error variance of GDP at business cycle frequencies. So the sign restrictions approach suggests that bouts of optimism and pessimism are, as the business press would suggest, a very important component in business cycle fluctuations.

Appendix H

BP Methodology: Johansen Cointegration Test

Table H.1: Cointegration Johansen test for 2 - variables VAR: ISTC, IBEX 35.

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	12.145	13.429	15.494	19.935
r <= 1	variable 2	0.894	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	11.251	12.297	14.264	18.520
r <= 1	variable 2	0.894	2.705	3.841	6.635

Table H.2: Cointegration Johansen test for 3 - variables VAR: ISTC, IBEX 35, Y

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	35.802	27.067	29.796	35.463
r <= 1	variable 2	12.275	13.429	15.494	19.935
r <= 2	variable 3	0.875	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	23.527	18.893	21.131	25.865
r <= 1	variable 2	11.400	12.297	14.264	18.520
r <= 2	variable 3	0.875	2.705	3.841	6.635

Table H.3: Cointegration Johansen test for 3 - variables VAR: ISTC, IBEX 35, C

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	46.114	27.067	29.796	35.463
r <= 1	variable 2	13.609	13.429	15.494	19.935
r <= 2	variable 3	2.226	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	32.506.527	18.893	21.131	25.865
r <= 1	variable 2	11.383	12.297	14.264	18.520
r <= 2	variable 3	2.226	2.705	3.841	6.635

Table H.4: Cointegration Johansen test for 3 - variables VAR: ISTC, IBEX 35, I

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	38.076	27.067	29.796	35.463
r <= 1	variable 2	13.861	13.429	15.494	19.935
r <= 2	variable 3	2.927	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	24.215	18.893	21.131	25.865
r <= 1	variable 2	10.934	12.297	14.264	18.520
r <= 2	variable 3	2.927	2.705	3.841	6.635

Table H.5: Cointegration Johansen test for 3 - variables VAR: ISTC, IBEX 35, Residential Investment

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	31.457	27.067	29.796	35.463
r <= 1	variable 2	6.704	13.429	15.494	19.935
r <= 2	variable 3	0.183	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	24.753	18.893	21.131	25.865
r <= 1	variable 2	6.520	12.297	14.264	18.520
r <= 2	variable 3	0.183	2.705	3.841	6.635

Table H.6: Cointegration Johansen test for 3 - variables VAR: ISTC, IBEX 35, Hours

NULL:		Trace Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	28.725	27.067	29.796	35.463
r <= 1	variable 2	4.584	13.429	15.494	19.935
r <= 2	variable 3	0.179	2.705	3.841	6.635
NULL:		Eigen Statistic	Crit. 90%	Crit. 95%	Crit. 99%
r <= 0	variable 1	22.873	18.893	21.131	25.865
r <= 1	variable 2	5.957	12.297	14.264	18.520
r <= 2	variable 3	0.179	2.705	3.841	6.635

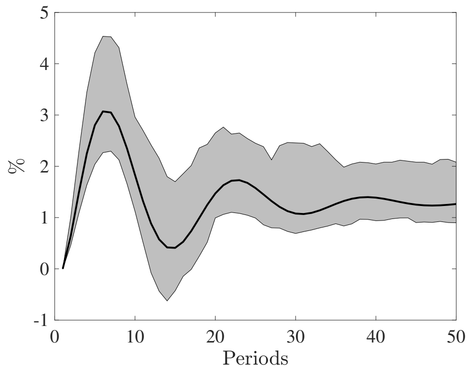
Appendix I

Bivariate VECM: ISTC and Macroeconomic Variables

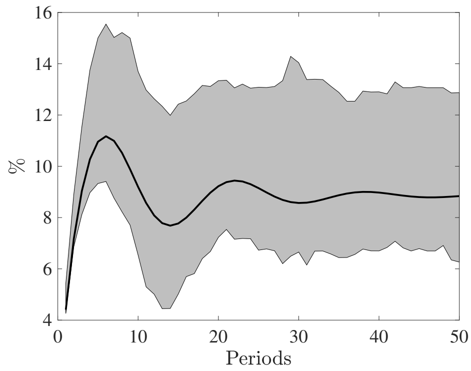
I.1 IRF 2-VAR: ISTC and Investment

Figure I.1: IRF Short and Long run restrictions: ISTC and Investment

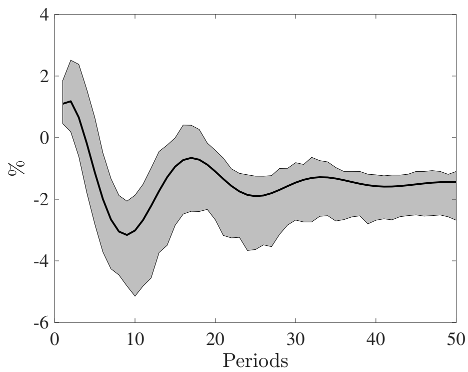
(a) IRF ISTC short run



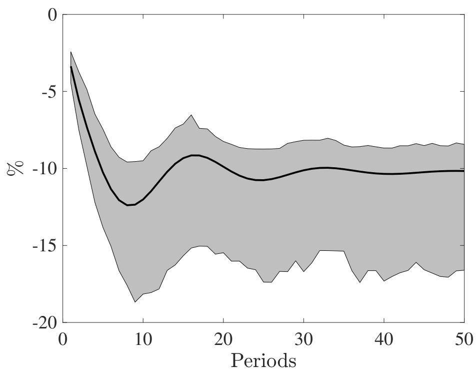
(b) IRF Investment short run



(c) IRF ISTC long run



(d) IRF Investment long run

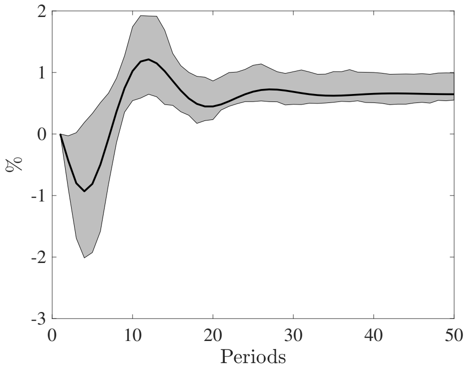


Note: The solid black lines represent the impulse responses functions of the ISTC and Investment to a unit aggregate news shock. The grey area represents the

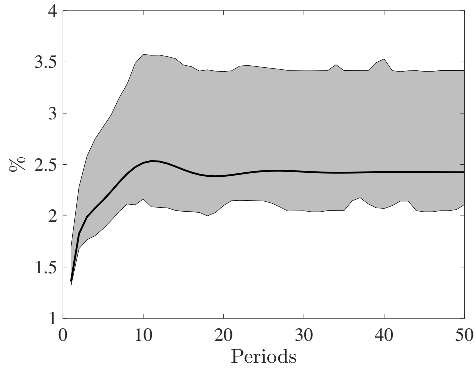
I.2 IRF 2-VAR: ISTC and Consumption

Figure I.2: IRF Short and Long run restrictions: ISTC and Consumption

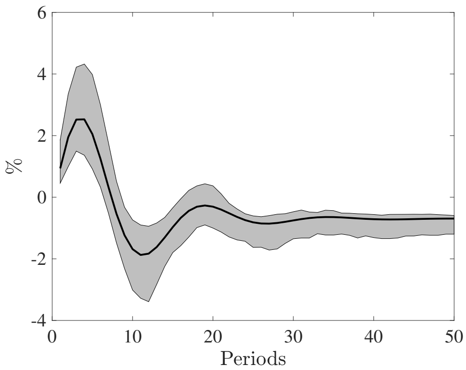
(a) IRF ISTC short run



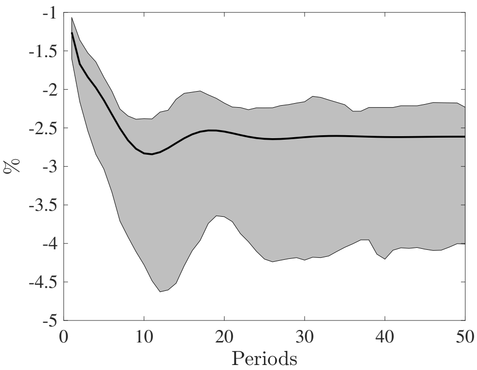
(b) IRF Consumption short run



(c) IRF IST long run



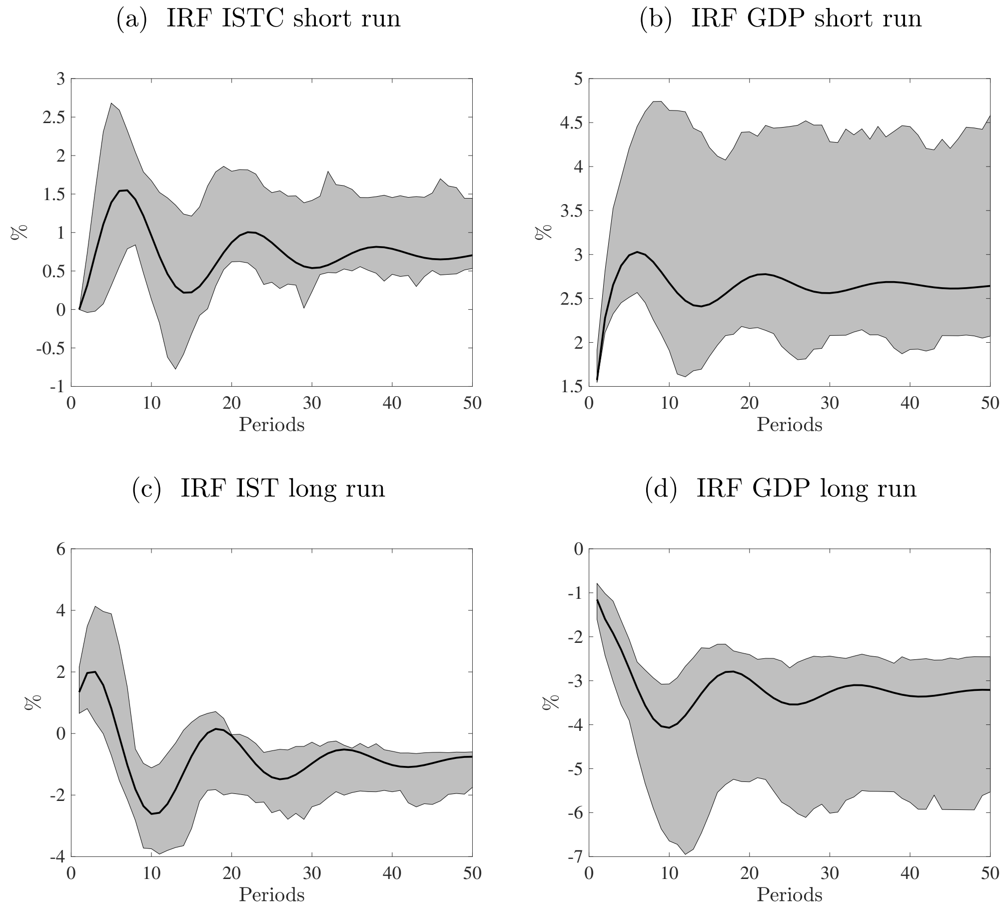
(d) IRF Consumption long run



Note: The solid black lines represent the impulse responses functions of the ISTC and Consumption to a unit aggregate news shock. The grey area represents the 5% − 95% confidence intervals. Impulse responses of ISTC to a unit aggregate news shock are given in the left panel; the responses of Consumption are given in the right panel.

I.3 IRF 2-VAR: IST and GDP

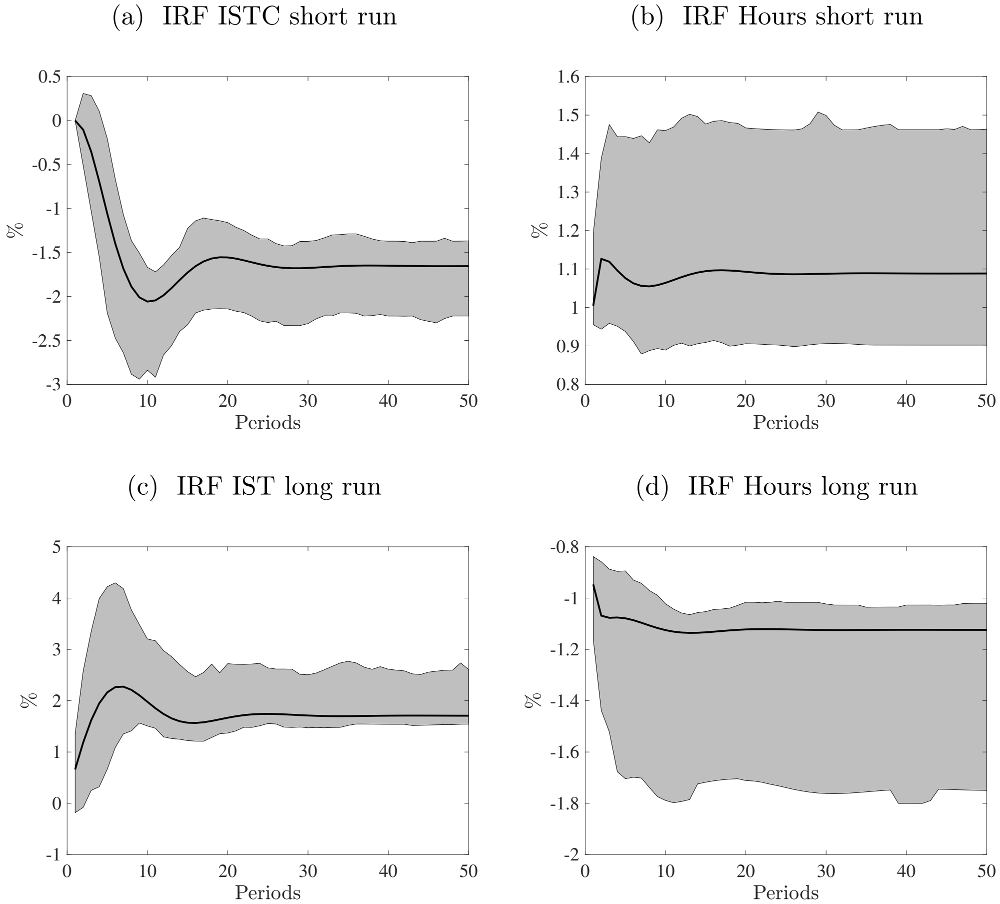
Figure I.3: IRF Short and Long run restrictions: ISTC and GDP



Note: The solid black lines represent the impulse responses functions of the ISTC and GDP to a unit aggregate news shock. The grey area represents the 5% − 95% confidence intervals. Impulse responses of ISTC to a unit aggregate news shock are given in the left panel; the responses of GDP are given in the right panel.

I.4 IRF 2-VAR: ISTC and Hours

Figure I.4: IRF Short and Long run restrictions: ISTC and Hours



(a) IRF ISTC short run

(b) IRF Hours short run

(c) IRF IST long run

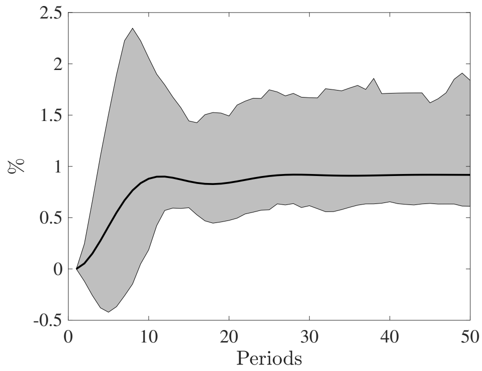
(d) IRF Hours long run

Note: The solid black lines represent the impulse responses functions of the ISTC and Hours to a unit aggregate news shock. The grey area represents the $5\% - 95\%$ confidence intervals. Impulse responses of ISTC to a unit aggregate news shock are given in the left panel; the responses of Hours are given in the right panel.

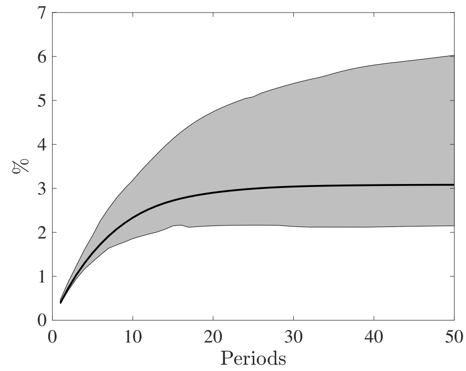
I.5 IRF 2-VAR: ISTC and Residential Investment

Figure I.5: IRF Short and Long run restrictions: ISTC and Residential Investment

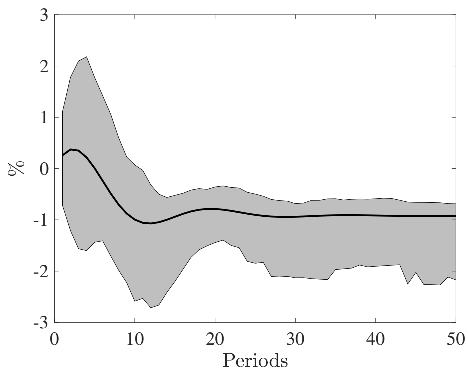
(a) IRF ISTC short run



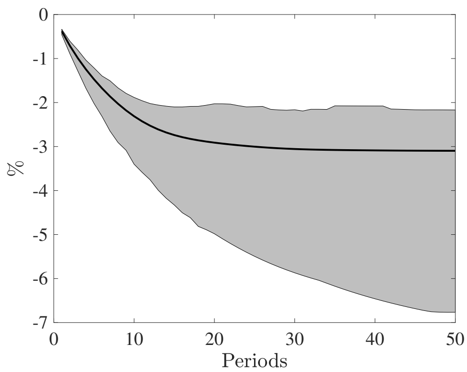
(b) IRFResidential Investment short run



(c) IRF IST long run



(d) IRF Residential Investment long run



Note: The solid black lines represent the impulse responses functions of the ISTC and Residential Investment to a unit aggregate news shock. The grey area represents the 5%−95% confidence intervals. Impulse responses of ISTC to a unit aggregate news shock are given in the left panel; the responses of Residential Investment are given in the right panel.

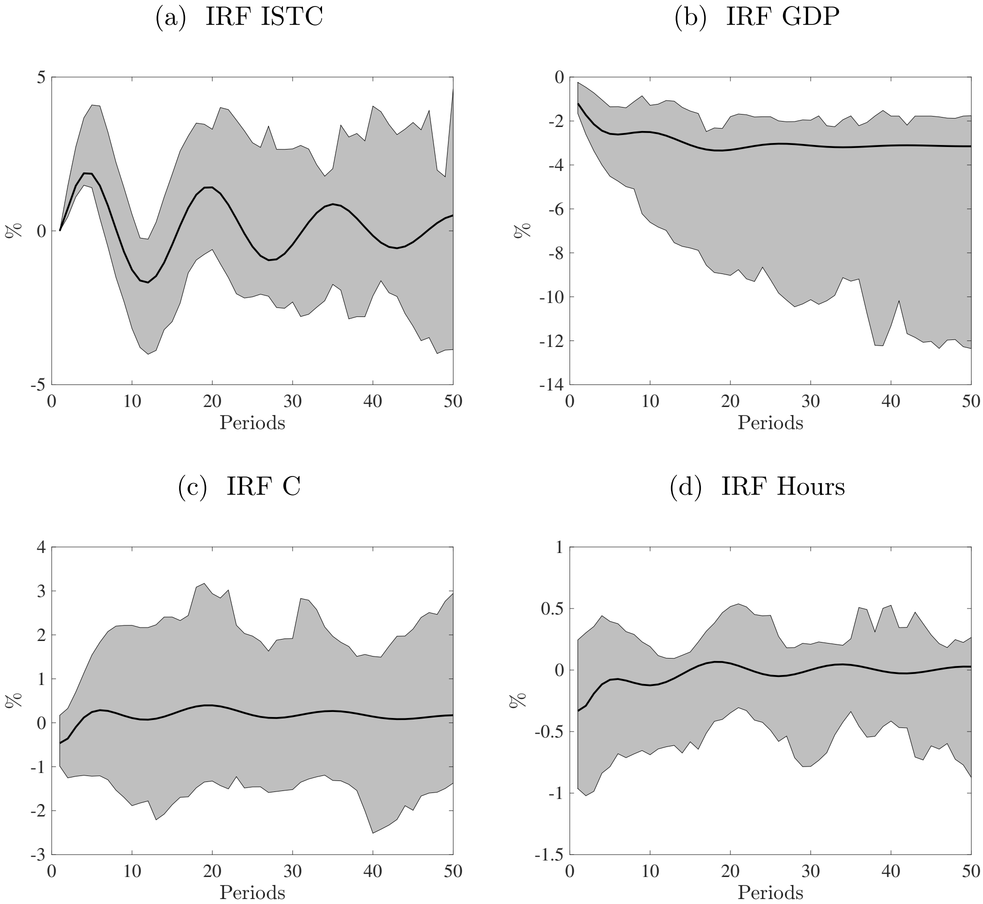
Appendix J

Alternative 4-VAR: ISTC, GDP, C, and Hours

J.1 Alternative VECM: ISTC, GDP, C, and Hours

Figure J.1 displays the IRF to news shock in a 4-variables VAR: ISTC, GDP, C, Hours.

Figure J.1: IRF 4 variables VAR: ISTC, GDP, Consumption, and Hours

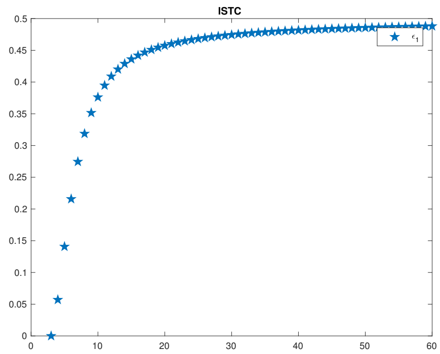


Note: The impulse response of the ISTC, IBEX 35, Consumption, and Hours. The solid black lines represent the impulse responses functions of the ISTC to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals. The VECM is estimated with one lag and four cointegrating relations.

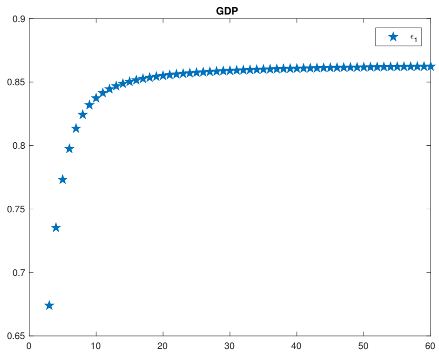
Figure J.2 displays the FEV to news shock in a 4-variables VAR: ISTC, GDP, C, Hours.

Figure J.2: FEV 4 variables VAR: ISTC, GDP, Consumption, and Hours

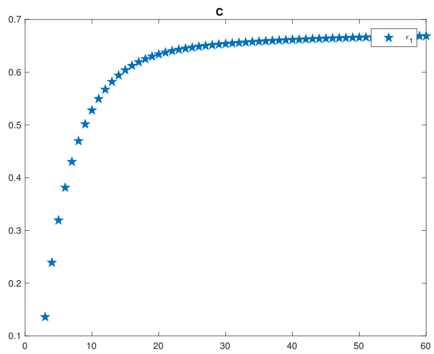
(a) FEV ISTC



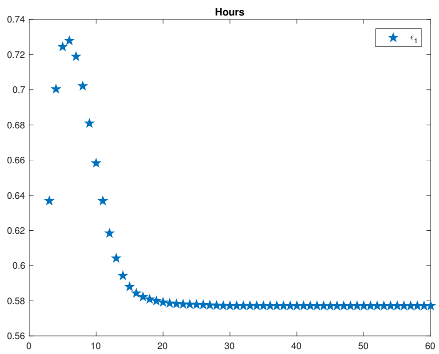
(b) FEV GDP



(c) FEV C



(d) FEV Hours



Note: The FEV of the ISTC, GDP, Consumption, and Hours to a unit aggregate news shock. The VECM is estimated with one lag and four cointegrating relations.

Appendix K

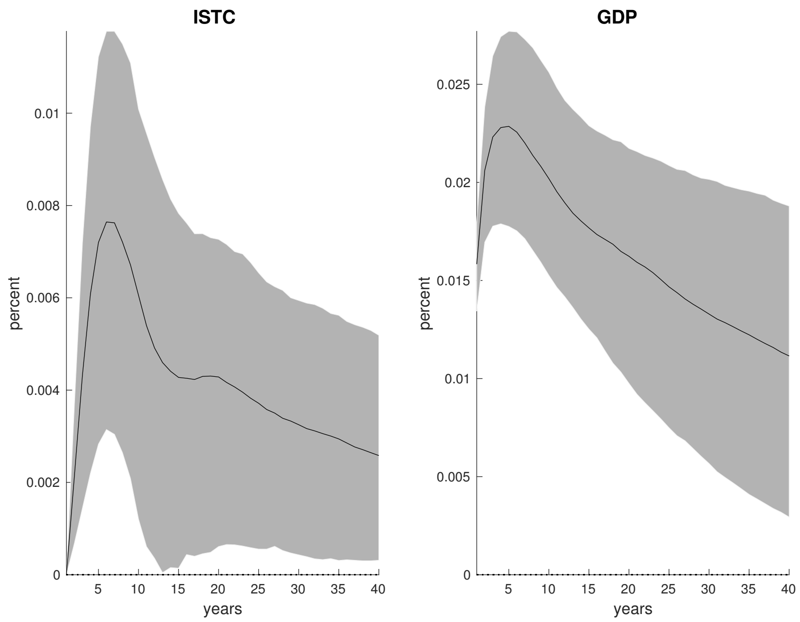
BS Methodology VAR Plots

K.1 2-variables VAR: ISTC and GDP

In a bivariate SVAR approach the variables are the ISTC as the measure of productivity, and the GDP as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

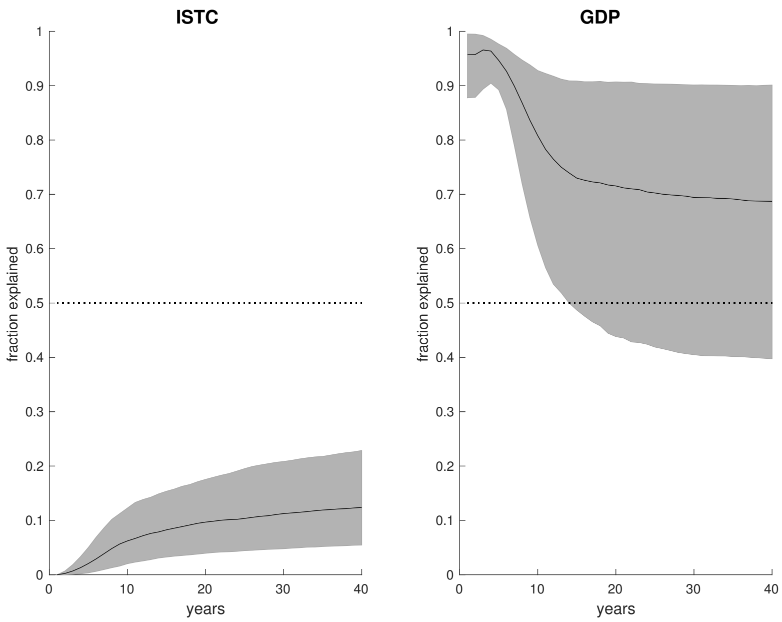
The figure K.1 presents the impulse response of a news shock on ISTC and GDP

Figure K.1: IRF 2-VAR: IST GDP



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and GDP to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the 16%−84% confidence intervals.

Figure K.2: FEV 2-VAR: ISTC GDP



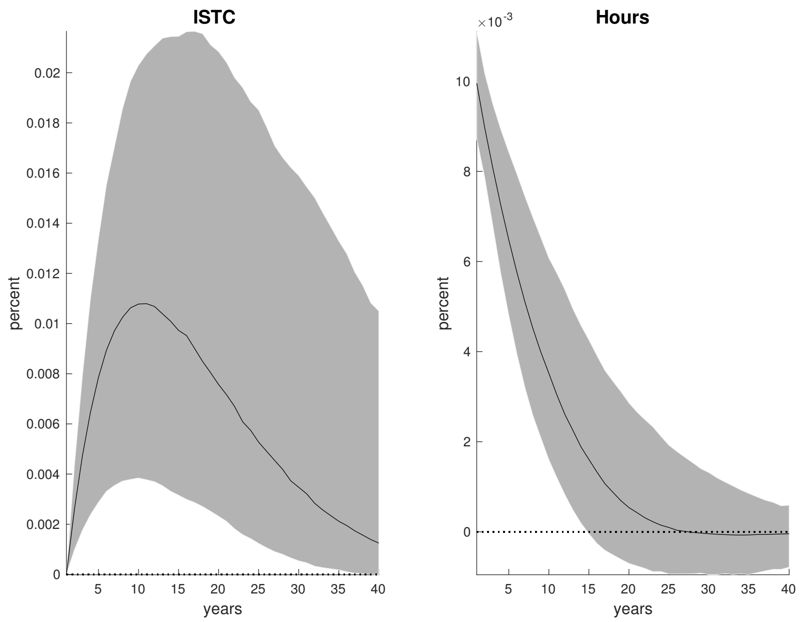
Note: The solid black lines represent the median FEV of the ISTC and Investment to a unit aggregate news shock. The grey area represents the 16%−84% confidence intervals.

K.2 2-variables VAR: ISTC and Hours

In a bivariate SVAR approach the variables are the ISTC as the measure of productivity, and the Hours as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

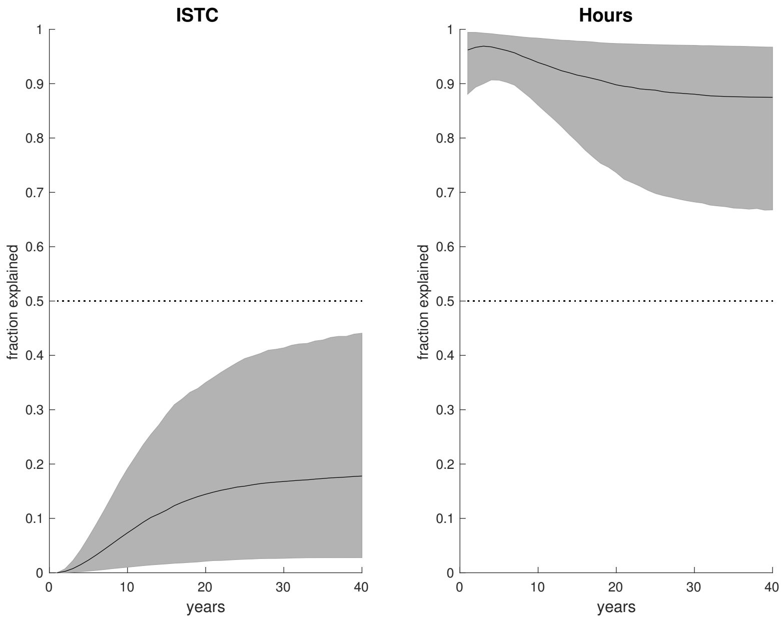
The figure K.3 presents the impulse response of a news shock on ISTC and Hours

Figure K.3: IRF 2-VAR: ISTC Hours



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and Hours to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the 16%−84% confidence intervals.

Figure K.4: FEV 2-VAR: ISTC Hours



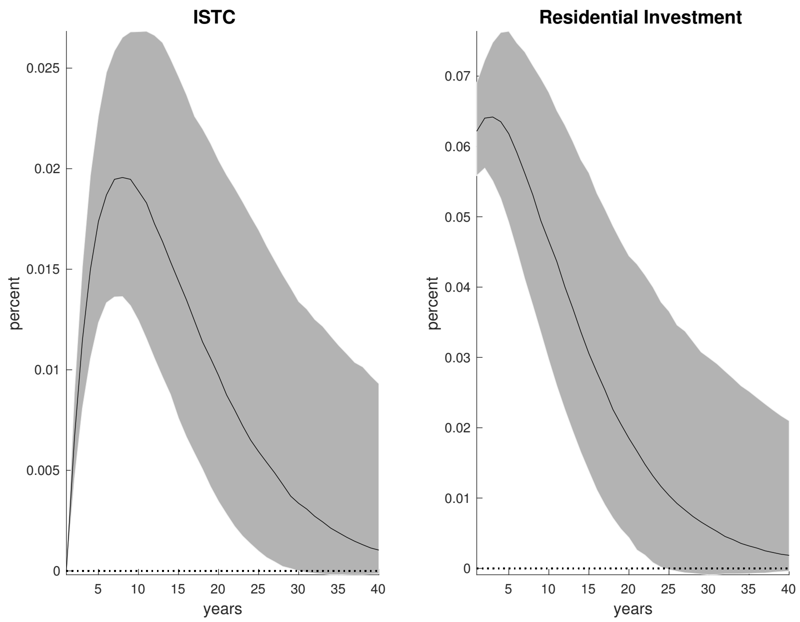
Note: The solid black lines represent the median FEV of the ISTC and Hours to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

K.3 2-variables VAR: ISTC and Residential Investment

In a bivariate SVAR the variables are the ISTC, and the Residential Investment as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

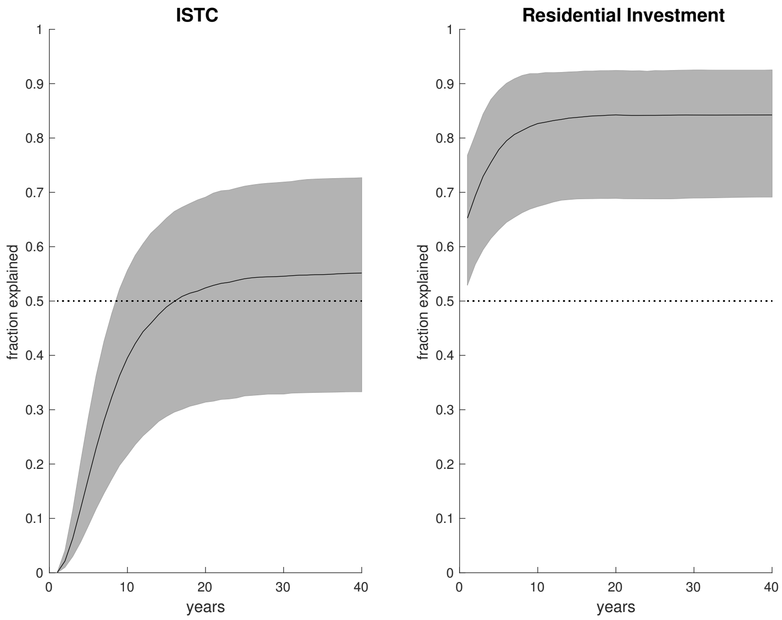
The figure K.5 presents the impulse response of a news shock on ISTC and Residential Investment

Figure K.5: IRF 2-VAR: ISTC Residential Investment



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and Residential Investment to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.6: FEV 2-VAR: ISTC Residential Investment



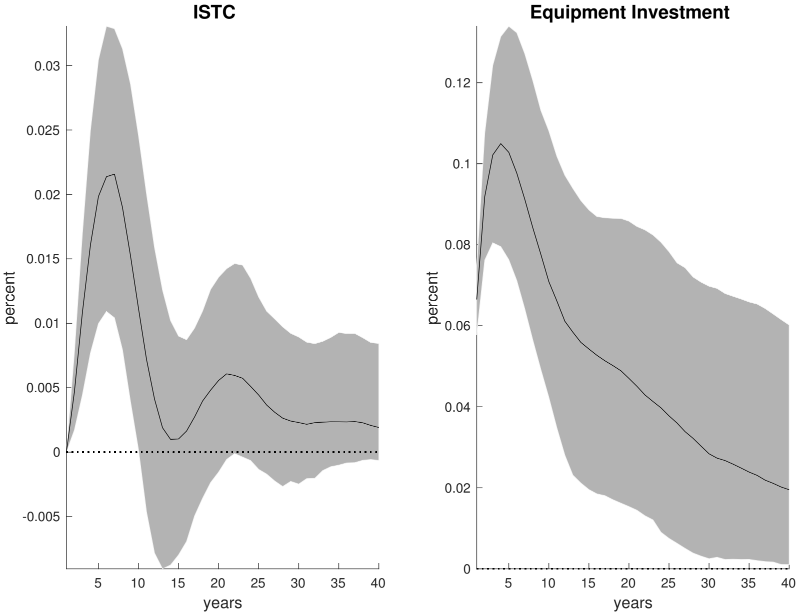
Note: The solid black lines represent the median FEV of the ISTC and Residential Investment to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

K.4 2-variables VAR: ISTC and Equipment Investment

In a bivariate SVAR the variables are the ISTC, and Equipment Investment as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

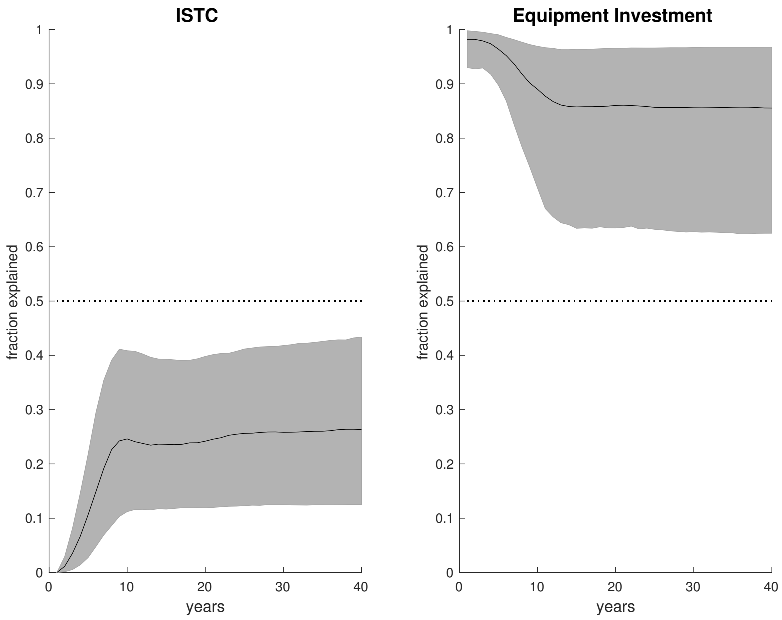
The figure K.7 presents the impulse response of a news shock on ISTC and Residential Investment

Figure K.7: IRF 2-VAR: ISTC Residential Investment



Note: BS identification; The solid black lines represent the impulse responses functions of the ISTC and Equipment Investment to a unit aggregate news shock and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.8: FEV 2-VAR: ISTC Equipment Investment



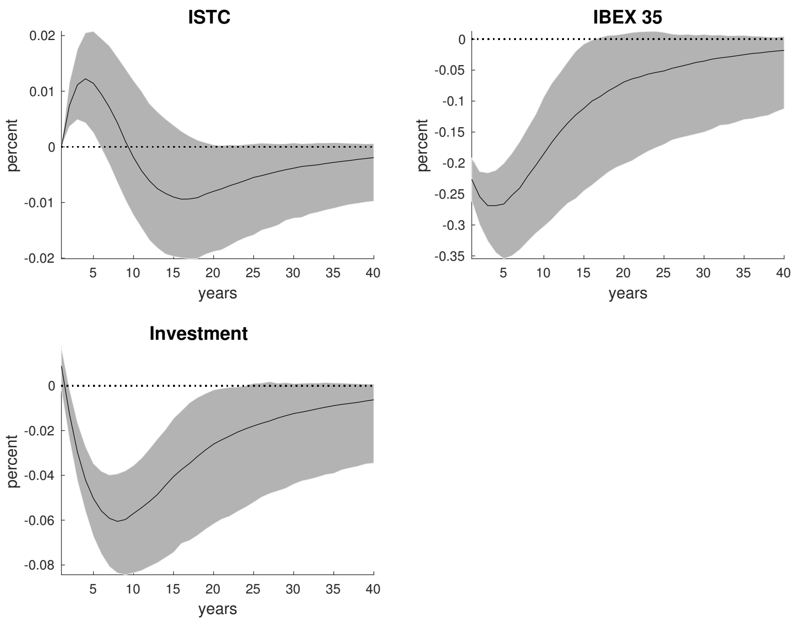
Note: The solid black lines represent the median FEV of the ISTC and Equipment Investment to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

K.5 3-variables VAR: ISTC, IBEX 35 and I

In a trivariate SVAR approach the variables are the ISTC as the measure of productivity, IBEX 35, and Investment as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

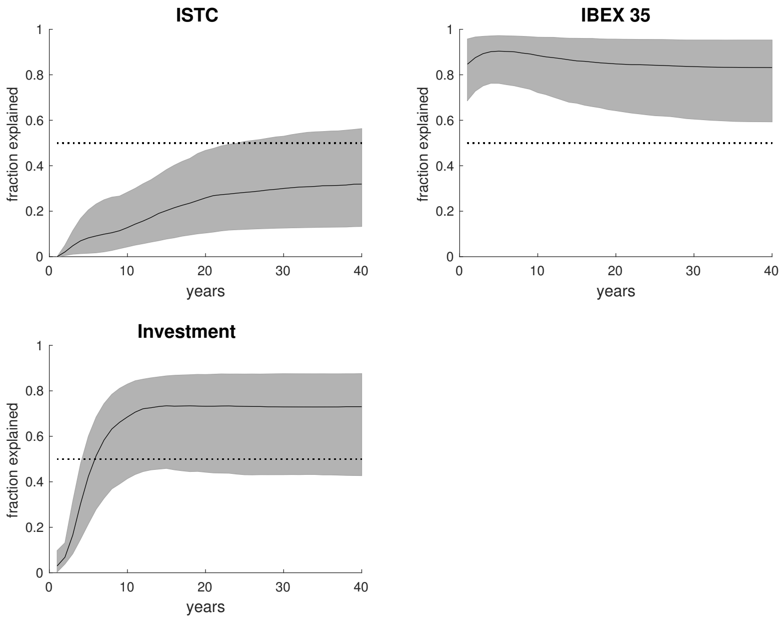
The figure K.9 presents the impulse response of a news shock on ISTC IBEX 35 and Investment

Figure K.9: IRF 3-VAR: ISTC IBEX 35 I



Note: The solid black lines represent the impulse responses functions of the ISTC IBEX 35 and Investment to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.10: FEV 3-VAR: ISTC IBEX 35 I



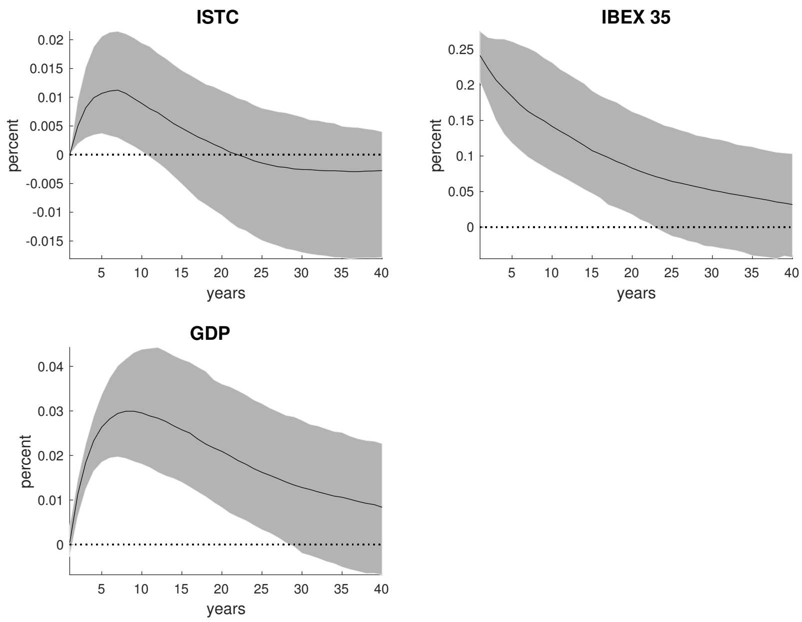
Note: The solid black lines represent the median FEV of the ISTC, IBEX 35 and Investment to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

K.6 3-variables VAR: ISTC, IBEX 35 and GDP

In a trivariate SVAR approach the variables are the ISTC as the measure of productivity, IBEX 35, and GDP as forward looking variable; according to a likelihood ratio test one lag is chosen for this estimation.

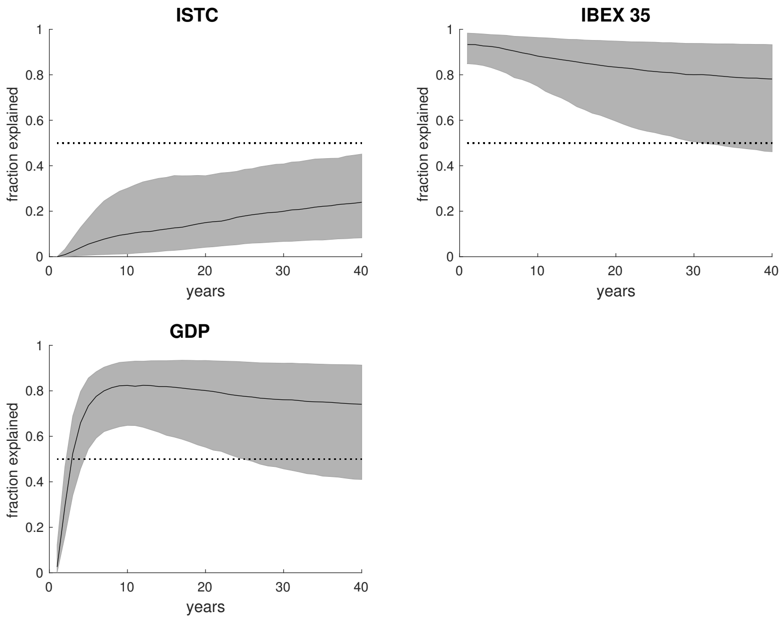
The figure K.11 presents the impulse response of a news shock on ISTC IBEX 35 and GDP

Figure K.11: IRF 3.VAR: ISTC IBEX 35 GDP



Note: The solid black lines represent the impulse responses functions of the ISTC IBEX 35 and GDPt to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.12: FEV 3.VAR: ISTC IBEX 35 GDP



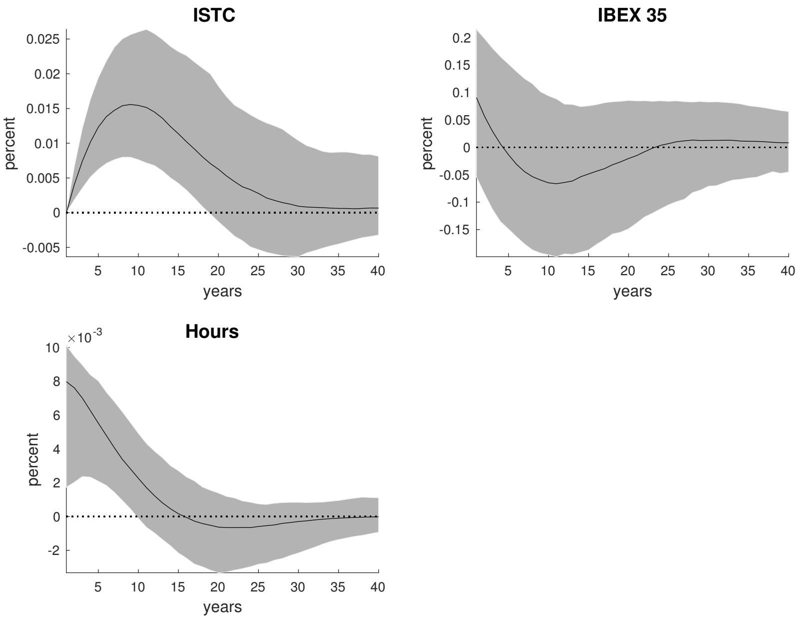
Note: The solid black lines represent the median FEV of the ISTC, IBEX 35 and GDP to a unit aggregate news shock. The grey area represents the 16% – 84% confidence intervals.

K.7 3-variables VAR: ISTC, IBEX 35 and Hours

In a trivariate SVAR approach the variables are the ISTC as the measure of productivity, IBEX 35, and Hours as forward looking variable; according to a likelihood ratio test one lag is chosen for Spanish data.

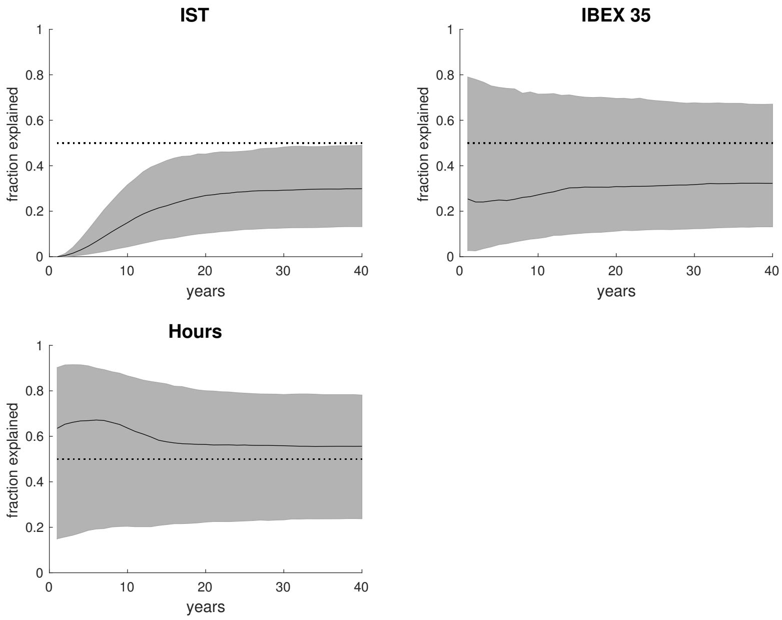
The figure K.13 presents the impulse response of a news shock on ISTC IBEX 35 and Hours

Figure K.13: IRF 3-VAR: ISTC IBEX 35 Hours



Note: The solid black lines represent the impulse responses functions of the ISTC IBEX 35 and Hours to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.14: FEV 3-VAR: ISTC IBEX 35 Hours



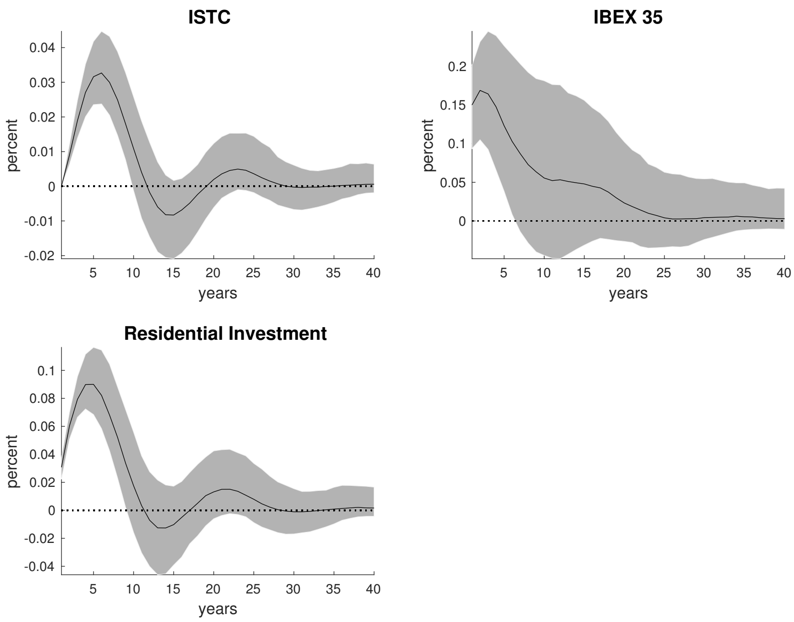
Note: The solid black lines represent the median FEV of the ISTC, IBEX 35 and Hours to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

K.8 3-variables VAR: ISTC, IBEX 35 and Residential Investment

In a trivariate SVAR approach the variables are the ISTC, IBEX 35, and Residential Investment; according to a likelihood ratio test one lag is chosen for this estimation.

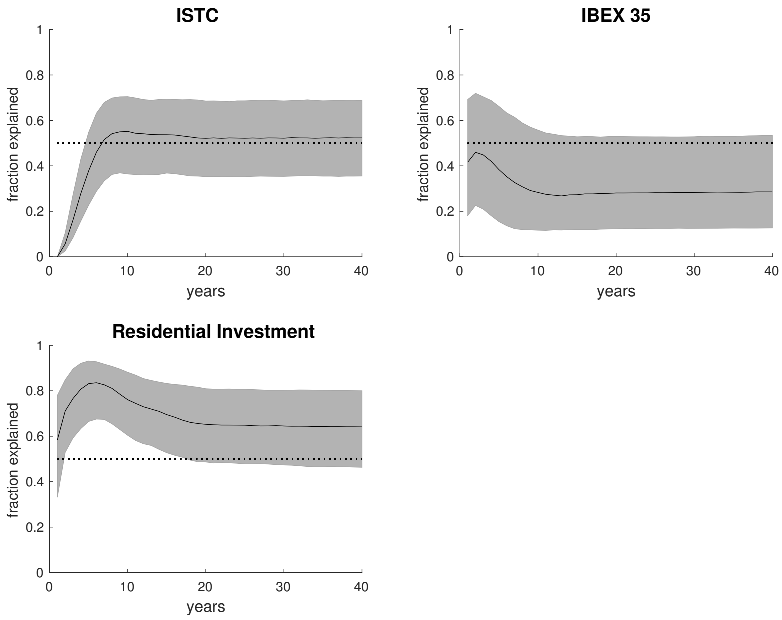
The figure K.15 presents the impulse response of a news shock on ISTC IBEX 35 and Residential Investment

Figure K.15: IRF 3-VAR: ISTC IBEX 35 Residential Invetment



Note: The solid black lines represent the impulse responses functions of the ISTC IBEX 35 and Residential Investment to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.16: FEV 3-VAR: ISTC IBEX 35 Residential Investment



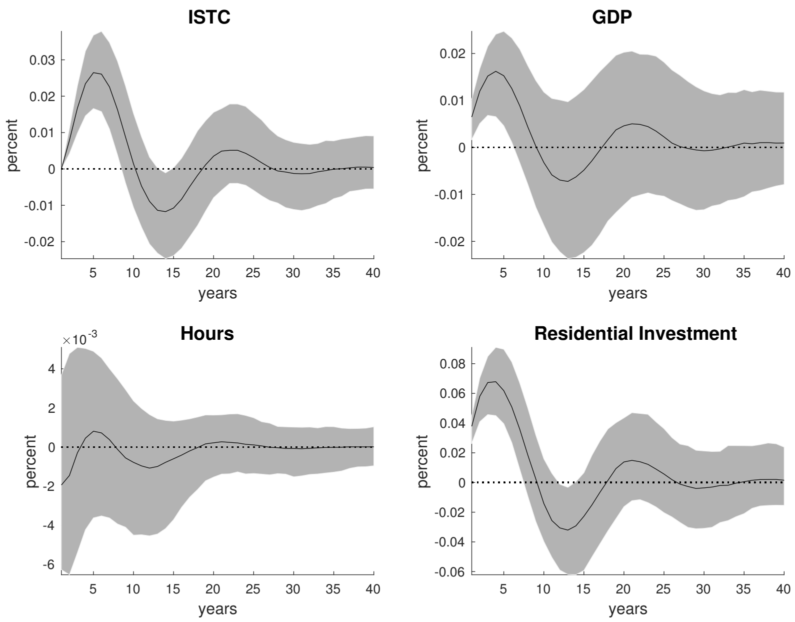
Note: The solid black lines represent the median FEV of the ISTC, IBEX 35 and Hours to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

K.9 4-variables VAR: ISTC, GDP, Hours and Residential Investment

In a four SVAR approach the variables are the ISTC as the measure of productivity, GDP, Hours and Residential Investment; according to a likelihood ratio test one lag is chosen for Spanish data.

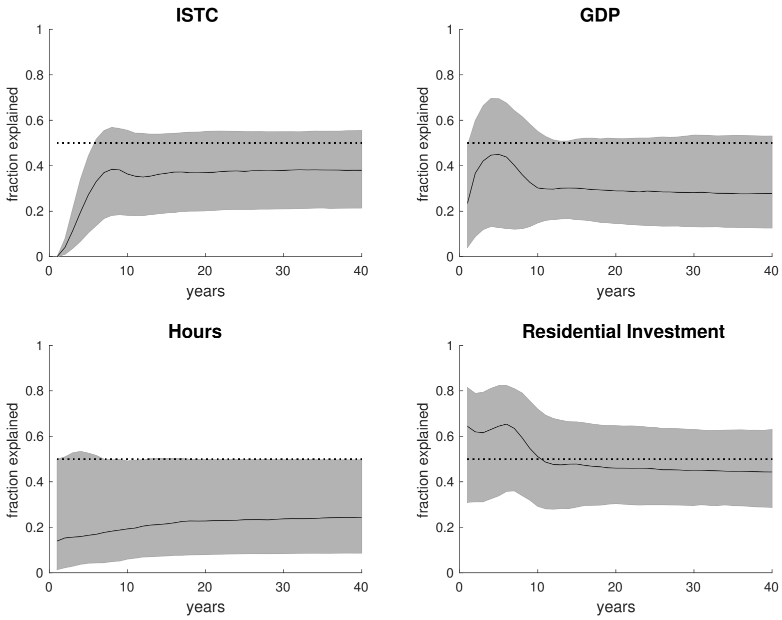
The figure K.17 presents the impulse response of a news shock on ISTC, GDP, Hours and Residential Investment.

Figure K.17: IRF 4-VAR: ISTC GDP Hours Residential I



Note: The solid black lines represent the impulse responses functions of the ISTC GDP, Hours and Residential Investment to a unit aggregate news shock. The grey area represents the $16\% - 84\%$ confidence intervals.

Figure K.18: FEV 4-VAR: ISTC GDP Hours Residential I

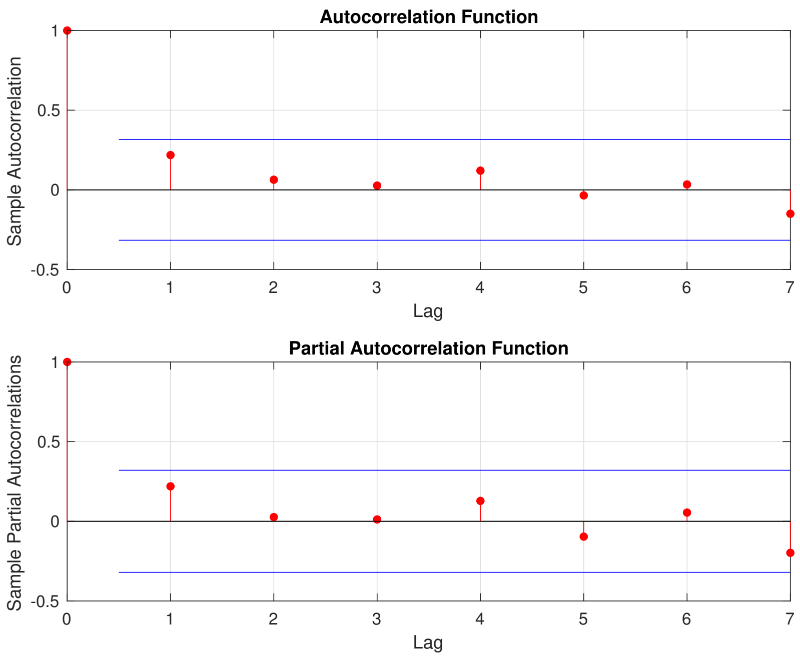


Note: The solid black lines represent the median FEV of the ISTC, GDP, Hours and Residential Investment to a unit aggregate news shock. The grey area represents the 16% − 84% confidence intervals.

Appendix L

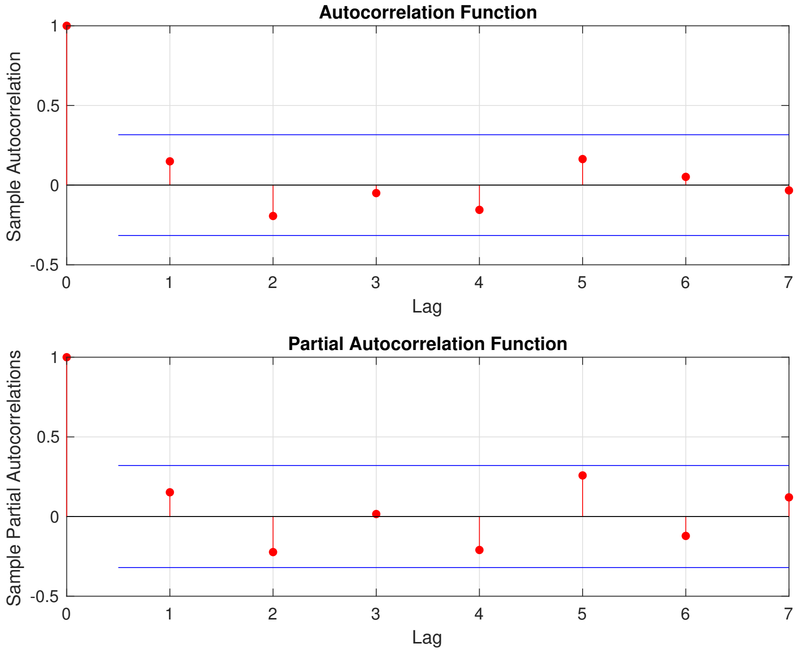
BS Methodology ACF and PACF Plots

Figure L.1: ACF and PACF 2-var: ISTC IBEX 35



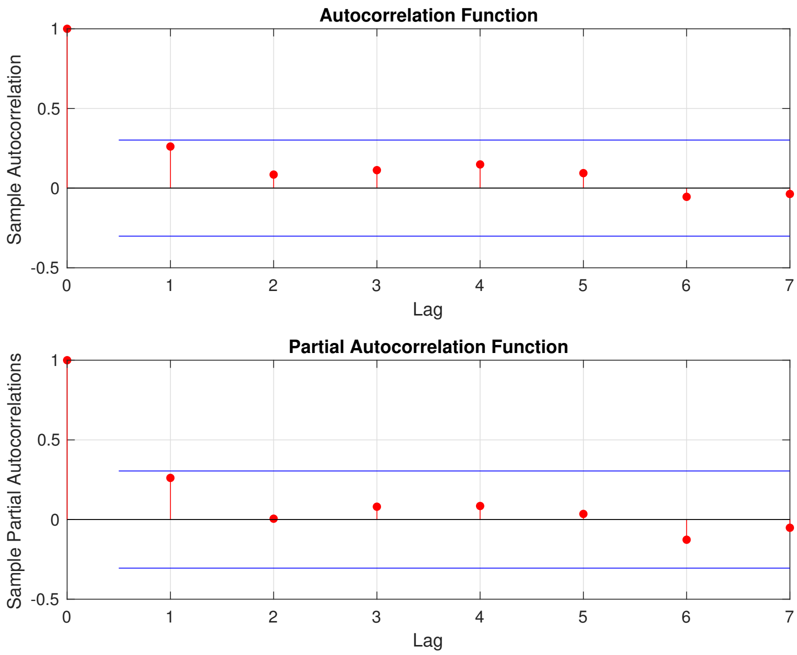
Note: Autocorrelation and partial autocorrelation function of the identification residuals of 2-VAR: ISTC IBEX 35

Figure L.2: ACF and PACF 2-var: ISTC C



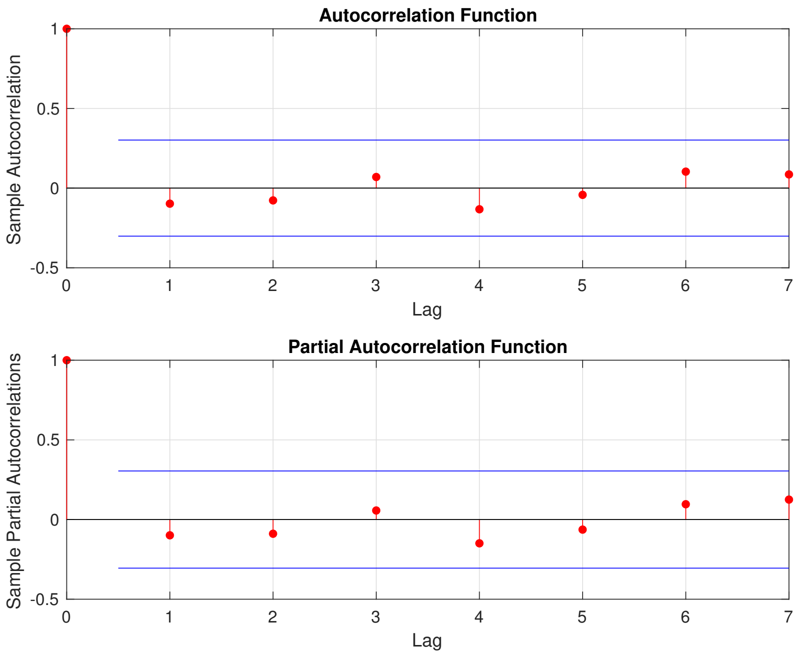
Note: Autocorrelation and partial autocorrelation function of the identification residuals of 2-var: ISTC C

Figure L.3: ACF and PACF 2-VAR: ISTC I



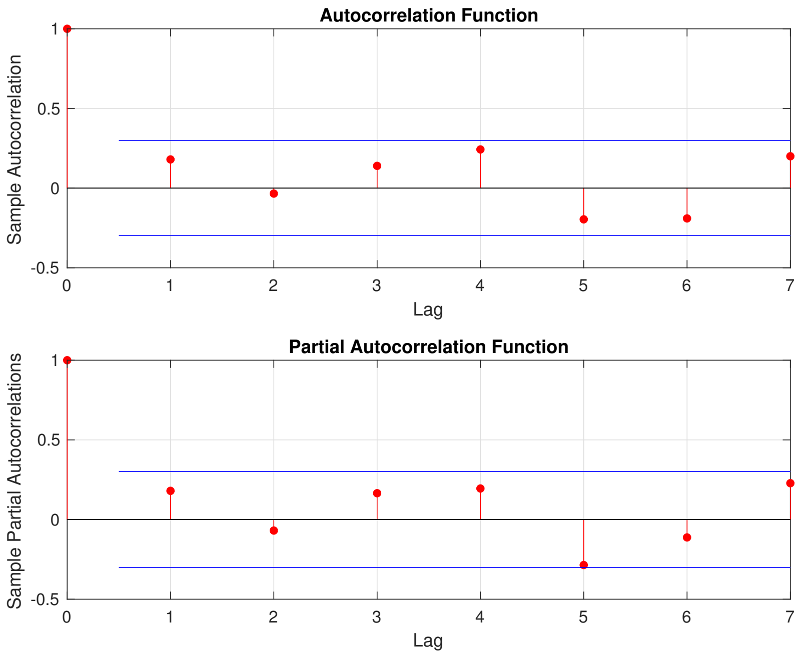
Note: Autocorrelation and partial autocorrelation function of the identification residuals 2-VAR: ISTC I

Figure L.4: ACF and PACF 2-VAR: ISTC GDP



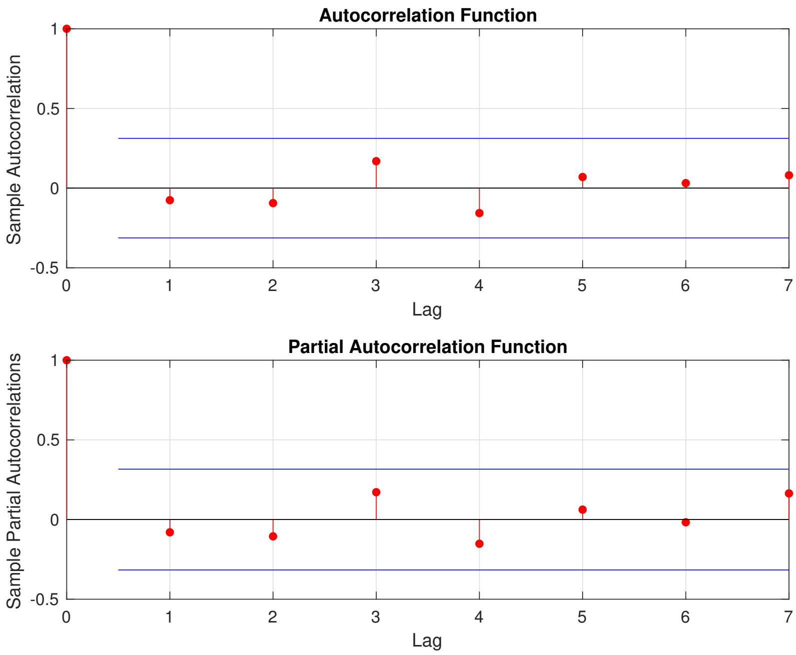
Note: Autocorrelation and partial autocorrelation function of the identification residuals 2-VAR: ISTC GDP

Figure L.5: ACF and PACF 2-VAR: ISTC Hours



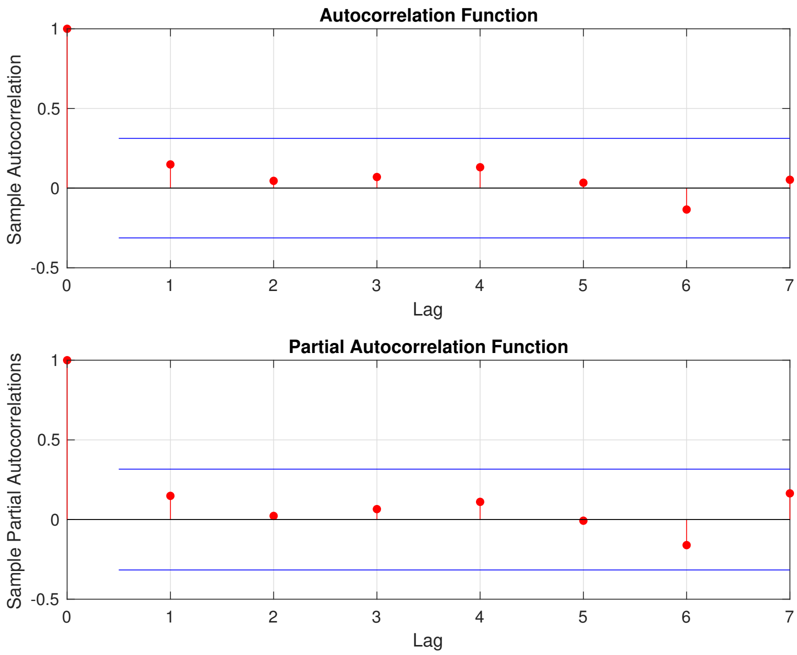
Note: Autocorrelation and partial autocorrelation function of the identification residuals 2-VAR ISTC Hours

Figure L.6: ACF and PACF 3-VAR: ISTC IBEX 35 C



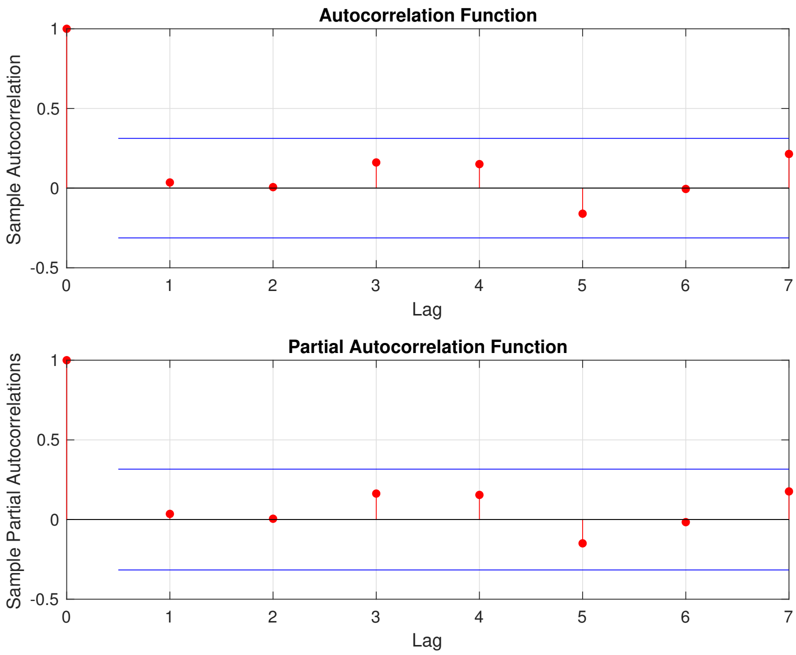
Note: 3-VAR: Autocorrelation and partial autocorrelation function of the identification residuals ISTC IBEX 35 C

Figure L.7: ACF and PACF 3-VAR: ISTC IBEX 35 I



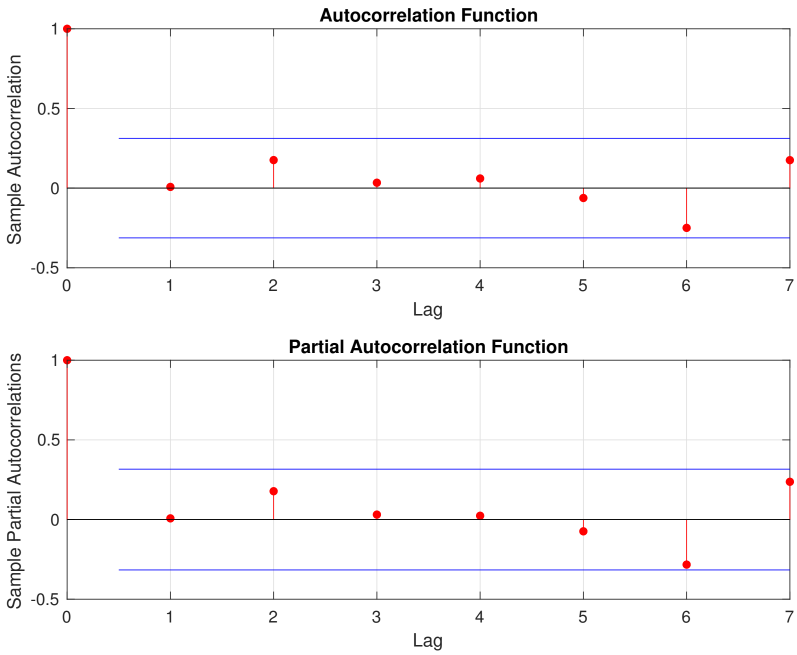
Note: Autocorrelation and partial autocorrelation function of the identification residuals 3-VAR: ISTC IBEX 35 I

Figure L.8: ACF and PACF function 3.VAR: ISTC IBEX 35 GDP



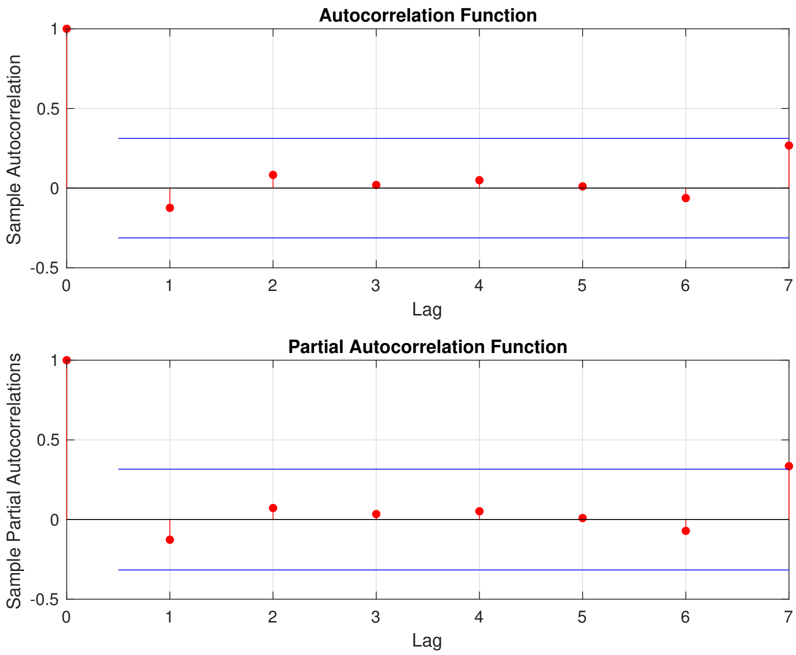
Note: Autocorrelation and partial autocorrelation function of the identification residuals 3.VAR: ISTC IBEX 35 GDP

Figure L.9: ACF and PACF 3-VAR: ISTC IBEX 35 Hours



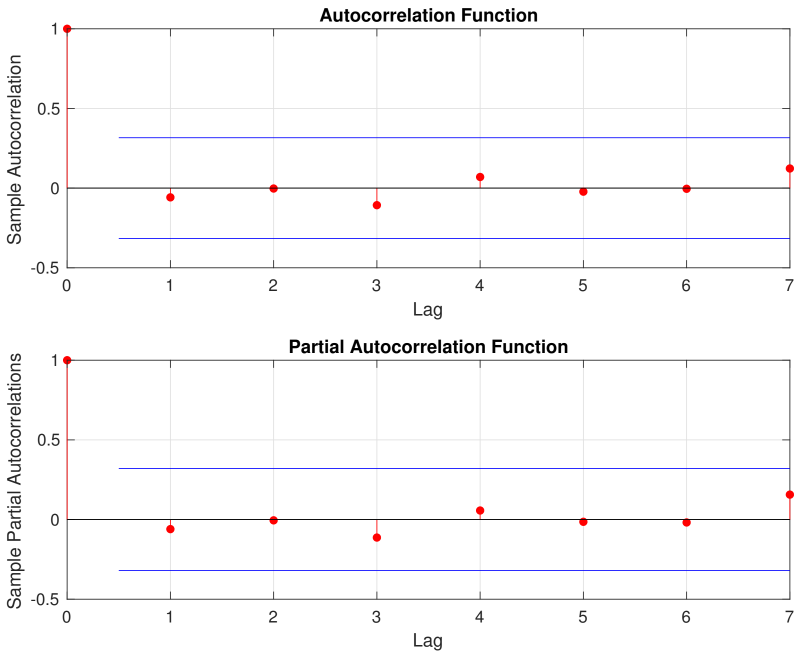
Note: Autocorrelation and partial autocorrelation function of the identification residuals 3-VAR: ISTC IBEX 35 Hours

Figure L.10: ACF and PACF 4-VAR: ISTC IBEX 35 GDP I



Note: Autocorrelation and partial autocorrelation function of the identification residuals 4-VAR: ISTC IBEX 35 GDP I

Figure L.11: ACF and PACF 4-VAR: ISTC GDP Hours Residential I



Note: Autocorrelation and partial autocorrelation function of the identification residuals 4-VAR: ISTC GDP Hours Residential I

Appendix M

Data

My data sources are the *EU KLEMS*[1] and *OECD* data base[2]. I use the period 1970 - 2015.

M.1 Relative Price of Investment and the Stock of Capital

The EU KLEMS September 2017 release is based on the NACE 2 industry classification and the new European System of National Accounts (ESA 2010). Compared with the previous one, ESA 1995, ESA 2010 includes more assets in the definition of Gross Fixed Capital Formation (GFCF). The database structure of capital and investment is organized in eleven categories, provides deflators for all categories and calculates the capital stock using a perpetual inventory method.

The procedure to construct the **Residential Investment**, **Business**

[1] The EU KLEMS project is funded by the European Commission, Research Directorate General as part of the 6th Framework Programme, Priority 8, "Policy Support and Anticipating Scientific and Technological Needs"; Examples of research based on this database: O'Mahony and Timmer (2008); van Ark et al. (2008); Inklaar et al. (2009)

[2] https://data.oecd.org

Structures and the composite **Equipment** follows Díaz and Franjo (2016):

Residential Investment contains category *Residential structures*,
Business Structures contains *Total Non-residential investment*,
Equipment contains all other categories corresponding to various types of business equipment, computer software and research and development as intellectual property, weapons systems, and investment in cultivated assets:

1. *Computing equipment*
2. *Communications equipment*
3. *Computer software and databases*
4. *Transport Equipment*
5. *Other Machinery and Equipment*
6. *Cultivated assets*
7. *Research and development*
8. *Other IPP assets*

I construct the implicit price deflator of *non durable goods* and *services*, $D_{nd,t}$ using the data from OECD.Stat[3], IPC series of ECOICOP.

To construct the composite *Equipment* (Paasche index), I take the implicit price deflator of each type of investment good, $D^j_{i,t}$ from EU KLEMS (base year 2010). I define the relative price of the investment good i in category e (*equipment)* as $q^e_{i,t} = D^e_{i,t}/D_{nd,t}$.

I construct a constant-price measure of investment in equipment as $X_{e,t} = \sum_i q^e_{i,0} X^e_{i,t}$.

[3] http://stats.oecd.org/index.aspx

Thus, the implicit price deflator of equipment is:

$$q_{e,t} = \frac{\sum_i q^e_{i,t} X^e_{i,t}}{X_{e,t}} \tag{M.1}$$

Next, I calculate the real stock so that

$$K_{e,t} = \frac{\sum_i q^e_{i,t} K^e_{i,t}}{q_{e,t}}, \tag{M.2}$$

where $K^e_{I,t}$ is the real capital stock calculated by EU KLEMS for each type of investment good. EU KLEMS constructs the stocks of structures and housing. I have calculated their relative price using the deflator of non durable goods and services.

The figure M.1 shows the relative prices of investment for each category (in units of non durable consumption goods and services) for Spain and Germany. I have normalized the relative prices so that 1970 is the base year for both countries.

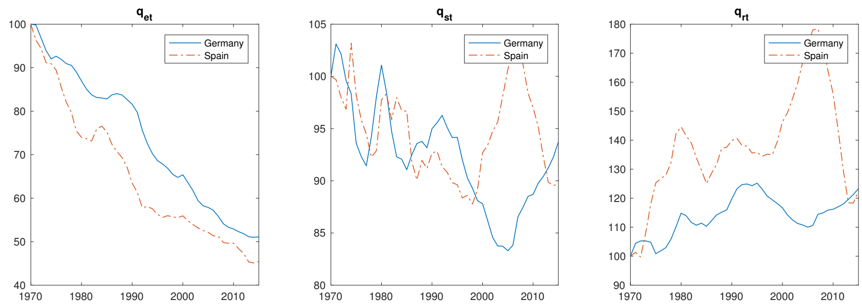


Figure M.1: Relative Prices of Investment, q_{it} - Spain vs Germany

The behavior of the relative price of equipment, shown in the left panel exhibits a downwards trend for both countries. It is interesting to note that as both prices have similar fluctuations, it implies that business cycles are correlated. The fall in the relative price in Spain is higher than Germany's in two periods: from 1970 to 1979 and from 1985 to 1991. Those two periods coincide exactly with the periods of housing boom in Spain, as we observe in the right panel.

The relative price of business structures, shown in the central panel exhibit a similar pattern until the 2000s. The coefficient of correlation from 1970 to 1998 is 0.60, while from 1999 to 2015 the coefficient of correlation is negative, -0.70. In Germany, however, the relative prices of structures is much more volatile than that of relative prices of residential investment; it fluctuate seven more than that of relative prices of residential investment.

The relative price of residential investment is shown in right panel. It is interesting to note that in Spain there were two small booms before the 2000s: the price reached to 144.6 in 1979, and there was a minor surge in 1991, when the price rose to 139.80 prior to the peak in 2007, reaching the value 178.4. The coefficient of correlation between the two countries is 0.65 from 1970 to 1998, while from 1999 to 2015 the coefficient of correlation is strongly negative, - 0.85.

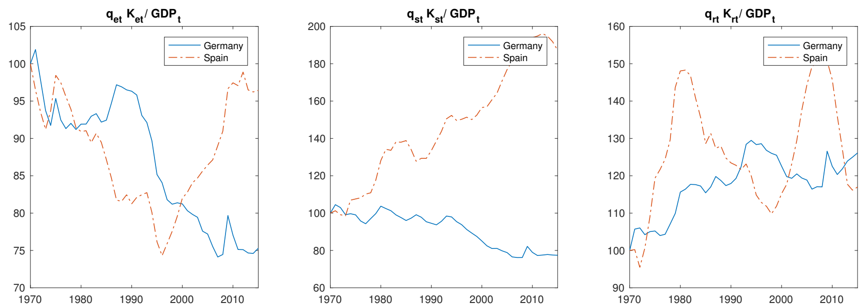


Figure M.2: $q_{it}K_{it}/GDP_t$

The figure M.2 shows the ratio of capital to GDP for each investment category for Spain and Germany. I have normalized them so that 1970 is the base year for both countries just as a counterfactual exercise to observe what would have happened if they had started at the same level. As we can see in the left panel, until 1999 Germany is more intensive in equipment than Spain. From 2000, Spain is more intensive in equipment capital than the German economy since the 2000s.

In the central panel, the ratio of business structures to GDP of Spain exhibit an increasing trend, while for Germany, the trend is slightly downward, though very stable.

The right panel in figure M.2 shows the ratio of residential capital to GDP. It is very noticeable the volatility in the housing stock in Spain that exhibit two period of strong increase in the ratio of residential capital to GDP: the first one from 1973 to 1981, and from 2000 until 2009. As for business structures, the most striking feature of the data is the relative stability of the German of the ratio of residential capital to GDP.

Appendix N

VAR Identification Methodology

N.1 Identifying News Shocks - BS methodology

Let $\mathbf{y}_t$ be a $k \times 1$ vector of observables of length T. Let the reduced form moving average representation in the levels of the observables be given as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t \tag{N.1}$$

where $B(L)$ is a $k \times k$ matrix polynomial in the lag operator, L, of moving average coefficients and u_t is the $k \times 1$ vector of reduced-form innovations. We assume there exists a linear mapping between innovations and structural shocks, ε_t, given as:

$$\mathbf{u}_t = \mathbf{A}_0\varepsilon_t \tag{N.2}$$

This implies the following structural moving average representation:

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\varepsilon_t \tag{N.3}$$

Where $\mathbf{C} = \mathbf{B}(\mathbf{L})\mathbf{A}_0$ and $\varepsilon_t = \mathbf{A}_0^{-1}\mathbf{u}_t$. The impact matrix must satisfy $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$, where $\mathbf{\Sigma}$ is the variance-covariance matrix of reduced-form innovations. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, $\tilde{A}$ (we choose the convenient Choleski decomposition), the entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a orthonormal matrix ($D' = D^{-1}$ and $DD' = I$, where I is the identity matrix).

The h step ahead forecast error is:

$$\mathbf{y}_{t+h} - E_{t-1}\mathbf{y}_{t+h} = \sum\nolimits_{\tau=0}^{h} \mathbf{B}_\tau \tilde{\mathbf{A}}_0 \mathbf{D} \varepsilon_{t+h-\tau} \tag{N.4}$$

where $B\tau$ is the matrix of moving average coefficients at horizon τ. The contribution to the forecasterror variance of variable i attributable to structural shock j at horizon h is then:

$$\Omega_{i,j}(h) = \frac{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \tilde{\mathbf{A}}_0 \mathbf{D} \mathbf{e}_j \mathbf{e}_j' \mathbf{D}' \tilde{\mathbf{A}}_0' \mathbf{B}_\tau{}' \right) \mathbf{e}_i}{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \mathbf{\Sigma} \mathbf{B}_\tau' \right) \mathbf{e}_i} \tag{N.5}$$

$$= \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \tilde{\mathbf{A}}_0 \gamma \gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{i,\tau}'}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \mathbf{\Sigma} \mathbf{B}_{i,\tau}'}$$

The $\mathbf{e}_i$ denote selection vectors with one in the ith place and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the jth column of $\mathbf{D}$, which will be denoted by γ. $\tilde{\mathbf{A}}_0\gamma$ is $k \times 1$ is a vector corresponding to the jth column of a possible orthogonalization and has the interpretation as an impulse vector. The selection vectors outside the parentheses in both numerator and denominator pick out the ith row of the matrix of moving average coefficients, which is denoted by $\mathbf{B}_{i,\tau}$.

Let q_t^i occupy the first position in the system, and let the unanticipated shock be indexed by 1 and the news shock by 2. Our identifying assumption implies that these two shocks account for all variation of q_t^i at all horizons:

Eqs. (2.1) and (2.2), imply that these two shocks account for all variation in q_t^i

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \quad \forall h \tag{N.6}$$

It is general not possible to force this restriction to hold at all horizons. Instead, we propose picking parts of the impact matrix to come as close as possible to making this expression hold over a finite subset of horizons.

With the surprise shock identified as the innovation in observed technology, $\Gamma_{1,1}(h)$ will be invariant at all h to alternative identifications of the other $k-1$ structural shocks. As such, choosing elements of A_0 to come as close as possible to making the above expression hold is equivalent to choosing the impact matrix to maximize contributions to $\Gamma_{1,2}(h)$ over h.

Since the contribution to the forecast error variance depends only on a single column of the impact matrix, this suggests choosing the second column of the impact matrix to solve the following optimization problem:

$$\gamma* = \arg\max \sum_{\mathbf{h=0}}^{\mathbf{H}} \Omega_{1,2}(h) = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau}\tilde{\mathbf{A}}_0 \gamma\gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{i,\tau}'}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \mathbf{\Sigma} \mathbf{B}_{i,\tau}'} \tag{N.7}$$

s.t.

$$\tilde{\mathbf{A}}_0(1,j) = 0 \quad \forall j > 1$$

$$\gamma(1,1) = 0 \tag{N.8}$$

$$\gamma'\gamma = 1 \tag{N.9}$$

So as to ensure that the resulting identification belongs to the space of possible orthogonalizations of the reduced form, the problem is expressed in terms of choosing γ conditional on an arbitrary orthogonalization, $\tilde{A}_0$. H represents the finite truncation horizon[1]. The first two constraints impose that the news shock has no contemporaneous effect on the level of q_t^i. The third restriction (that γ have unit length) ensures that γ is a column vector belonging to an orthonormal matrix.

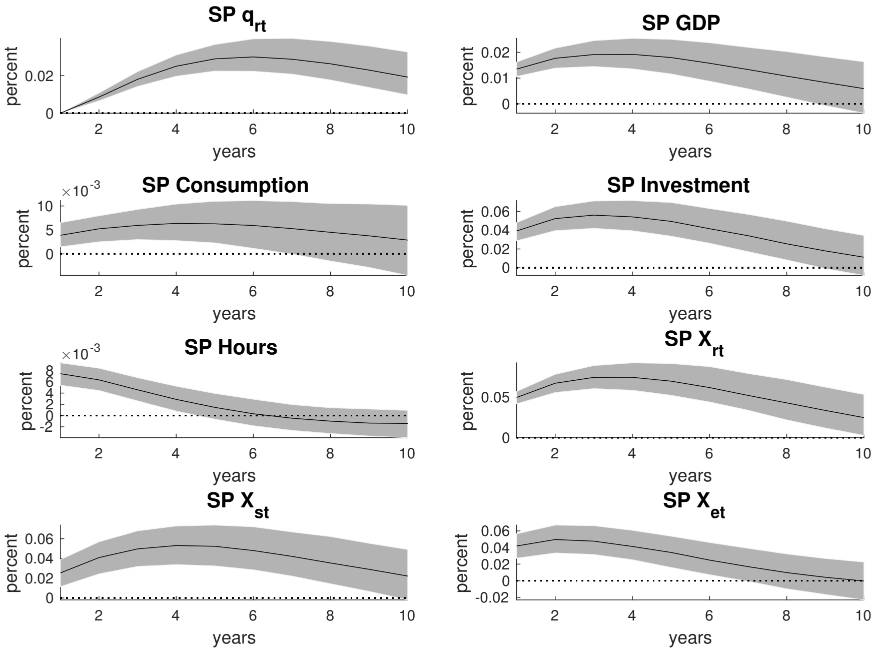
[1] The finite truncation horizon in this paper is 10 periods

Appendix O

Benchmark VAR Identification

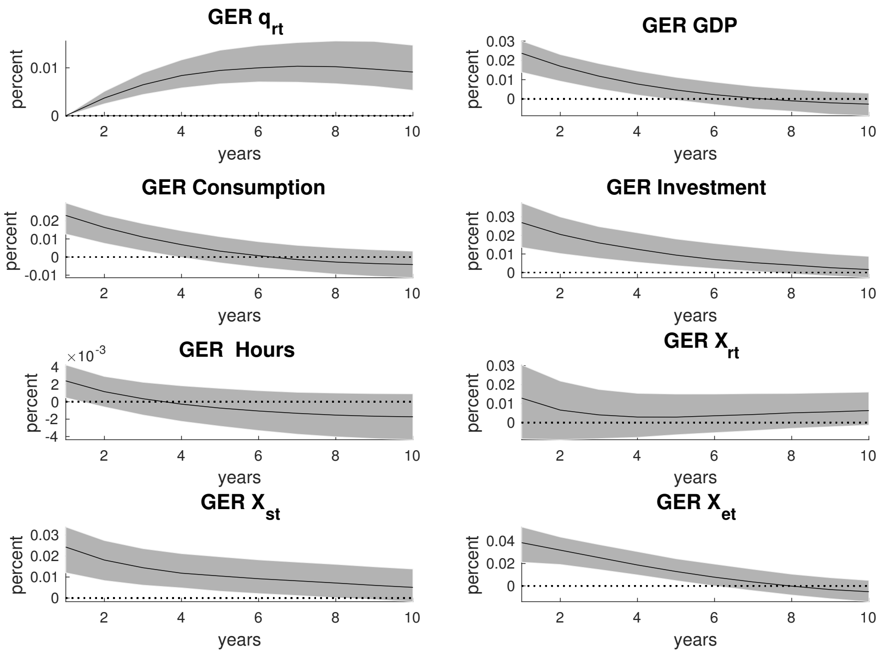
O.1 IRF q_{rt} News Shock

Figure O.1: Spain IRF q_{rt} news shock



Note: Median responses to a news shock on relative price of residential investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

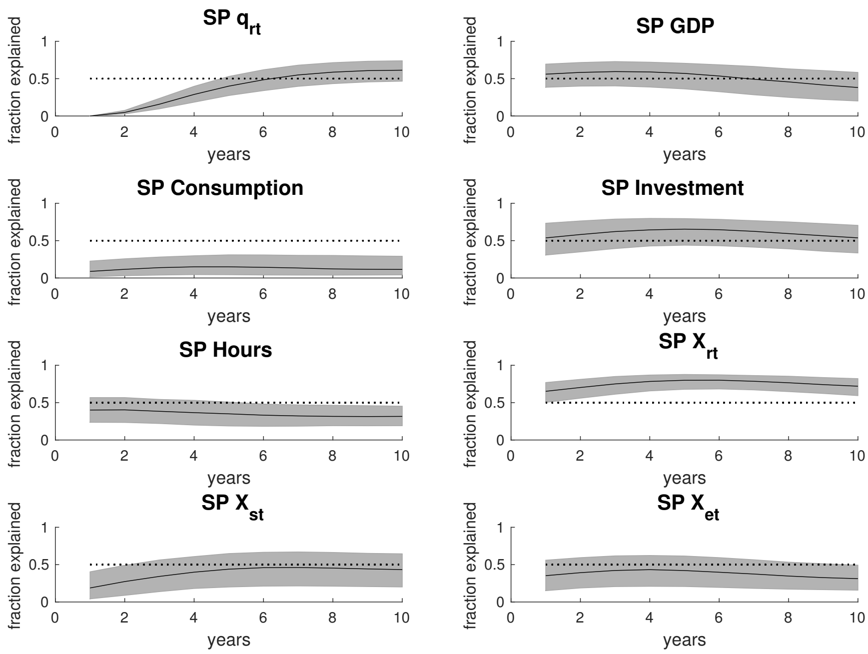
Figure O.2: Germany IRF q_{rt} news shock



Note: Median responses to a news shock on relative price of residential investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

O.2 FEV q_{rt} News Shock

Figure O.3: Spain FEV q_{rt} news shock

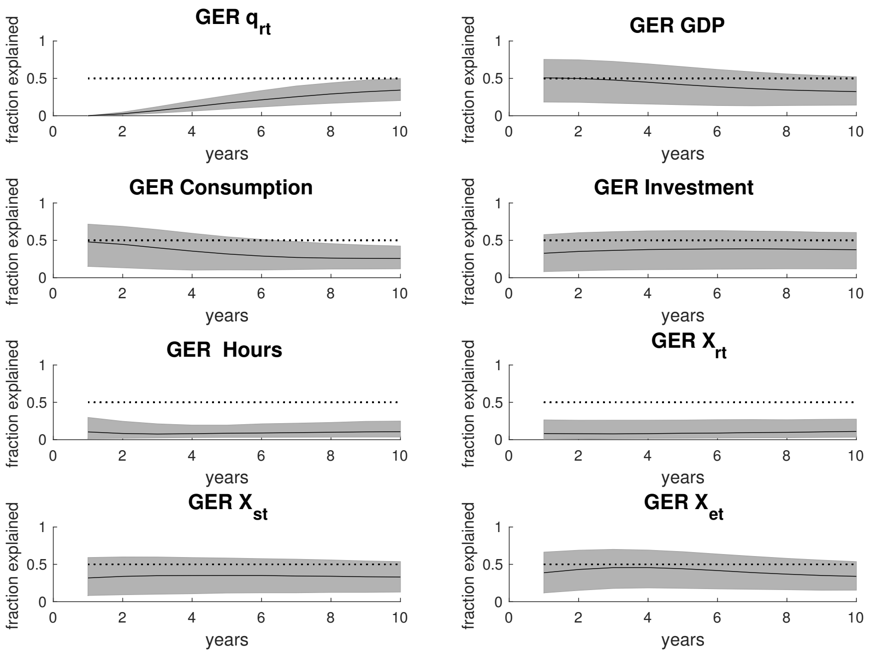


Note: Median responses to a news shock on relative price of residential investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Table O.1: Spain - Maximum Forecast Error Variance (FEV) - q_{rt} news shock

Spain	q_{rt}	GDP_t	C_t	I_t	Hours	X_r	X_s	X_e
Median contribution	0.61	0.59	0.15	0.65	0.40	0.80	0.46	0.43
Year	10	3	5	5	1	4	7	5

Figure O.4: Germany FEV q_{rt} news shock



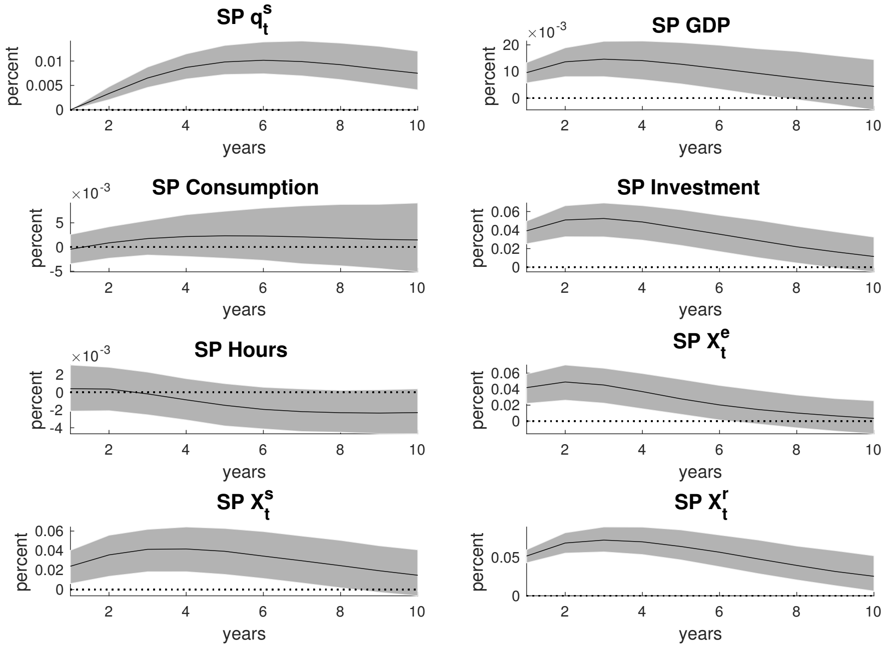
Note: Median responses to a news shock on relative price of residential investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Table O.2: Germany - Maximum Forecast Error Variance (FEV) - q_{rt} news shock

Germany	q_{rt}	GDP_t	C_t	I_t	Hours	X_r	X_s	X_e
Median contribution	0.31	0.51	0.48	0.39	0.11	-	0.35	0.46
Year	10	2	1	9	10	3	4	10

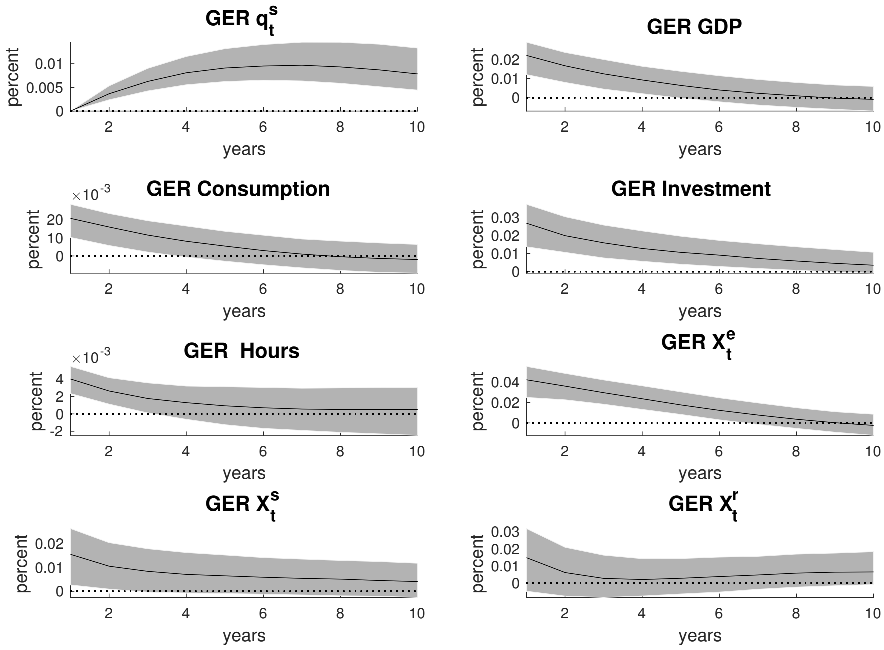
O.3 IRF q_{st} News Shocks

Figure O.5: Spain IRF q_{st} news shock



Note: Median responses to a news shock on relative price of business structures investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure O.6: Germany IRF q_{st} news shock



Note: Median responses to a news shock on relative price of business structures investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

O.4 FEV q_{st} News Shocks

Figure O.7: Spain FEV - q_{st} news shock

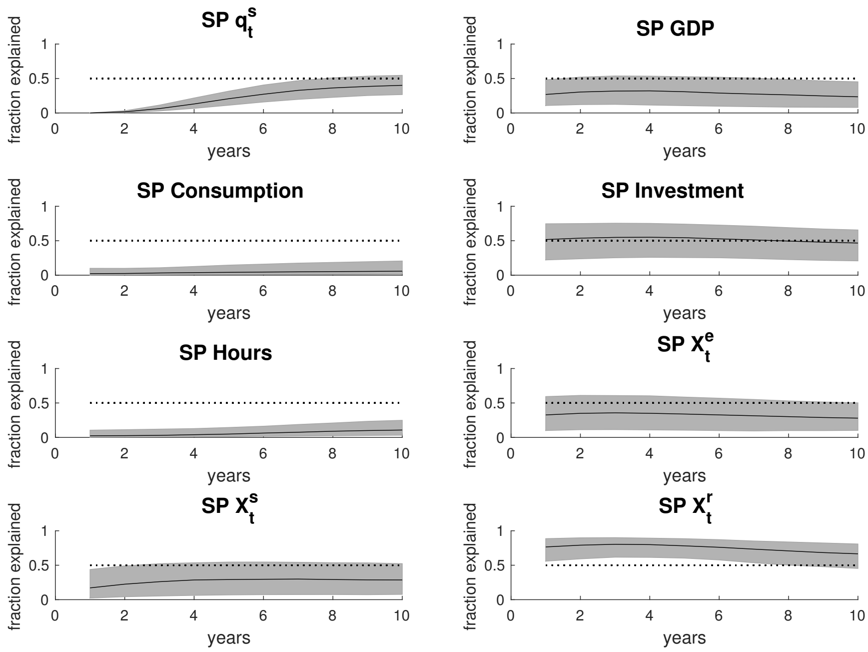


Table O.3: Spain - Maximum Forecast Error Variance (FEV) - q_{st} news shock

Spain	q_{st}	GDP_t	C_t	I_t	$Hours_t$	X_e	X_s	X_r
Median contribution	0.40	0.32	0.06	0.55	0.11	0.36	0.30	0.80
Year	10	4	10	4	10	3	7	3

Figure O.8: Germany FEV - q_{st} news shock

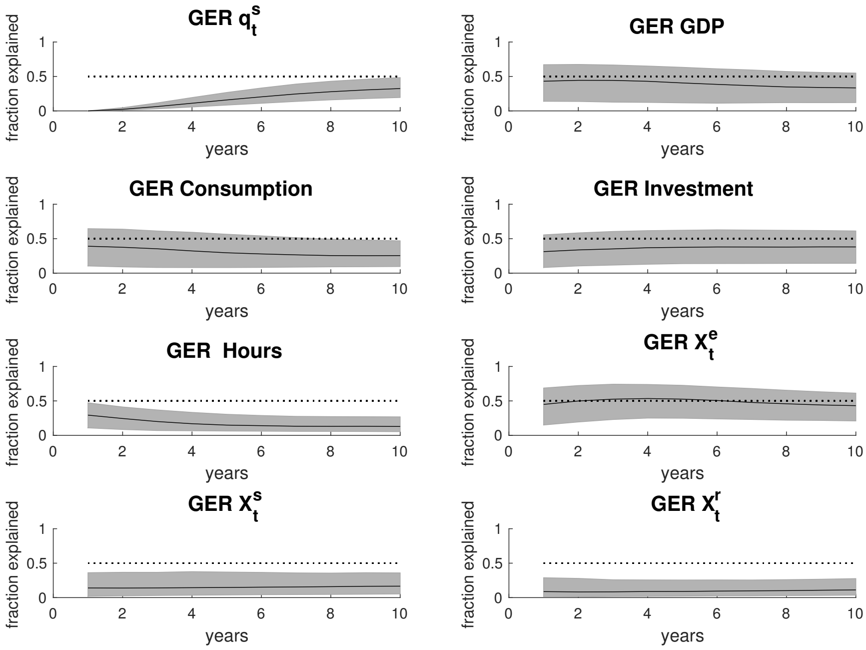
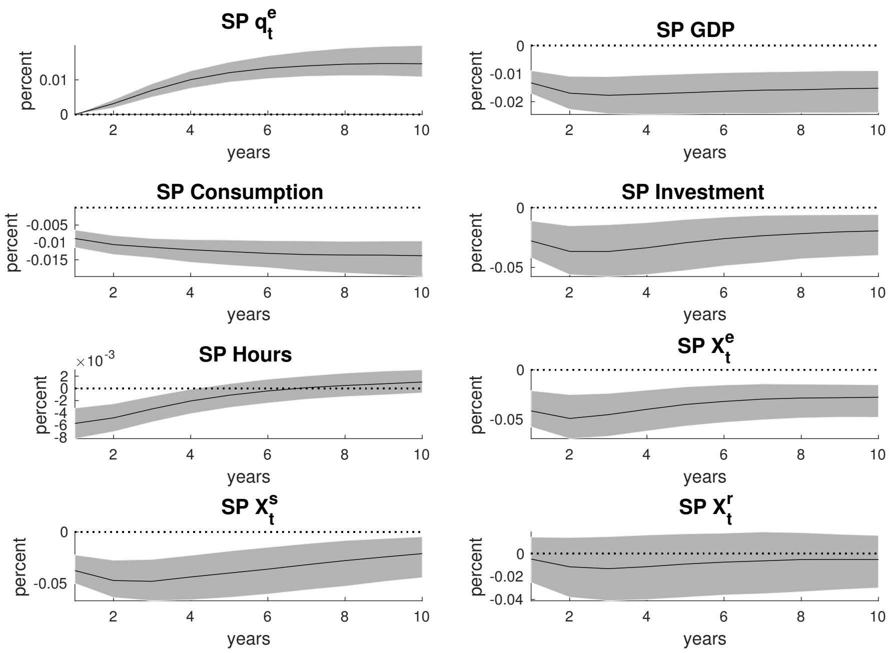


Table O.4: GERMANY - Maximum Forecast Error Variance (FEV) - q_{st} news shock

Germany	q_{st}	GDP_t	C_t	I_t	$Hours_t$	X_e	X_s	X_r
Median contribution	0.32	0.44	0.39	0.38	0.29	0.53	0.17	0.11
Year	10	2	1	9	1	4	10	10

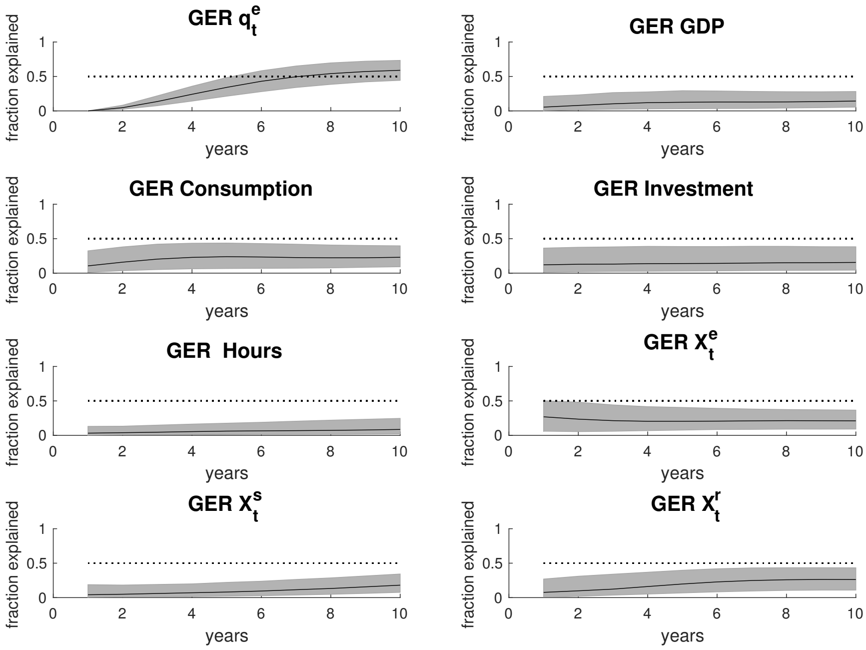
O.5 IRF q_{et} News Shocks

Figure O.9: Spain IRF q_{et} news shock



Note: Median responses to a news shock on relative price of equipment investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure O.10: Germany IRF q_{et} news shock



Note: Median responses to a news shock on relative price of equipment investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

O.6 FEV q_{et} News Shocks

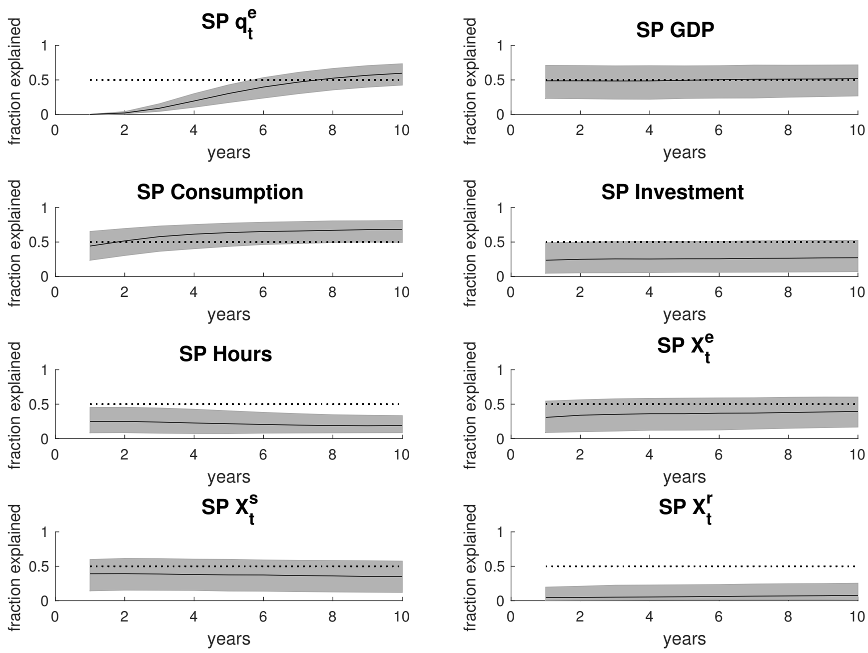


Figure O.11: Spain FEV - q_{et} news shock

Spain	q_{et}	GDP_t	C_t	I_t	$Hours_t$	X_e	X_s	X_r
Median contribution	0.60	0.52	0.68	0.27	0.25	0.39	0.39	0.08
Year	10	10	10	10	1	10	2	10

Table O.5: Spain - Maximum Forecast Error Variance (FEV) - q_{et} news shocks

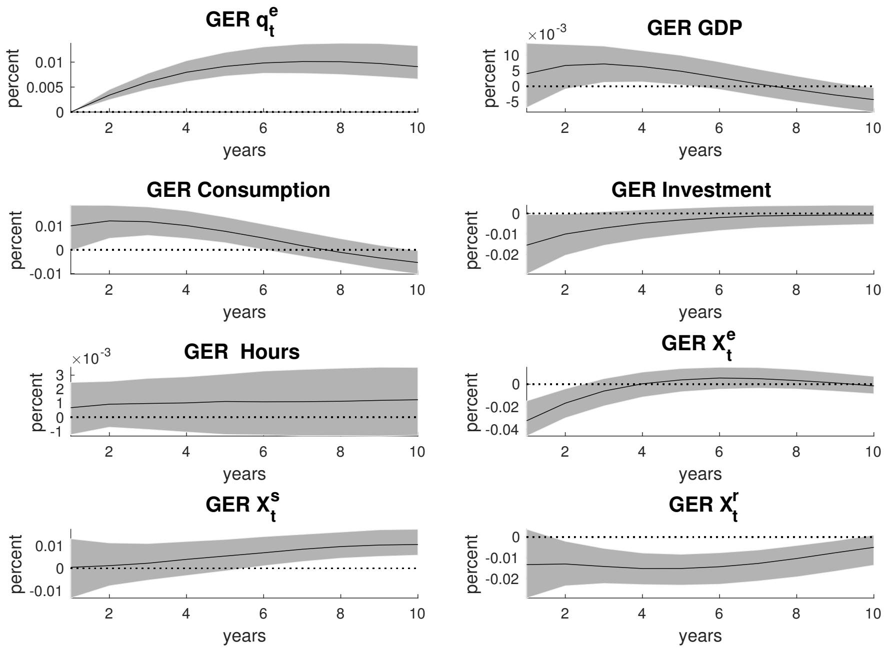


Figure O.12: Germany FEV - q_{et} news shock

Germany	q_{et}	GDP_t	C_t	I_t	$Hours_t$	X_e	X_s	X_r
Median contribution	0.59	0.14	0.24	0.16	0.09	0.27	0.18	0.26
Year	10	10	5	10	10	1	10	9

Table O.6: Germany - Maximum Forecast Error Variance (FEV) - q_{et} news shock

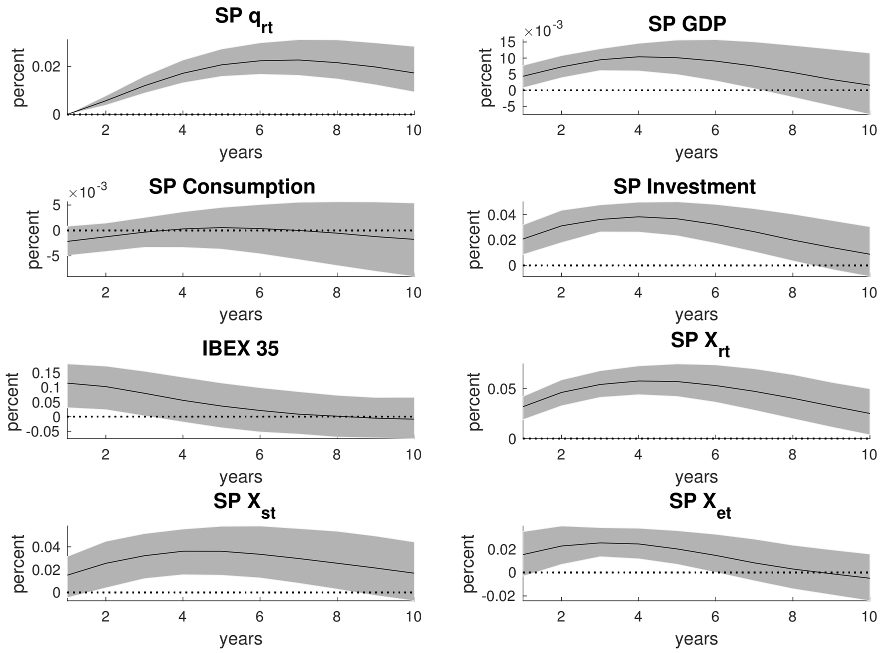
Appendix P

Alternative VAR Identification

The alternative VAR includes the logs of eight variables: relative price of investment, q_{it}, GDP, GDP_t, consumption, C_t, aggregate investment, X_t, equipment investment, X_{et}, business structures investment, X_{st}, residential investment, X_{rt}, and IBEX 35 for Spain, or DAX for Germany.

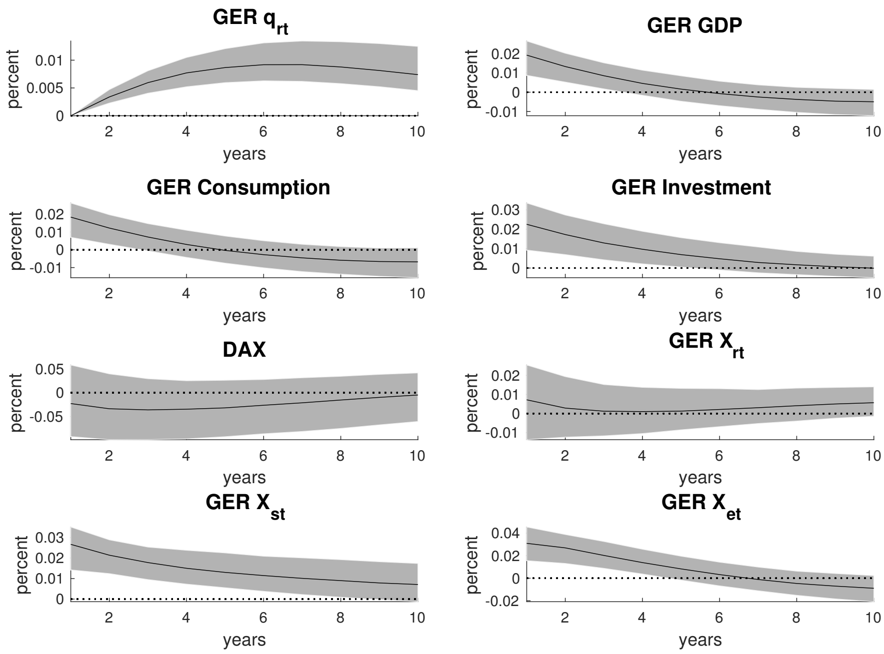
P.1 IRF q_{rt} News Shock

Figure P.1: Spain IRF q_{rt} news shock; alternative VAR



Note: Median responses to a news shock on relative price of residential investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure P.2: GERMANY IRF q_{rt} news shock; alternative VAR



Note: Median responses to a news shock on relative price of residential investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

P.2 FEV q_{rt} News Shock

Figure P.3: SPAIN FEV - q_{rt} news shock; alternative VAR

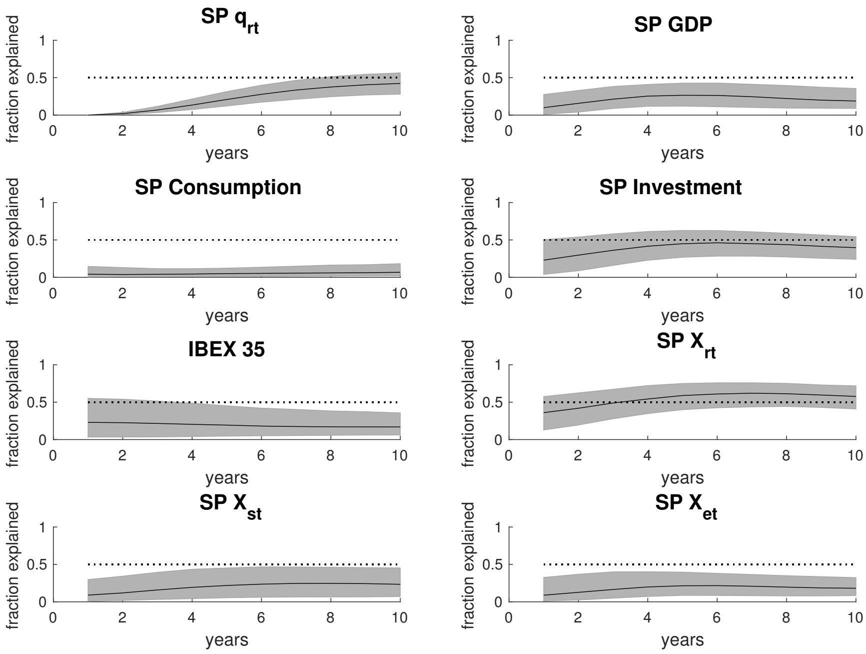


Table P.1: SPAIN - Maximum Forecast Error Variance (FEV) - q_{rt} news shock; alternative VAR

Spain	q_{rt}	GDP_t	C_t	I_t	IBEX 35	X_e	X_s	X_r
Median contribution	0.41	0.27	0.06	0.46	0.21	0.22	0.23	0.62
Year	10	5	10	5	1	5	7	6

Figure P.4: GERMANY - Maximum Forecast Error Variance (FEV) - q_{rt} news shock; alternative VAR

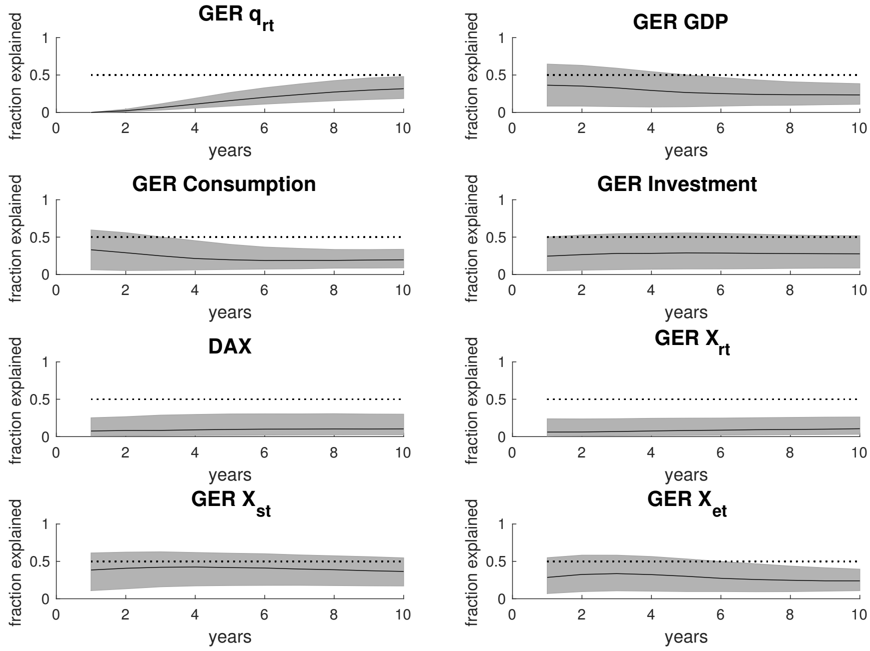
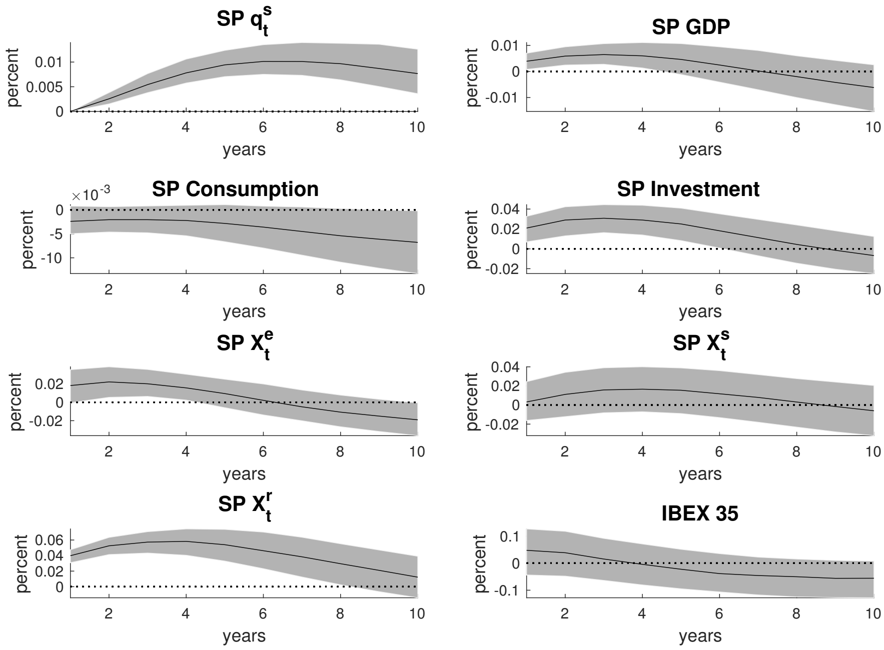


Figure P.5: GERMANY - Forecast Error Variance (FEV) - q_{rt} news shock; alternative VAR

Germany	q_{rt}	GDP_t	C_t	I_t	DAX	X_e	X_s	X_r
Median contribution	0.32	0.38	0.41	0.20	0.11	0.19	0.41	0.12
Year	10	1	1	6	10	4	5	10

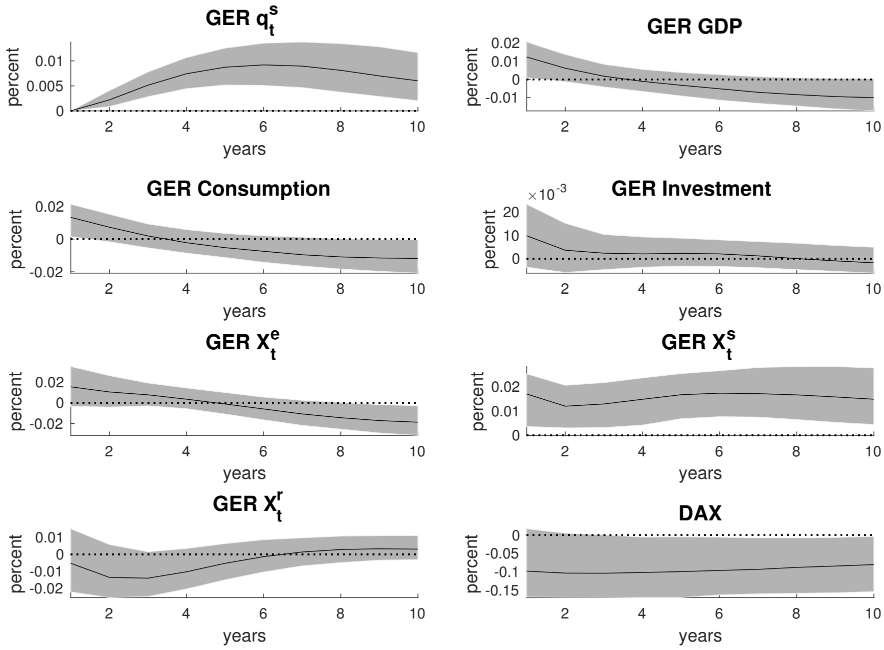
P.3 IRF q_{st} News Shock

Figure P.6: Spain IRF q_{st} news shock; alternative VAR



Note: Median responses to a news shock on relative price of business structures investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure P.7: Germany IRF q_{st} news shock;alternative VAR



Note: Median responses to a news shock on relative price of business structures investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

P.4 FEV q_{st} News Shock

Figure P.8: Spain - Forecast Error Variance (FEV) - q_{st} news shock; alternative VAR

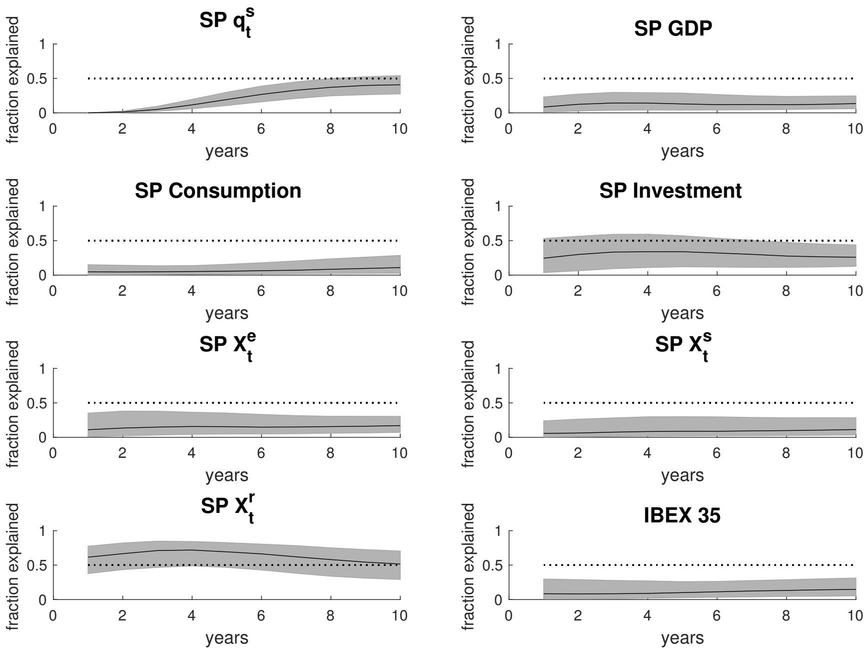


Table P.2: Spain - Maximum Forecast Error Variance (FEV) - q_{st} news shock; alternative VAR

Spain	q_{st}	GDP_t	C_t	I_t	X_e	X_s	X_r	IBEX 35
Median contribution	0.41	0.14	0.11	0.34	0.17	0.11	0.72	0.15
Year	10	3	10	5	10	10	4	10

Figure P.9: GERMANY - Forecast Error Variance (FEV) - q_{st} news shock; alternative VAR

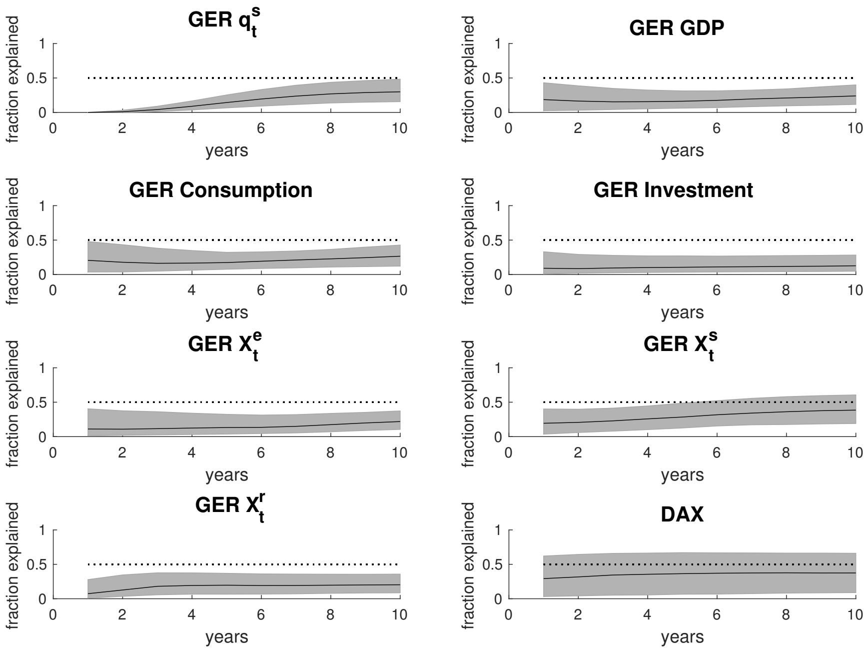
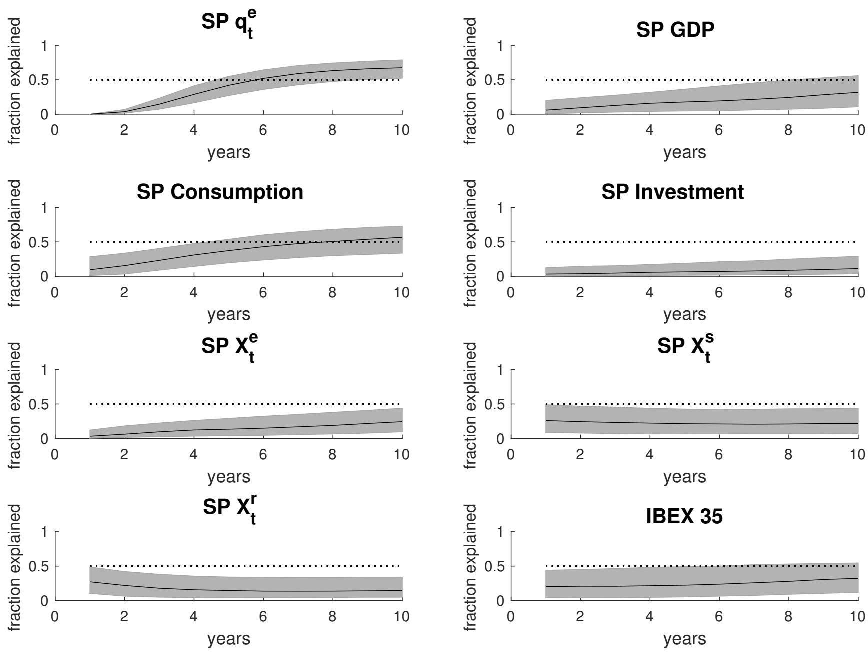


Table P.3: GERMANY - Maximum Forecast Error Variance (FEV) - q_{st} news shock; alternative VAR

Germany	q_{st}	GDP_t	C_t	I_t	X_e	X_s	X_r	DAX
Median contribution	0.30	0.24	0.27	0.13	0.22	0.38	0.20	0.38
Year	10	10	10	10	10	10	10	8

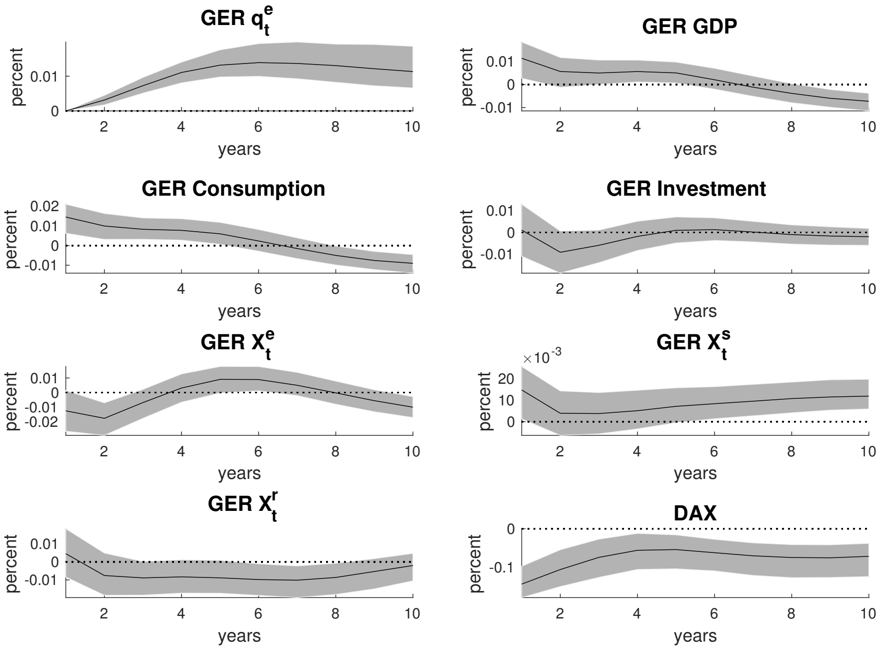
P.5 IRF q_{et} News Shock

Figure P.10: Spain IRF- q_{et} news shock; alternative VAR



Note: Median responses to a news shock on relative price of equipment investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure P.11: Germany IRF - q_{et} news shock; alternative VAR



Note: Median responses to a news shock on relative price of equipment investment (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

P.6 FEV q_{et} News Shock

Figure P.12: Spain FEV - q_{et} news shock - alternative VAR

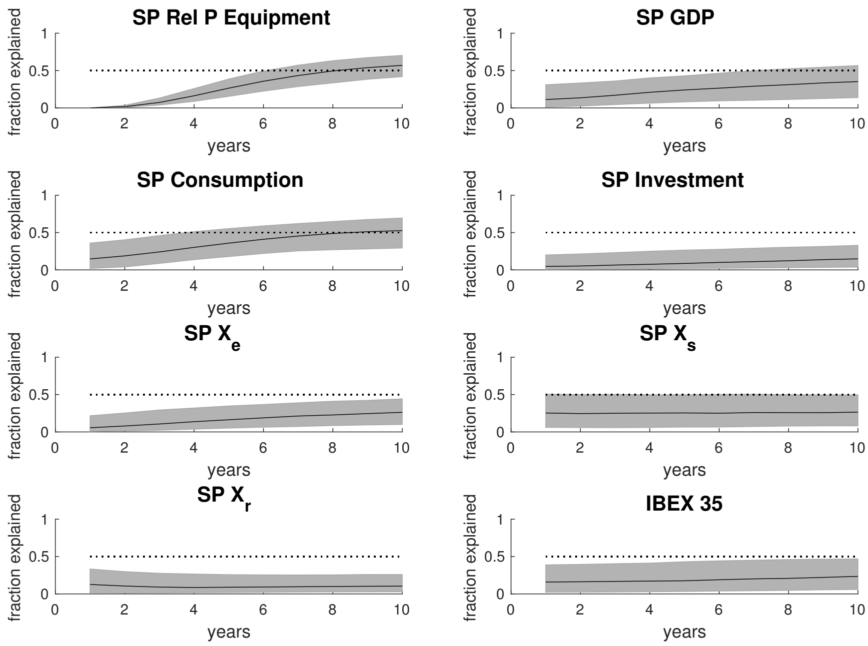


Table P.4: Spain - Maximum Forecast Error Variance (FEV) - q_{et} news shock; alternative VAR

Spain	q_{et}	GDP_t	C_t	I_t	X_e	X_s	X_r	IBEX 35
Median contribution	0.67	0.32	0.57	0.11	0.24	0.26	0.27	0.32
Year	10	10	10	10	10	1	1	10

Figure P.13: Germany FEV - q_{et} news shock; alternative VAR

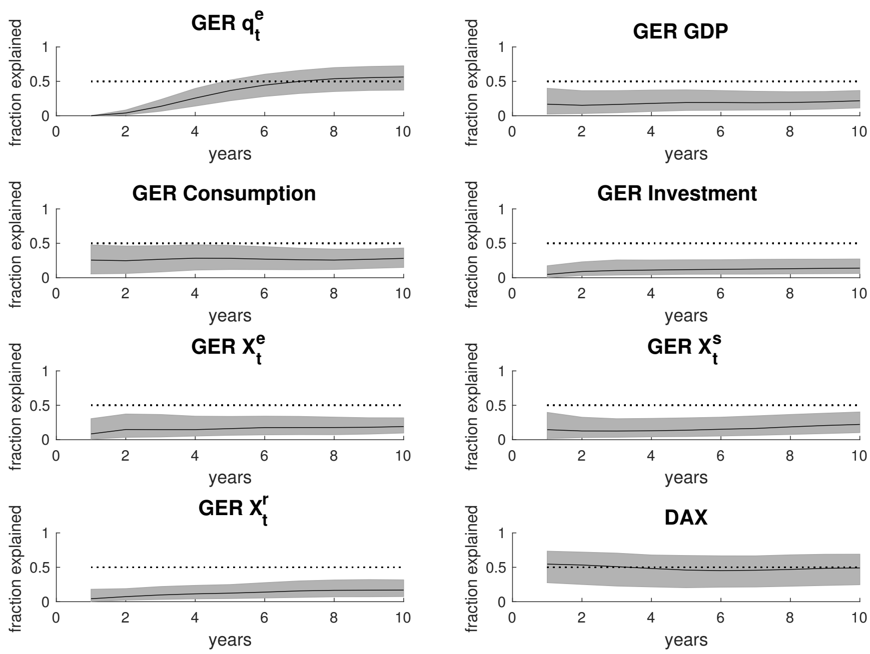


Table P.5: Germany - Maximum Forecast Error Variance (FEV) - q_{et} news shock; alternative VAR

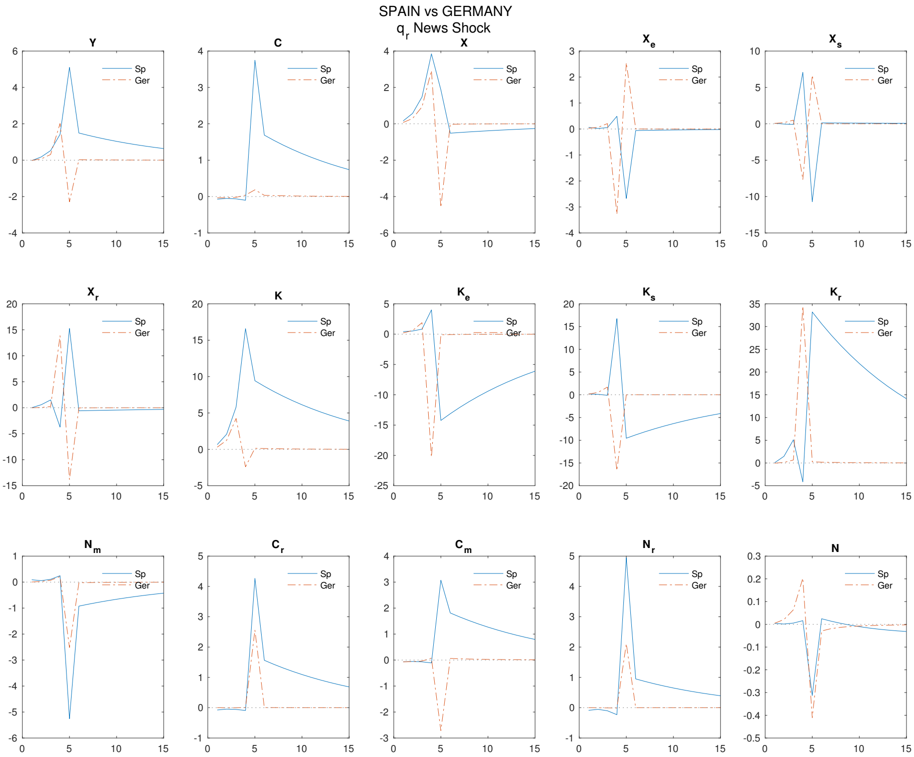
Germany	q_{et}	GDP_t	C_t	I_t	X_e	X_s	X_r	DAX
Median contribution	0.56	0.22	0.28	0.14	0.19	0.22	0.17	0.55
Year	10	10	4	10	10	10	10	1

Appendix Q

Theoretical Model Simulation

Q.1 q_{rt} News Shock Effects

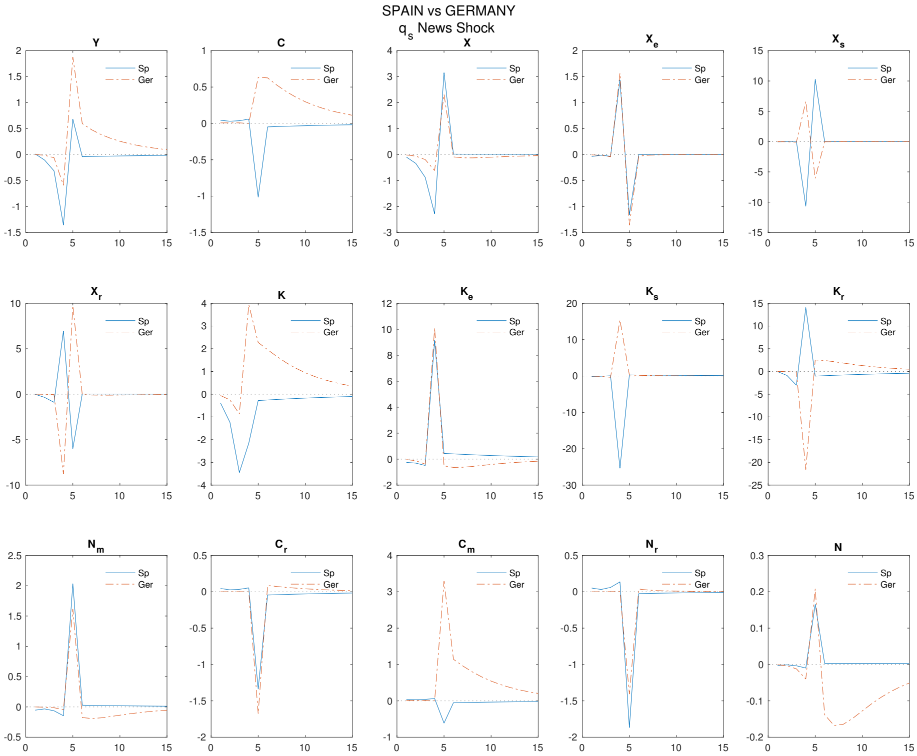
Figure Q.1: q_{rt} news shock effects on all model's variables



Note: Figure Q.1 shows the overall IRFs of model's variables following a news shock on the relative prices of residential investment increases of 1%.

Q.2 q_{st} News Shock Effects

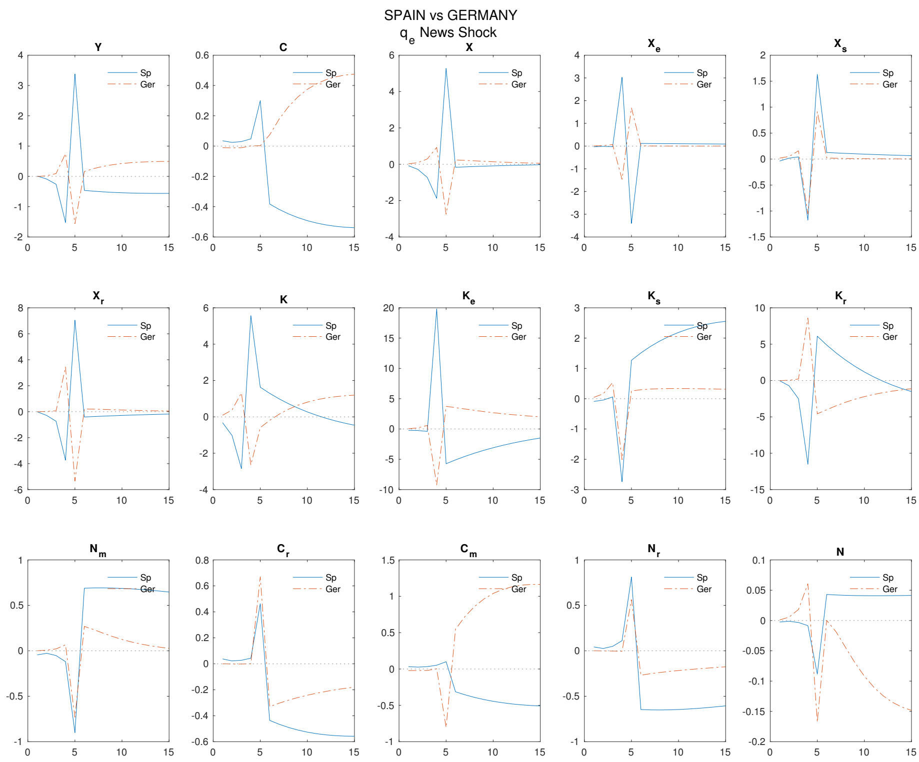
Figure Q.2: q_{st} news shock effects on all model's variables



Note: Figure Q.2 shows the overall IRFs of model's variables following a news shock on the relative prices of business structures increases of 1%.

Q.3 q_{et} News Shock Effects

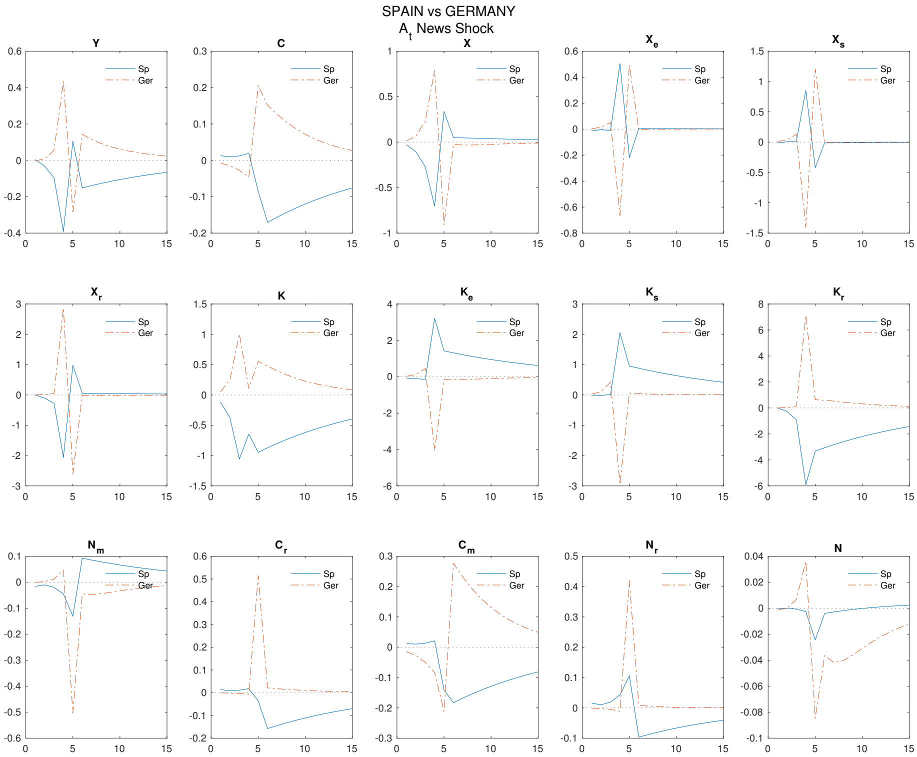
Figure Q.3: q_{et} news shock effects on all model's variables



Note: Figure Q.3 shows the overall IRFs of model's variables following a news shock on the relative prices of equipment investment decreases of 1%.

Q.4 A_t News Shock Effects

Figure Q.4: A_t News Shock



Note: Figure Q.4 shows the IRFs model variables following a news shock on the home production TFP of a magnitude of 1%

Appendix R

Theoretical Two-sector Model

R.1 Environment Two-sector Model

The model uses the class of preferences proposed by Jaimovich and Rebelo (2009) that have the ability to parameterize the strength of the short-run wealth effect on the labor supply. These preferences nest the two classes of utility functions: those characterized in King et al. (1988) - (when parameter $\gamma = 1$) - and in Greenwood et al. (1988) ($\gamma = 0$)

Characteristics:

- Introduce a weak short-run wealth effect on the labor supply.
- It helps to generate a rise in hours worked in response to positive news.

$$U(C_t, N_t, \chi_t) = \frac{\left(C_t - \psi N_t^{\theta} \chi_t\right)^{1-\sigma} - 1}{1-\sigma} \tag{R.1}$$

where

$$\chi_t = C_t^{\gamma} \chi_{t-1}^{1-\gamma} \tag{R.2}$$

The presence of χ_t makes preferences non-time-separable in consumption and hours worked.

$$N_t = N_{m,t} + N_{r,t} \tag{R.3}$$

I introduce the home production

$$C_t = (\omega C_{m,t}^{\eta} + (1-\omega)C_{r,t}^{\eta})^{1/\eta} \tag{R.4}$$

$C_{m,t}$ is market consumption

$$C_{r,t} = A_{r,t} K_{r,t}^{1-\theta_h} N_{r,t}^{\theta_r} \tag{R.5}$$

is home production.

R.2 Utility Function

$$U(C_{m,t}, C_{r,t}, N_{m,t}, N_{r,t}, \chi_t) = \frac{\left(\left(\omega C_{m,t}^{\eta} + (1-\omega)C_{r,t}^{\eta}\right)^{1/\eta} - \psi(N_{m,t}+N_{r,t})^{\theta_n}\chi_t\right)^{1-\sigma} - 1}{1-\sigma} \tag{R.6}$$

the household budget constraint is

$$\begin{aligned} &C_{mt} + q_{e,t}K_{e,t+1} + q_{s,t}K_{s,t+1} + q_{r,t}K_{r,t+1} \\ &= W_t N_{m,t} + r_{e,t}K_{e,t} + r_{s,t}K_{s,t} + q_{e,t}(1-\delta_e)K_{e,t} + q_{s,t}(1-\delta_s)K_{s,t} + q_{r,t}(1-\delta_r)K_{r,t} \end{aligned} \tag{R.7}$$

R.3 Household's Problem

$$\max_{C_t, N_t, \chi_t} \sum_{t=0}^{\infty} \beta^t U\Big(U(C_{m,t}, C_{r,t}, N_{m,t}, N_{r,t}, \chi_t)\Big) \tag{R.8}$$

s. t.

$$\begin{aligned} &C_{mt} + q_{e,t}K_{e,t+1} + q_{s,t}K_{s,t+1} + q_{r,t}K_{r,t+1} \\ &= W_t N_{m,t} + r_{e,t}K_{e,t} + r_{s,t}K_{s,t} + q_{e,t}(1-\delta_e)K_{e,t} + q_{s,t}(1-\delta_s)K_{s,t} + q_{r,t}(1-\delta_h)K_{r,t} \end{aligned}$$

$$\chi_t = C_t^{\gamma}\chi_{t-1}^{1-\gamma},$$
$$C_t = \left(\omega C_{m,t}^{\eta} + (1-\omega)C_{r,t}^{\eta}\right)^{1/\eta},$$
$$C_{rt} = A_t K_{r,t}^{1-\theta_r} N_{r,t}^{\theta_r},$$

$$Y_t = Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s} N_{m,t}^{1-\alpha_e-\alpha_s},$$
$$Y_t = C_t + q_{e,t}X_{e,t} + q_{s,t}X_{s,t} + q_{r,t}X_{r,t},$$
$$X_t = X_{e,t} + X_{s,t} + X_{r,t},$$

$$K_{e,t+1} = \Theta_{e,t}X_{e,t} + (1-\delta_e)K_{e,t},$$
$$K_{s,t+1} = \Theta_{s,t}X_{s,t} + (1-\delta_s)K_{s,t},$$
$$K_{r,t+1} = \Theta_{r,t}X_{r,t} + (1-\delta_r)K_{r,t},$$

$$q_{e,t} = 1/\Theta_{e,t}$$
$$q_{s,t} = 1/\Theta_{s,t}$$
$$q_{h,t} = 1/\Theta_{h,t}$$

$$ln\ Z_t = (1-\rho_Z)ln\bar{Z} + \rho_Z ln\ Z_{t-1} + \varepsilon_t^Z,$$
$$ln\ A_t = (1-\rho_A)ln\bar{A} + \rho_A ln\ A_{t-1} + \varepsilon_t^A,$$
$$ln\ q_{e,t} = (1-\rho_{q_e})ln\bar{q_e} + \rho_{q_e} ln\ q_{e,t-1} + \varepsilon_t^{q_e},$$
$$ln\ q_{s,t} = (1-\rho_{q_s})ln\bar{q_s} + \rho_{q_s} ln\ q_{s,t-1} + \varepsilon_t^{q_s},$$
$$ln\ q_{r,t} = (1-\rho_{q_r})ln\bar{q_r} + \rho_{q_r} ln\ q_{r,t-1} + \varepsilon_t^{q_r} + \varepsilon_{t-1}^{news},$$

R.4 Household's Maximization Problem

R.4.1 Langrangian Function

$$\max_{C_t,N_t,K_{r,t+1},K_{e,t+1},K_{s,t+1},\chi_t} \mathcal{L}:$$

$$\sum_{t=0}^{\infty}\beta^t\Bigg\{\Bigg[\frac{\Big((\omega C_{m,t}^{\eta}+(1-\omega)C_{h,t}^{\eta})^{1/\eta}-\psi(N_{m,t}+N_{r,t})^{\theta_n}X_t\Big)^{1-\sigma}-1}{1-\sigma}\Bigg]$$
$$-\lambda_t\Big(C_{m,t}+q_{e,t}K_{e,t+1}+q_{s,t}K_{s,t+1}+q_{r,t}K_{r,t+1}$$
$$-w_tN_{m,t}-(r_{e,t}+q_{e,t}(1-\delta_e))K_{e,t}-(r_{s,t}+q_{s,t}(1-\delta_s))K_{s,t}-q_{r,t}(1-\delta_r)K_{r,t}\Big)$$
$$-\mu_t\Big(\chi_t-(\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{\frac{\gamma}{\eta}}\chi_{t-1}^{1-\gamma}\Big)-\xi_t\Big(C_{rt}-A_tK_{r,t}^{1-\theta_r}N_{r,t}^{\theta_r}\Big)\Bigg\} \quad \text{(R.9)}$$

R.4.2 FOC

$$\frac{\partial\mathcal{L}}{\partial C_{m,t}}:\Big((\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{1/\eta}-\psi(N_{m,t}+N_{r,t})^{\theta_n}\chi_t\Big)^{-\sigma}\omega C_{m,t}^{\eta-1}(\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{1/\eta-1}$$
$$+\mu_t\Big(\gamma\omega C_{m,t}^{\eta-1}(\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{\gamma/\eta-1}\chi_{t-1}^{1-\gamma}\Big)=\lambda_t \quad \text{(R.10)}$$

$$\frac{\partial\mathcal{L}}{\partial C_{r,t}}:\Big((\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{1/\eta}-\psi(N_{m,t}+N_{r,t})^{\theta_n}\chi_t\Big)^{-\sigma}(1-\omega)C_{r,t}^{\eta-1}(\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{1/\eta-1}$$
$$+\mu_t\Big(\gamma(1-\omega)C_{r,t}^{\eta-1}(\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{\gamma/\eta-1}\chi_{t-1}^{1-\gamma}\Big)=\xi_t \quad \text{(R.11)}$$

$$\frac{\partial\mathcal{L}}{\partial N_{m,t}}:\Big((\omega C_{m,t}^{\eta}+(1-\omega)C_{r,t}^{\eta})^{1/\eta}-\psi(N_{m,t}+N_{r,t})^{\theta_n}\chi_t\Big)^{-\sigma}\psi\theta_n(N_{m,t}+N_{r,t})^{\theta_n-1}\chi_t=\lambda_tw_t \quad \text{(R.12)}$$

$$\frac{\partial \mathcal{L}}{\partial N_{r,t}} : \left((\omega C_{m,t}^{\eta} + (1-\omega) C_{r,t}^{\eta})^{1/\eta} - \psi (N_{m,t} + N_{r,t})^{\theta_n} \chi_t \right)^{-\sigma} \psi \theta_n (N_{m,t} + N_{r,t})^{\theta_n - 1} \chi_t$$
$$= \xi_t (\theta_r A_t K_{r,t}^{1-\theta_r} N_{r.t}^{\theta_r - 1}) \quad \text{(R.13)}$$

$$\frac{\partial \mathcal{L}}{\partial \chi_t} : \left((\omega C_{m,t}^{\eta} + (1-\omega) C_{r,t}^{\eta})^{1/\eta} - \psi (N_{m,t} + N_{r,t})^{\theta_n} \chi_t \right)^{-\sigma} \psi (N_{m,t} + N_{r,t})^{\theta_n} + \mu_t =$$
$$E_t \left[\mu_{t+1} \beta \left((1-\gamma)(\omega C_{m,t+1}^{\eta} + (1-\omega) C_{r,t+1}^{\eta})^{\gamma/\eta} \chi_t^{-\gamma} \right) \right] \quad \text{(R.14)}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_t} : C_{m,t} + q_{e,t} K_{e,t+1} + q_{s,t} K_{s,t+1} + q_{r,t} K_{r,t+1}$$
$$= w_t N_{m,t} + r_{e,t} K_{e,t} + r_{s,t} K_{s,t} + q_{e,t}(1-\delta_e) K_{e,t} + q_{s,t}(1-\delta_s) K_{s,t} + q_{r,t}(1-\delta_r) K_{r,t} \quad \text{(R.15)}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_t} : \chi_t = (\omega C_{m,t}^{\eta} + (1-\omega) C_{r,t}^{\eta})^{\frac{\gamma}{\eta}} \chi_{t-1}^{1-\gamma} \quad \text{(R.16)}$$

$$\frac{\partial \mathcal{L}}{\partial \xi_t} : C_{rt} = A_t K_{r,t}^{1-\theta_h} N_{r,t}^{\theta_r} \quad \text{(R.17)}$$

$$\frac{\partial \mathcal{L}}{\partial K_{e,t+1}} : \lambda_t = \beta E_t \left[\lambda_{t+1} \frac{r_{e,t+1} + q_{e,t+1}(1-\delta_e)}{q_{e,t}} \right] \quad \text{(R.18)}$$

$$\frac{\partial \mathcal{L}}{\partial K_{s,t+1}} : \lambda_t = \beta E_t \left[\lambda_{t+1} \frac{r_{s,t+1} + q_{s,t+1}(1-\delta_s)}{q_{s,t}} \right] \quad \text{(R.19)}$$

$$\frac{\partial \mathcal{L}}{\partial K_{r,t+1}} : \lambda_t = \beta E_t \left[\lambda_{t+1} \frac{q_{r,t+1}(1-\delta_r)}{q_{r,t}} + \xi_{t+1} \frac{(1-\theta_r) A_{t+1} K_{r,t+1}^{-\theta_r} N_{r,t+1}^{\theta_r}}{q_{r,t}} \right] \quad \text{(R.20)}$$

R.5 Stochastic Shocks

$$ln\ Z_t = (1 - \rho_Z) ln\bar{Z} + \rho_Z ln\ Z_{t-1} + \varepsilon_t^Z \tag{R.21}$$

$$ln\ A_t = (1 - \rho_A) ln\bar{A} + \rho_A ln\ A_{t-1} + \varepsilon_t^A \tag{R.22}$$

$$ln\ q_{e,t} = \rho_{q_e} ln\ q_{e,t-1} + \varepsilon_t^{q_e} \tag{R.23}$$

$$ln\ q_{s,t} = \rho_{q_s} ln\ q_{s,t-1} + \varepsilon_t^{q_s} \tag{R.24}$$

$$ln\ q_{r,t} = \rho_{q_r} ln\ q_{r,t-1} + \varepsilon_t^{q_r} + \varepsilon_{t-4}^{news} \tag{R.25}$$

R.6 Firm's Problem

Firm Producing Final Good

$$\max_{K_{e,t},K_{s,t},N_t} \Pi_t = Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s} N_t^{1-\alpha_e-\alpha_s} - r_{e,t}K_{e,t} - r_{s,t}K_{s,t} - w_t N_{m,t}. \quad \text{(R.26)}$$

R.6.1 FOC

$$\frac{\partial \Pi_t}{\partial K_{e,t}} : \alpha_e Z_t K_{e,t}^{\alpha_e-1} K_{s,t}^{\alpha_s} N_{m,t}^{1-\alpha_e-\alpha_s} = r_{e,t} \quad \text{(R.27)}$$

$$\frac{\partial \Pi_t}{\partial K_{s,t}} : \alpha_s Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s-1} N_{m,t}^{1-\alpha_e-\alpha_s} = r_{s,t} \quad \text{(R.28)}$$

$$\frac{\partial \Pi_t}{\partial N_t} : (1-\alpha_e-\alpha_s) Z_t K_{e,t}^{\alpha_e-1} K_{s,t}^{\alpha_s} N_{m,t}^{-\alpha_e-\alpha_s} = w_t \quad \text{(R.29)}$$

Appendix S

Alternative Theoretical Two-sector Model

S.1 Environment Two-sector Model

There is a continuum of households indexed by $j \in (0,1)$. Each household consumes, supplies labour, makes investment and capital utilization decisions. Preferences of households are defined over stochastic processes for total consumption C_t and worked hours L_t as follows:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(C_t, L_t), \tag{S.1}$$

where the utility function is:

$$u(C_t, L_t) = \gamma ln(C_t) + (1-\gamma) ln(1-L_t) \tag{S.2}$$

The total consumption, C_t, is a composite consumption of market goods and services, $C_{m,t}$, and nonmarket consumption, $C_{h,t}$, that must be produced at home, and the total available time endowment of the economy is normalized to 1. Each household supplies labour to labour market, $L_{m,t}$, and to home production, $L_{h,t}$. Henceforth, leisure is defined as $1 - L_{m,t} - L_{h,t}$.

It is assumed that total consumption is given by a CES function such as:

$$C_t = \left(\omega C_{m,t}^{\eta} + (1-\omega)C_{h,t}^{\eta}\right)^{1/\eta} \tag{S.3}$$

η is the parameter measuring the willingness of agents to substitute between the two goods, and ω is the proportion of each good in the total consumption.

The parameter η is key for the relationship between home production activities and market activities since the elasticity of substitution between market goods and home production goods is defined as $\epsilon = 1/(1-\eta)$. If η is equal to 1, the two goods are perfect substitutes, and if $\eta = 0$, total consumption is a Cobb-Douglas function of both goods so they are complements.

Therefore, we write the utility function as

$$U(C_{m,t}, C_{h,t}, L_{m,t}, L_{h,t}) = \left[\gamma ln\left(\omega C_{m,t}^{\eta} + (1-\omega)C_{h,t}^{\eta}\right)^{1/\eta} + (1-\gamma)ln(1 - L_{m,t} - L_{h,t})\right] \tag{S.4}$$

The household maximizes utility subject to several constraints. First, it owns the total capital, K_t, divided between capital used to produce market goods and services and nonmarket capital.

$$K_t = K_{m,t} + K_{h,t}, \text{ where } K_{m,t} = K_{e,t} + K_{s,t} \tag{S.5}$$

The capital for market goods and services $K_{m,t}$ is split between equipment, K_e, and business structures, K_s, while the nonmarket capital are residential structures, $K_{h,t}$. The household combines nonmarket capital with hours to produce the nonmarket good according to the home production function:

$$C_{h,t} = A_t K_{h,t+1}^{\theta} L_{h,t}^{1-\theta} \tag{S.6}$$

The constrain says that home consumption must be produced at home and cannot be bought or sold on the market.

The household's capital stock evolves according to the law of motion

$$K_{i,t+1} = X_{i,t} + (1-\delta_i)K_{i,t}, \ i = e, s, h, \text{ for all } t \tag{S.7}$$

$$\max_{C_t,L_m,L_h,I_t} \sum_{t=0}^{\infty} \beta^t \left[\gamma ln\left(\omega C_{m,t}^{\eta} + (1-\omega)C_{h,t}^{\eta}\right)^{1/\eta} + (1-\gamma)ln(1-L_{m,t}-L_{h,t})\right] \tag{S.8}$$

$$\begin{aligned}
\text{s.t. } & C_{m,t} + I_t + B_{t+1} = W_t L_{m,t} + R_{k,t}K_t + (1+R_{b,t})B_t, \\
& C_{h,t} = A_t K_{h,t+1}^{\theta} L_{h,t}^{1-\theta}, \\
& Y = Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s} L_t^{1-\alpha_e-\alpha_s}, \\
& I_t = I_{e,t} + I_{s,t} + I_{h,t}, \\
& K_t = K_{e,t} + K_{s,t} + K_{h,t}, \\
& K_{e,t+1} = X_{e,t} + (1-\delta_e)K_{e,t},, \\
& K_{s,t+1} = X_{s,t} + (1-\delta_s)K_{s,t}, \\
& K_{h,t+1} = X_{h,t} + (1-\delta_h)K_{h,t}, \\
& b_{t+1} \geq -\underline{\text{b}}, \\
& k_{j0},\ j = e, s, h, \text{ and } a_0 \text{ given,}
\end{aligned}$$

S.2 Household Productivity, A_t, News Shock

Agents are hit by news in $t-2$ that lead to change in expectations about future housing sector productivity, A_t, that could be interpreted as a shift in preferences for houses.

If we analyze the aggregate variables, output, investment, and consumption, the "news shock" has the features of an aggregate demand shock:

- In period t in Spain it increases output due to increase in investment, with no effects on aggregate consumption
- In period t_2 Spanish output and investment keep increasing
- In period t_3 are returning to the steady state.
- **Mild negative effects in long run** for the Spanish economy with output and investment below steady state.

- In period t in Germany the output increase is stronger than the Spanish one, but is followed by an important fall in second period

- The strong increase in investment in first and second period is contra balance the fall in aggregate consumption

- From period t_3 on, the Germany output, investment and consumption are higher than the steady state.

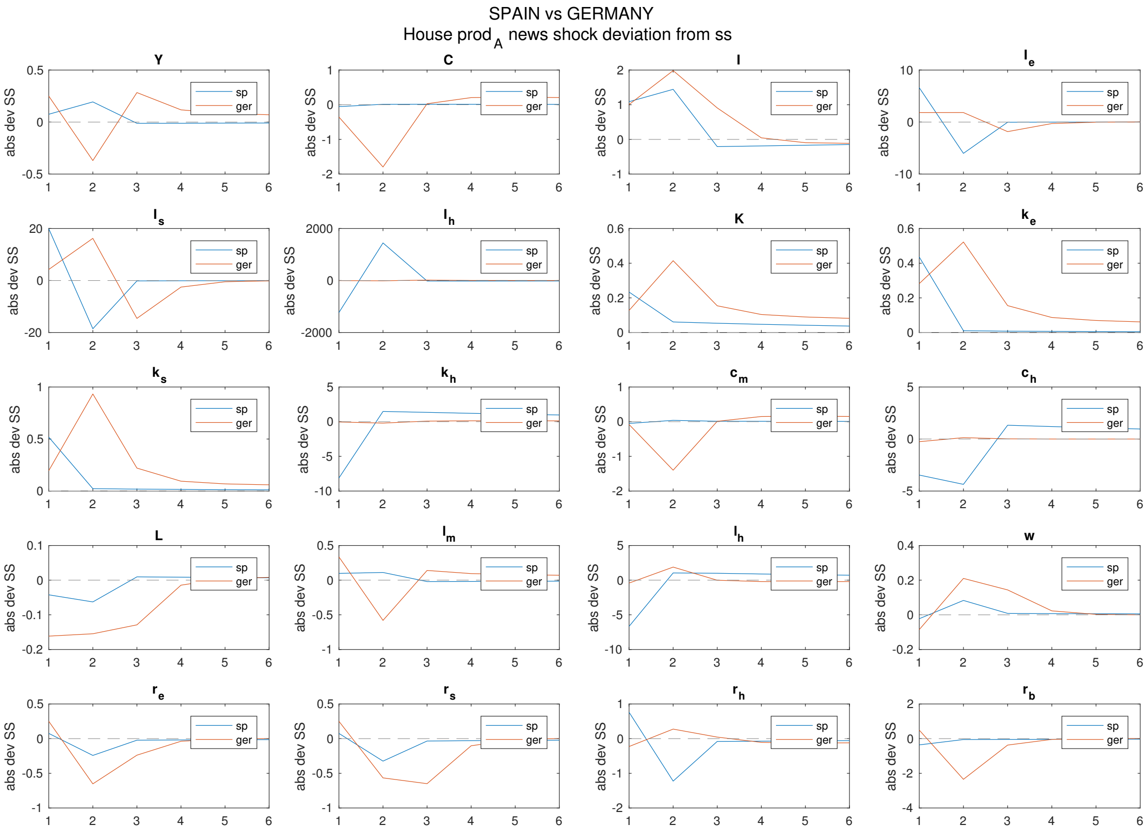
- **Positive effects in long run** for the German economy with output, investment and aggregate consumption higher than the steady state.

- **No effects in long run** for output, aggregate investment and consumption for the Spanish and German economy

Table S.1: Calibrated parameters - I

Parameters	γ	ω	η	α_e	α_s	θ
SPAIN	0.39	0.89	0.801	0.13	0.10	0.48
GERMANY	0.6	0.67	0.323	0.1422	0.1126	0.38

Figure S.1: A_t news shock (household productivity)



S.2.1 A_t News Shock Effects on Housing, Structures and Equipment

The model key feature is that it permit to capture the differences of investment's decisions of the Spanish and German households when news shocks hits.

In this section we describe the paths around the steady state for investment and capital accumulation looking at equipment, structures and housing individually. We report first the investment's effects and compare them between the two economies when agents are hit by news in $t-2$ that lead to change in expectations about future housing sector productivity, and discuss theirs implications.

- In period t, at the shock impact, in Spain we observe an increase in equipment and structures investment and a strong fall housing investment.

- In contrast, in period t_2 the model's response is completely changed: a strong increase in housing investment for 2 periods that is much higher than the previous fall, and also a decrease much more accentuated and persistent than the initial gain in equipment and structures investment.

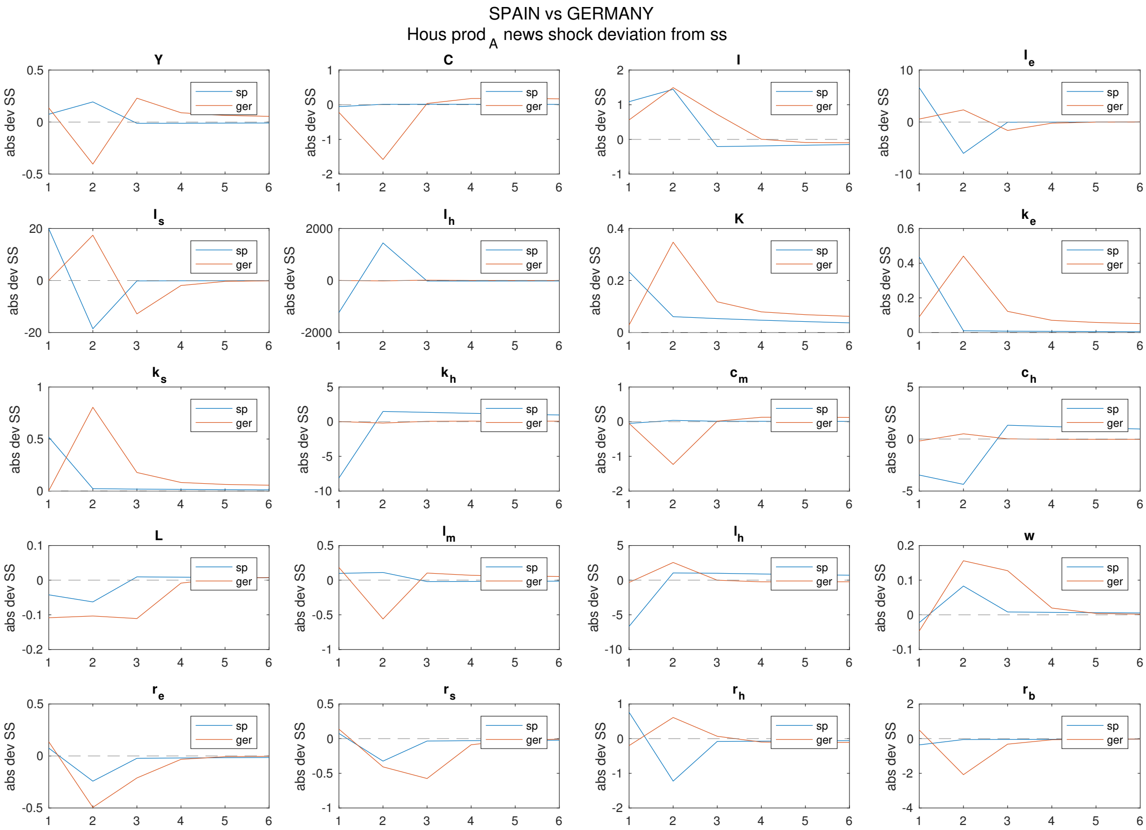
- For the German economy, there is little positive response on impact for equipment and structures investment, while housing is not at all affected at any horizon.

- While the increase in equipment investment is positive up to third period, the structures investment is very strong in the second followed by a persistent fall.

Table S.2: Calibrated parameters - I

Parameters	γ	ω	η	α_e	α_s	θ
SPAIN	0.39	0.89	0.801	0.13	0.10	0.48
GERMANY	0.6	0.67	0.323	0.1422	0.1126	0.414

Figure S.2: A_t news shock effects on investment cateories



Once again there are big differences between the two economies: there is an evident shift in investment as a news shock hits household preferences. For the German economy it has no effects on housing investment, while it increases investment in structures and equipment. In contrast, the model predicts positive gains in housing investment for Spain, with negative investment in structures and equipment.

The capital accumulation response of the model due to a news shock in the household preferences favors a steady housing accumulation in Spain, and a strong and persistent accumulation in structures and equipment in Germany.

S.3 q_h News Shock

Agents are hit by news in $t-2$ that lead to changes in the houses prices expectations.

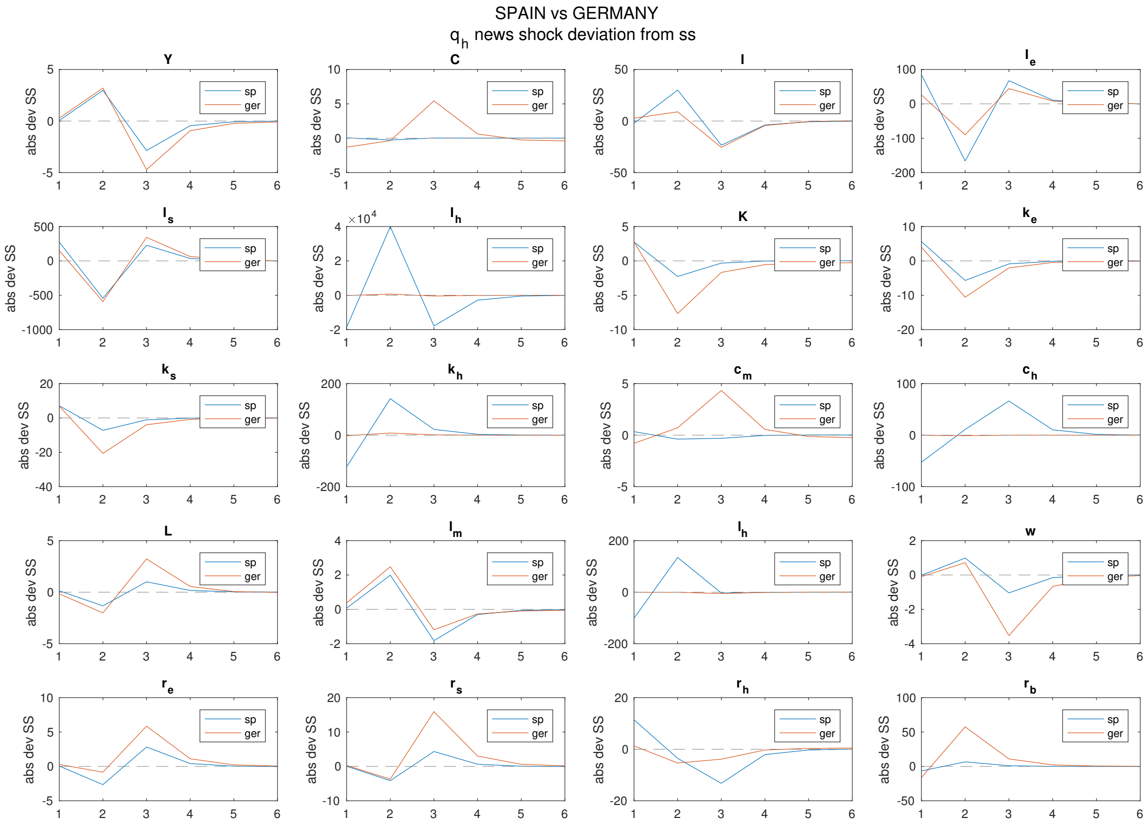
The effects on output, and aggregate investment, in both countries are similar:

- Practically no effects in t in output and investment
- In period t_2 output and investment increase in both countries, with stronger effects on Spanish investment.
- In period t_3 fall in output and investment in both countries, but with lower fall for the Spanish output
- From period t_5 output and investment in both countries are back to steady state values.
- While there are no important effects over the aggregate consumption in Spain, in Germany after small fall in the first period, there is an increase from period 2 to 4 when is back to steady state values.

Table S.3: Calibrated parameters - II

Parameters	γ	ω	η	α_e	α_s	θ
SPAIN	0.39	0.89	0.801	0.13	0.10	0.48
GERMANY	0.6	0.67	0.323	0.1422	0.1126	0.38

Figure S.3: IST q_h news shock effects on aggregate variables



S.3.1 q_h News Shock Effects on Housing, Structures and Equipment

In this section we describe the fluctuations around the steady state for investment and capital accumulation looking at equipment, structures and housing when agents are hit by news shocks in $t-2$ that lead to change in expectations about IST, q_h, and discuss theirs implications. We report the investment and capital accumulation effects and compare them between the two economies:

- The news shock has the same effect for both economies in equipment and structures investment: increase on impact followed by a fall in the second period and and mild persistent increase in the third period.

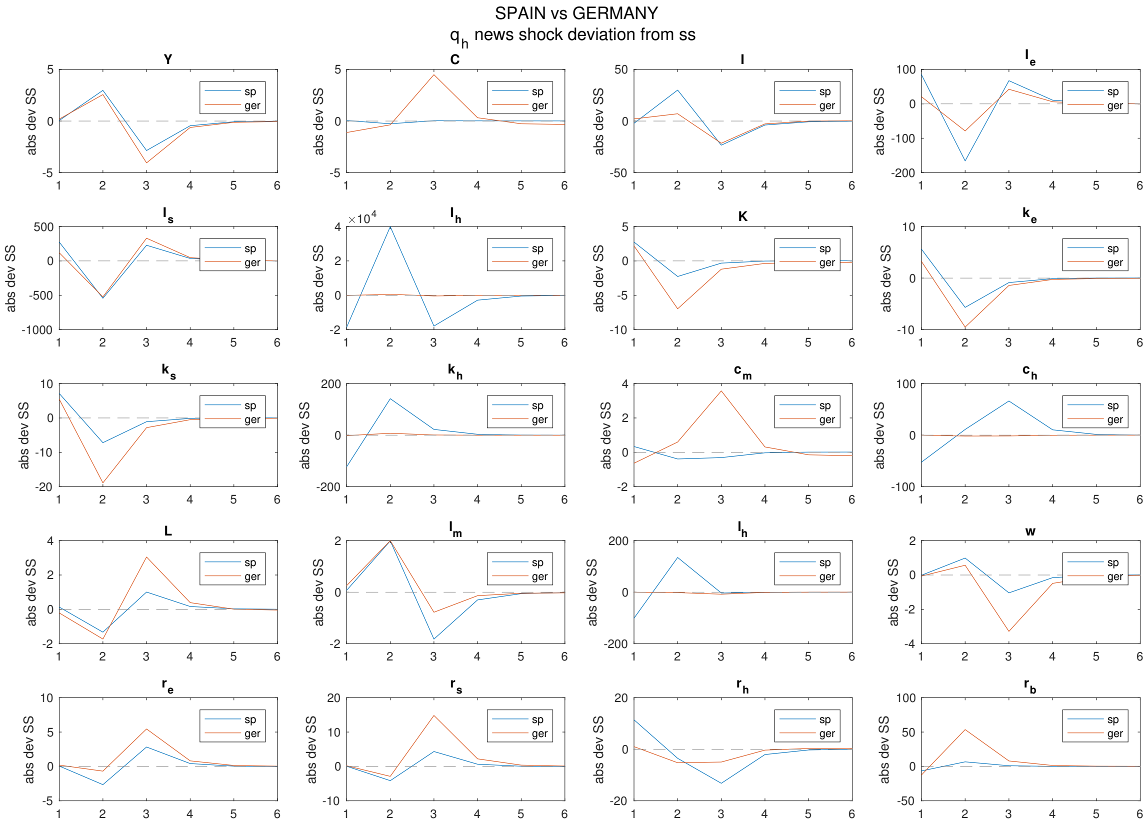
- The differences are very evident for housing investment; while there is no effect for the German housing investment, for the Spanish economy there is an important increase in the second period, followed by a mild fall in the third period.

- The effects on capital accumulation is positive for the Spanish housing capital, while for Germany, an q_h news shock has negative capital accumulations effects.

Table S.4: Calibrated parameters - I

Parameters	γ	ω	η	α_e	α_s	θ
SPAIN	0.39	0.89	0.801	0.13	0.10	0.48
GERMANY	0.6	0.67	0.323	0.1422	0.1126	0.414

Figure S.4: IST q_h news shock effects on investment cateories



The model predict a null effect of news shock on q_h on both economies when we analyze investment and capital accumulation in structures and equipment. In terms of housing investment, while for the German economy the news shock has no effects, the model predicts strong gains in housing investment capital accumulation n the residential sector for Spanish economy.

S.4 Household's Maximization Problem

$$\max_{C_t, L_m, L_h, I_t} \sum_{t=0}^{\infty} \beta^t \left[\gamma ln \left(\omega C_{m,t}^{\eta} + (1-\omega) C_{h,t}^{\eta} \right)^{1/\eta} + (1-\gamma) ln(1 - L_{m,t} - L_{h,t}) \right] \tag{S.9}$$

$$\begin{aligned}
\text{s.t. } & C_{m,t} + I_t + B_{t+1} = W_t L_{m,t} + R_{k,t} K_t + (1 + R_{b,t}) B_t, \\
& C_{h,t} = A_t K^{\theta}_{h,t+1} L^{1-\theta}_{h,t}, \\
& Y = Z_t K^{\alpha_e}_{e,t} K^{\alpha_s}_{s,t} L^{1-\alpha_e-\alpha_s}_t, \\
& I_t = I_{e,t} + I_{s,t} + I_{h,t}, \\
& K_t = K_{e,t} + K_{s,t} + K_{h,t}, \\
& K_{e,t+1} = X_{e,t} + (1 - \delta_e) K_{e,t},, \\
& K_{s,t+1} = X_{s,t} + (1 - \delta_s) K_{s,t}, \\
& K_{h,t+1} = X_{h,t} + (1 - \delta_h) K_{h,t}, \\
& b_{t+1} \geq -\underline{\text{b}}, \\
& k_{j0},\ j = e, s, h, \text{ and } a_0 \text{ given},
\end{aligned}$$

S.4.1 Langrangian Function

$$\begin{aligned}
\max_{C_t, L_m, L_h, I_t} \mathcal{L} : \sum_{t=0}^{\infty} \beta^t \Big[& \gamma ln \big(\omega c^{\eta}_{m,t} + (1-\omega) c^{\eta}_{h,t}\big)^{1/\eta} + (1-\gamma) ln(1 - l_{m,t} - l_{h,t}) \\
& - \lambda_t \big[c_{m,t} + q_{e,t} k_{e,t+1} + q_{s,t} k_{s,t+1} + q_{h,t} k_{h,t+1} + b_{t+1} \\
-w_{m,t} l_{m,t} - r_{e,t} k_{e,t} - r_{s,t} k_{s,t} - r_{h,t} k_{h,t} & - q_{e,t}(1-\delta_e) k_{e,t} - q_{s,t}(1-\delta_s) k_{s,t} - q_{h,t}(1-\delta_h) k_{h,t} - (1+r_{b,t}) b_t \big] \\
& - \xi_t [c_{h,t} - A_t k^{\theta}_{h,t+1} l^{1-\theta}_{h,t}] \Big]
\end{aligned} \tag{S.10}$$

S.4.2 FOC

$$\frac{\partial \mathcal{L}}{\partial c_{m,t}} : \frac{\gamma \omega c^{\eta-1}_{m,t}}{\big(\omega c^{\eta}_{m,t} + (1-\omega) c^{\eta}_{h,t}\big)} - \lambda_t = 0 \tag{S.11}$$

$$\frac{\partial \mathcal{L}}{\partial c_{h,t}} : \frac{\gamma (1-\omega) c^{\eta-1}_{h,t}}{\big(\omega c^{\eta}_{m,t} + (1-\omega) c^{\eta}_{h,t}\big)} - \xi_t = 0 \tag{S.12}$$

$$\frac{\partial \mathcal{L}}{\partial l_{m,t}} : -\frac{(1-\gamma)}{(1 - l_{m,t} - l_{h,t})} + \lambda_t w_{m,t} = 0 \tag{S.13}$$

$$\frac{\partial \mathcal{L}}{\partial l_{h,t}} : -\frac{(1-\gamma)}{(1 - l_{m,t} - l_{h,t})} + \xi_t \ \Big((1-\theta) A_t k^{\theta}_{h,t+1} l^{-\theta}_{h,t}\Big) = 0 \tag{S.14}$$

$$\frac{\partial \mathcal{L}}{\partial k_{e,t+1}} : -\lambda_t q_{e,t} + E_t\Big[\lambda_{t+1}\beta(r_{e,t+1} + q_{e,t+1}(1-\delta_e))\Big] = 0 \tag{S.15}$$

$$\frac{\partial \mathcal{L}}{\partial k_{s,t+1}} : -\lambda_t q_{s,t} + E_t\Big[\lambda_{t+1}\beta(r_{s,t+1} + q_{s,t+1}(1-\delta_s))\Big] = 0 \tag{S.16}$$

$$\frac{\partial \mathcal{L}}{\partial k_{h,t+1}} : -\lambda_t q_{h,t} + \xi_t \theta A_t k_{h,t+1}^{\theta-1} l_{h,t}^{1-\theta} + E_t\Big[\lambda_{t+1}\beta(r_{h,t+1} + q_{h,t+1}(1-\delta_h))\Big] = 0 \tag{S.17}$$

$$\frac{\partial \mathcal{L}}{\partial b_{t+1}} : -\lambda_t + E_t\left[\lambda_{t+1}\beta(1 + r_{b,t+1})\right] = 0 \tag{S.18}$$

S.5 Firm's Problem

S.5.1 Firm producing final good

$$\max_{K_{e,t},K_{s,t},L_t} \Pi_t = Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s} L_t^{1-\alpha_e-\alpha_s} - r_{e,t}K_{e,t} - r_{s,t}K_{s,t} - w_t L_t. \tag{S.19}$$

S.5.2 FOC

$$\frac{\partial \Pi_t}{\partial K_{e,t}} : \alpha_e Z_t K_{e,t}^{\alpha_e-1} K_{s,t}^{\alpha_s} L_t^{1-\alpha_e-\alpha_s} = r_{e,t} \tag{S.20}$$

$$\frac{\partial \Pi_t}{\partial K_{s,t}} : \alpha_s Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s-1} L_t^{1-\alpha_e-\alpha_s} = r_{s,t} \tag{S.21}$$

$$\frac{\partial \Pi_t}{\partial L_t} : (1-\alpha_e-\alpha_s) Z_t K_{e,t}^{\alpha_e-1} K_{s,t}^{\alpha_s} L_t^{-\alpha_e-\alpha_s} = w_t \tag{S.22}$$

S.5.3 Firms Producing Capital Goods

Firms producing equipment, structures, and housing goods are perfectly competitive and solve the problem:

$$\max_{X_{jt},I_{jt}} q_{jt}X_{jt} - I_{jt} \tag{S.23}$$

s.t. $0 \leq X_{jt} \leq \Theta_{jt}I_{jt}, \quad j = e, s, h.$

S.6 FOC

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta}\right)} = \lambda_t \tag{S.24}$$

$$\frac{\gamma(1-\omega)c_{h,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta}\right)} = \xi_t \tag{S.25}$$

$$\frac{(1-\gamma)}{\gamma(1-l_{m,t}-l_{h,t})} = \frac{\omega c_{m,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta}\right)} w_{m,t} \tag{S.26}$$

$$\frac{(1-\gamma)}{\gamma(1-l_{m,t}-l_{h,t})} = \frac{(1-\omega)c_{h,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta}\right)} \Big((1-\theta)A_t k_{h,t+1}^{\theta} l_{h,t}^{-\theta}\Big) \tag{S.27}$$

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta}\right)} q_{e,t} = E_t\Big[\beta \frac{\gamma\omega c_{m,t+1}^{\eta-1}}{\left(\omega c_{m,t+1}^{\eta} + (1-\omega)c_{h,t+1}^{\eta}\right)} (r_{e,t+1} + q_{e,t+1}(1-\delta_e))\Big] \tag{S.28}$$

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta}\right)} q_{s,t} = E_t\Big[\beta \frac{\gamma\omega c_{m,t+1}^{\eta-1}}{\left(\omega c_{m,t+1}^{\eta} + (1-\omega)c_{h,t+1}^{\eta}\right)} (r_{s,t+1} + q_{s,t+1}(1-\delta_s))\Big] \tag{S.29}$$

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta}+(1-\omega)c_{h,t}^{\eta}\right)}q_{h,t}+\frac{\gamma(1-\omega)c_{h,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta}+(1-\omega)c_{h,t}^{\eta}\right)}\theta A_t k_{h,t+1}^{\theta-1}l_{h,t}^{1-\theta}=$$
$$E_t\Big[\beta\frac{\gamma\omega c_{m,t+1}^{\eta-1}}{\left(\omega c_{m,t+1}^{\eta}+(1-\omega)c_{h,t+1}^{\eta}\right)}(r_{h,t+1}+q_{h,t+1}(1-\delta_h))\Big] \quad \text{(S.30)}$$

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{\left(\omega c_{m,t}^{\eta}+(1-\omega)c_{h,t}^{\eta}\right)}=E_t\left[\beta\frac{\gamma\omega c_{m,t+1}^{\eta-1}}{\left(\omega c_{m,t+1}^{\eta}+(1-\omega)c_{h,t}^{\eta}\right)}(1+r_{a,t+1})\right] \quad \text{(S.31)}$$

$$C=\omega c_{m,t}^{\eta}+(1-\omega)c_{h,t}^{\eta} \quad \text{(S.32)}$$

$$C_{h,t}=A_t K_{s,t+1}^{\theta}L_{h,t}^{1-\theta} \quad \text{(S.33)}$$

$$Y_t=Z_t K_{e,t}^{\alpha_e}K_{s,t}^{\alpha_s}L_t^{1-\alpha_e-\alpha_s} \quad \text{(S.34)}$$

$$r_{e,t}=\alpha_e Z_t K_{e,t}^{\alpha_e-1}K_{s,t}^{\alpha_s}L_t^{1-\alpha_e-\alpha_s} \quad \text{(S.35)}$$

$$r_{s,t}=\alpha_s Z_t K_{e,t}^{\alpha_e}K_{s,t}^{\alpha_s-1}L_t^{1-\alpha_e-\alpha_s} \quad \text{(S.36)}$$

$$r_{h,t}=\theta A_t K_{s,t+1}^{\theta-1}L_{h,t}^{1-\theta} \quad \text{(S.37)}$$

$$w_t=(1-\alpha_e-\alpha_s)Z_t K_{e,t}^{\alpha_e}K_{s,t}^{\alpha_s}L_t^{-\alpha_e-\alpha_s} \quad \text{(S.38)}$$

$$Y_t=c_t+I_{s,t}+I_{e,t}+I_{h,t} \quad \text{(S.39)}$$

$$I_{e,t}=q_{e,t}k_{e,t+1}-q_{e,t}(1-\delta_e)k_{e,t} \quad \text{(S.40)}$$

$$I_{s,t}=q_{s,t}k_{s,t+1}-q_{s,t}(1-\delta_s)k_{s,t} \quad \text{(S.41)}$$

$$I_{h,t} = q_{h,t}k_{h,t+1} - q_{h,t}(1-\delta_h)k_{h,t} \tag{S.42}$$

$$q_{e,t} = 1/\Theta_{e,t} \tag{S.43}$$

$$q_{s,t} = 1/\Theta_{s,t} \tag{S.44}$$

$$q_{h,t} = 1/\Theta_{h,t} \tag{S.45}$$

$$ln\ Z_t = (1-\rho_Z)ln\bar{Z} + \rho_Z ln\ Z_{t-1} + \varepsilon_t^Z + \varepsilon_{t-2}^Z \tag{S.46}$$

$$ln\ A_t = (1-\rho_A)ln\bar{A} + \rho_A ln\ A_{t-1} + \varepsilon_t^A + \varepsilon_{t-2}^A \tag{S.47}$$

$$ln\ q_{e,t} = \rho_{q_e} ln\ q_{e,t-1} + \varepsilon_t^{q_e} + \varepsilon_{t-2}^{q_e} \tag{S.48}$$

$$ln\ q_{s,t} = \rho_{q_s} ln\ q_{s,t-1} + \varepsilon_t^{q_s} + \varepsilon_{t-2}^{q_s} \tag{S.49}$$

$$ln\ q_{h,t} = \rho_{q_h} ln\ q_{h,t-1} + \varepsilon_t^{q_h} + \varepsilon_{t-2}^{q_h} \tag{S.50}$$

S.6.1 FOC Equations

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{C_t} = \lambda_t \tag{S.51}$$

$$\frac{\gamma(1-\omega)c_{h,t}^{\eta-1}}{C_t} = \xi_t \tag{S.52}$$

$$\frac{(1-\gamma)}{\gamma(1-l_{m,t}-l_{h,t})} = \frac{\omega c_{m,t}^{\eta-1}}{C_t} w_{m,t} \tag{S.53}$$

$$\frac{(1-\gamma)}{\gamma(1-l_{m,t}-l_{h,t})} = \frac{(1-\theta)(1-\omega)c_{h,t}^{\eta-1}}{C_t}\frac{C_{h,t}}{L_{h,t}} \tag{S.54}$$

$$\frac{c_{m,t}^{\eta-1}}{C_t}q_{e,t} = E_t\Big[\beta\frac{c_{m,t+1}^{\eta-1}}{C_{t+1}}(r_{e,t+1}+q_{e,t+1}(1-\delta_e))\Big] \tag{S.55}$$

$$\frac{c_{m,t}^{\eta-1}}{C_t}q_{s,t} = E_t\Big[\beta\frac{c_{m,t+1}^{\eta-1}}{C_{t+1}}(r_{s,t+1}+q_{s,t+1}(1-\delta_s))\Big] \tag{S.56}$$

$$\frac{\omega c_{m,t}^{\eta-1}}{C_t}q_{h,t} + \frac{\theta(1-\omega)c_{h,t}^{\eta-1}}{C_t}\frac{C_{h,t}}{L_{h,t}} = E_t\Big[\beta\frac{\omega c_{m,t+1}^{\eta-1}}{C_{t+1}}(r_{h,t+1}+q_{h,t+1}(1-\delta_h))\Big] \tag{S.57}$$

$$\frac{\gamma\omega c_{m,t}^{\eta-1}}{C_t} = E_t\left[\beta\frac{\gamma\omega c_{m,t+1}^{\eta-1}}{C_{t+1}}(1+r_{a,t+1})\right] \tag{S.58}$$

$$C_t = \omega c_{m,t}^{\eta} + (1-\omega)c_{h,t}^{\eta} \tag{S.59}$$

$$C_{h,t} = A_t K_{s,t+1}^{\theta} L_{h,t}^{1-\theta} \tag{S.60}$$

$$Y_t = Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s} L_t^{1-\alpha_e-\alpha_s} \tag{S.61}$$

$$r_{e,t} = \alpha_e Z_t K_{e,t}^{\alpha_e-1} K_{s,t}^{\alpha_s} L_t^{1-\alpha_e-\alpha_s} \tag{S.62}$$

$$r_{e,t} = \alpha_e \frac{Y_t}{K_{e,t}} \tag{S.63}$$

$$r_{s,t} = \alpha_s Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s-1} L_t^{1-\alpha_e-\alpha_s} \tag{S.64}$$

$$r_{s,t} = \alpha_s \frac{Y_t}{K_{s,t}} \tag{S.65}$$

$$r_{h,t} = \theta A_t K_{s,t+1}^{\theta-1} L_{h,t}^{1-\theta} \tag{S.66}$$

$$r_{h,t} = \theta \frac{C_{h,t}}{L_{h,t}} \tag{S.67}$$

$$w_t = (1 - \alpha_e - \alpha_s) Z_t K_{e,t}^{\alpha_e} K_{s,t}^{\alpha_s} L_t^{-\alpha_e-\alpha_s} \tag{S.68}$$

$$w_t = (1 - \alpha_e - \alpha_s) \frac{Y_t}{L_t} \tag{S.69}$$

$$Y_t = c_t + I_{s,t} + I_{e,t} + I_{h,t} \tag{S.70}$$

$$I_{e,t} = q_{e,t} k_{e,t+1} - q_{e,t}(1 - \delta_e) k_{e,t} \tag{S.71}$$

$$I_{s,t} = q_{s,t} k_{s,t+1} - q_{s,t}(1 - \delta_s) k_{s,t} \tag{S.72}$$

$$I_{h,t} = q_{h,t} k_{h,t+1} - q_{h,t}(1 - \delta_h) k_{h,t} \tag{S.73}$$

$$q_{e,t} = 1/\Theta_{e,t} \tag{S.74}$$

$$q_{s,t} = 1/\Theta_{s,t} \tag{S.75}$$

$$q_{h,t} = 1/\Theta_{h,t} \tag{S.76}$$

$$ln\ Z_t = (1 - \rho_Z) ln \bar{Z} + \rho_Z ln\ Z_{t-1} + \varepsilon_t^Z + \varepsilon_{t-2}^Z \tag{S.77}$$

$$ln\ A_t = (1 - \rho_A) ln \bar{A} + \rho_A ln\ A_{t-1} + \varepsilon_t^A + \varepsilon_{t-2}^A \tag{S.78}$$

$$ln\ q_{e,t} = \rho_{q_e} ln\ q_{e,t-1} + \varepsilon_t^{q_e} + \varepsilon_{t-2}^{q_e} \tag{S.79}$$

$$ln\ q_{s,t} = \rho_{q_s} ln\ q_{s,t-1} + \varepsilon_t^{q_s} + \varepsilon_{t-2}^{q_s} \tag{S.80}$$

$$ln\ q_{h,t} = \rho_{q_h} ln\ q_{h,t-1} + \varepsilon_t^{q_h} + \varepsilon_{t-2}^{q_h} \tag{S.81}$$

S.7 Steady State

$$C = \omega c_m^{\eta} + (1-\omega) c_h^{\eta} \tag{S.82}$$

$$C_h = K_h^{\theta} L_h^{1-\theta} \tag{S.83}$$

$$Y = K_e^{\alpha_e} K_s^{\alpha_s} L^{1-\alpha_e-\alpha_s} \tag{S.84}$$

$$r_e = \alpha_e \frac{Y}{K_e} \tag{S.85}$$

$$r_s = \alpha_s \frac{Y}{K_s} \tag{S.86}$$

$$r_h = \theta \frac{C_h}{L_h} \tag{S.87}$$

$$w = (1-\alpha_e-\alpha_s) \frac{Y}{L} \tag{S.88}$$

$$Y = C + I_s + I_e + I_h \tag{S.89}$$

$$I_e = q_{e,} \delta_e k_e \tag{S.90}$$

$$I_s = q_s \delta_s k_s \tag{S.91}$$

$$I_h = q_h \delta_h k_h \tag{S.92}$$

$$q_e = 1/\Theta_e \tag{S.93}$$

$$q_s = 1/\Theta_s \tag{S.94}$$

$$q_h = 1/\Theta_h \tag{S.95}$$

$$ln\ Z_t = (1-\rho_Z) ln\bar{Z} + \rho_Z ln\ Z_{t-1} + \varepsilon_t^Z + \varepsilon_{t-2}^Z \tag{S.96}$$

$$ln\ A_t = (1-\rho_A) ln\bar{A} + \rho_A ln\ A_{t-1} + \varepsilon_t^A + \varepsilon_{t-2}^A \tag{S.97}$$

$$ln\ q_{e,t} = \rho_{q_e} ln\ q_{e,t-1} + \varepsilon_t^{q_e} + \varepsilon_{t-2}^{q_e} \tag{S.98}$$

$$ln\ q_{s,t} = \rho_{q_s} ln\ q_{s,t-1} + \varepsilon_t^{q_s} + \varepsilon_{t-2}^{q_s} \tag{S.99}$$

$$ln\ q_{h,t} = \rho_{q_h} ln\ q_{h,t-1} + \varepsilon_t^{q_h} + \varepsilon_{t-2}^{q_h} \tag{S.100}$$

S.8 Two-sector Model Simulation

S.8.1 Calibration III

Table S.5: Calibration - III

Parameters	γ	ω	η	α_e	α_s	θ
SPAIN	0.36	0.61	0.28	0.13	0.11	0.48
GERMANY	0.46	0.36	0.83	0.14	0.11	0.37

Figure S.5: A_h news shock effects on aggregate variables

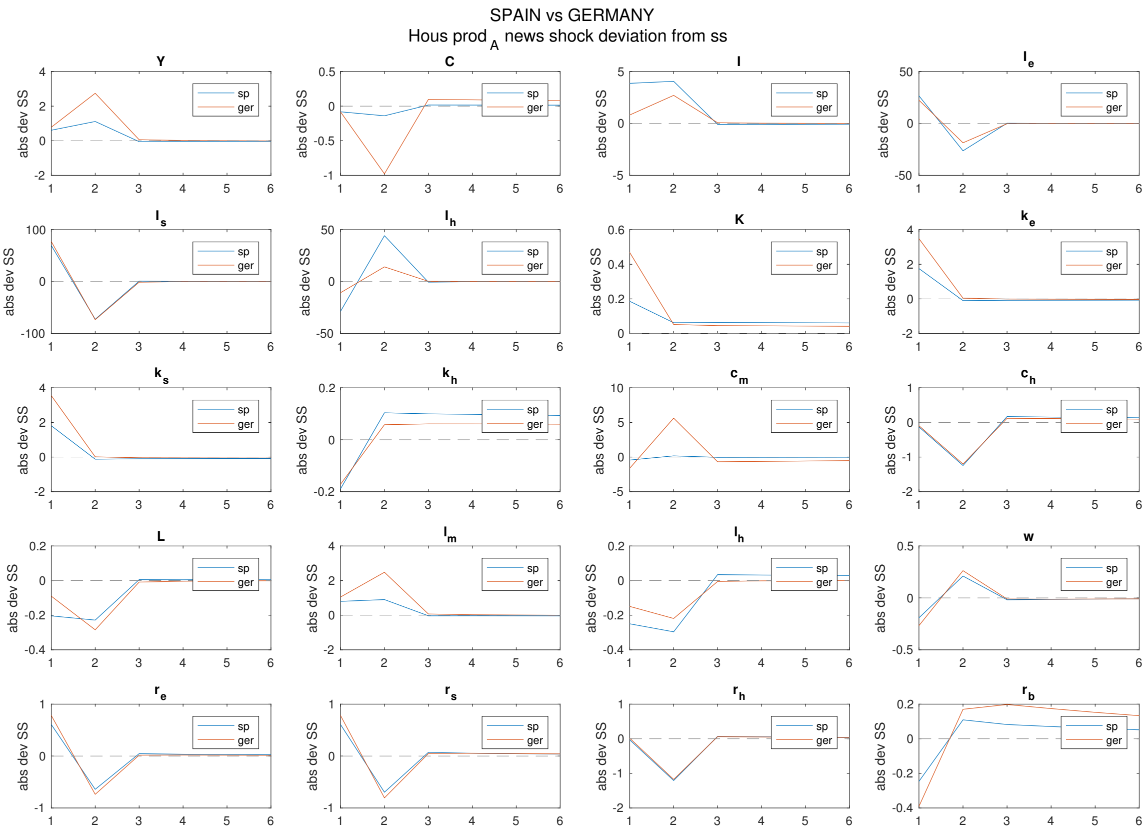
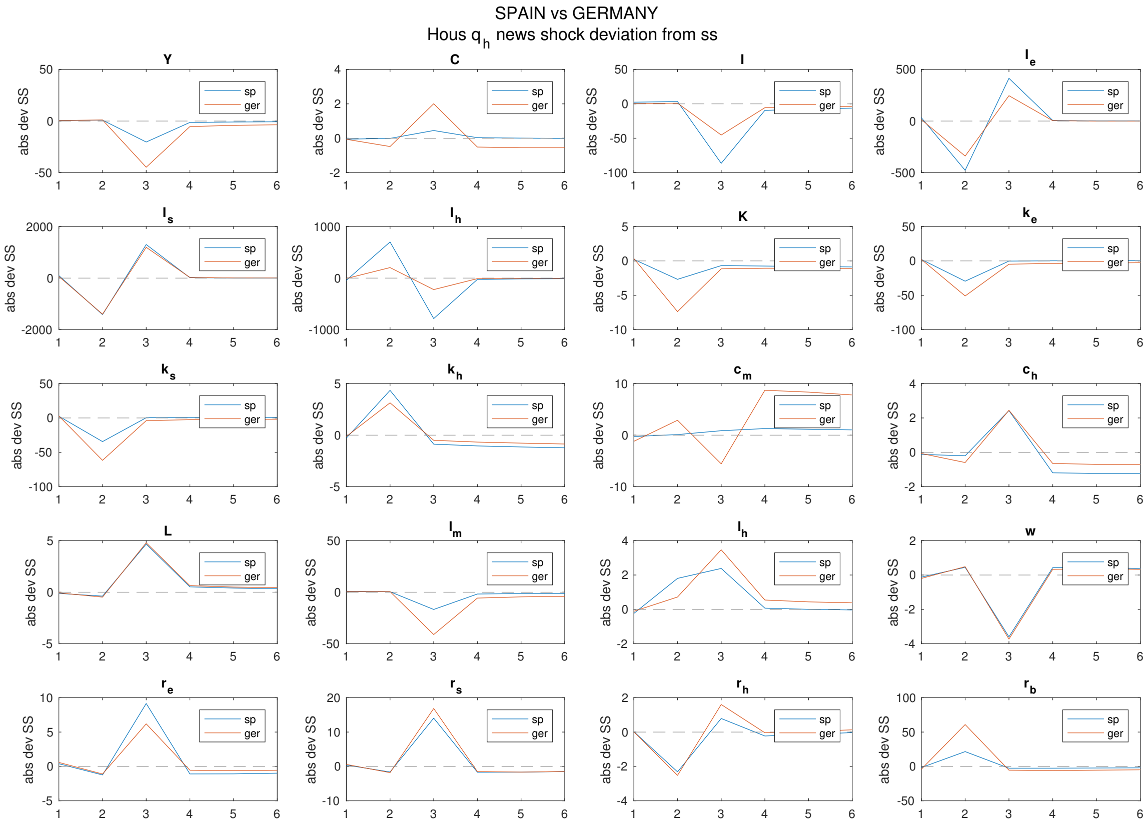


Figure S.6: IST q_h news shock effects on aggregate variables



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