Financial and Information Frictions in DSGE models

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PhD Thesis

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Thesis submitted to the Université catholique de Louvain and the Universidad del País Vasco

Acknowledgments

Completing this thesis has been an incredible journey that has taken me to live in many cities worldwide -Bilbao, Louvain-la-Neuve, Brussels, Frankfurt, and Washington, DC. In each of these places, I have met remarkable people who have helped me along the way, contributing not just to this thesis but also to my growth as a researcher and an individual.

First and foremost, I want to express my deepest gratitude to my thesis supervisors, Jesús Vázquez and Luca Pensieroso. Thank you for accepting me as your PhD student and guiding me from my first steps as a graduate student to the completion of this thesis. Luca, I am grateful for your patience and for teaching me the importance of distilling a clear and comprehensible message from complex analysesâa skill that will guide me throughout my career. Jesús, I owe you my passion for exploring the role of expectations in macroeconomics. Your commitment to rigorous research and your strong personal and professional ethics have not only made me a better economist but also a better person.

I am also deeply grateful to the members of my thesis jury, Francesca Monti, Javier Andrés, and Miguel Casares, for their willingness to participate in my defense and for their invaluable feedback. Your insightful comments and suggestions have greatly enriched this work and pushed me to think more critically.

I would like to extend my appreciation to the fellow PhD students I have met along the way not only from Louvain and Bilbao but also from various other institutions. Your friendship, intellectual exchanges, and shared challenges have significantly shaped my experience and have left a lasting impact on my development as an economist.

My deepest thanks go to the colleagues and mentors I have had the pleasure of working with at the European Central Bank and the International Monetary Fund. Special thanks to Caterina Mendicino, Daria Finnochiaro, Hannah Hempel, Jesper Lindé, Kalin Nikolov, Mara Pirovano, and Roland Meeks for their guidance and for the opportunities to collaborate and learn from them. A special mention goes to Valerio Scalone, who gave me my first opportunity at the ECB and has been an invaluable mentor ever since. Valerio, your support, wisdom, and encouragement have played a crucial role in my professional journey, and I am immensely grateful for everything I have learned from you.

On a personal level, I want to thank my friends who have been a constant source of support and have made the ups and downs of the PhD process much more bearable. To my family, who, despite being small, have been my unwavering support throughout these years. Thank you for always being there. To my mother, in particular, your strength and sacrifice since the loss of my father have been a constant source of inspiration. Your resilience has been my greatest example.

Finally, I want to express my deepest gratitude to Candela, for always being there when I needed her the most. Thank you for your unwavering support throughout these years, for enduring the distance and the constant changes of cities, for helping me escape from the daily challenges, and for celebrating every bit of good news. Your love and patience have been a constant source of strength, and I couldn't have done this without you.

This thesis is as much yours as it is mine. Thank you all.

To my mother and the memory of my father,

for their unconditional love and support.

Contents

Chapter 1

General introduction

This thesis focuses on the analysis of two main independent issues: (i) the characterization of expectations in structural models, and (ii) the role of borrower-based macroprudential (BBM) policies in building up financial resilience. The analysis on agents' expectations is divided into two chapters. The first assesses the empirical importance of future economic events that agents expect to be realized. More precisely, it focuses on the role of financial frictions in the origination and transmission of the effect of these types of anticipated (news) shocks. The second chapter analyzes the implications of relaxing agents rationality for the transmission mechanism of news shocks. Regarding the analysis of BBM policies, a non-linear DSGE model that allows to assess the cost and benefits of such policies is developed. The model explicitly incorporates credit demand and credit supply frictions allowing a comprehensive analysis of these policies on both households and banks resilience. Both questions (i) and (ii) are mainly analyzed through the prism of DSGE models. Hence, as an introductory chapter to motivate the use of such models, I show that DSGE models are well-suited to address these questions.

The first chapter serves as a defense for the New Keynesian DSGE models as workhorses of modern macroeconomics. DSGE models are widely used to explain macroeconomic dynamics and assessing economic policy. One of the main criticisms is that aggregate fluctuations are driven by exogenous disturbances: All events that affect macroeconomic variables that are not explicitly modeled are captured by exogenous shocks in these models. This chapter shows that even though these shocks are completely exogenous, they are well-suited to capture recognizable economic events and they are not just black boxes that allow matching the data. This chapter shows that the estimated DSGE model with financial frictions provides a close link between structural shock realizations and their dynamics effects with well-known historical events reported in the literature. Thus, the identification of the nominal and real rigidities in addition to the identification of structural shock realizations for each quarter allows us to derive a historical variance decomposition of real output that turns out to be rather precise in explaining the fluctuations of the selected periods featuring major recessions.

We find that the shocks that mainly caused the Great Depression are (i) the risk premium shock capturing the 1929 stock market crash and the consequent financial turmoil; (ii) monetary policy shocks representing shifts in (an inappropriate monetary) policy; and (iii) the wage and price markup shocks associated with important changes in legislation which, for instance, allowed firms to reach collusive price agreements (the 1933 NIRA Act), and allowed workers to organize themselves into unions independently from their employers (the 1935 Wagner Act).

The estimated price markup shock identifies the oil crisis as the main driving force of the Stagflation. Nevertheless, the overall increase in wages may also played an important role in this recession. Thus, there was resilience to the cutting of real wages of unskilled workers through changes in the minimum wage laws.

The estimated DSGE model identifies two shocks as the main causes for the Great Recession: (i) The monetary policy shock that captures the expansive monetary policy conducted by the Fed at the beginning of the 2000s; and (ii) the negative risk premium shock that captures the undervaluation of financial risk up to 2008, and the positive realizations of this shock capturing the pessimism that suddenly surrounded the whole economy after the subprime lending crisis.

This empirical evidence suggested by the estimation of a standard New Keynesian DSGE model is in line with the empirical findings and broader wisdom about these three specific severe recession periods. This finding motivates the use of the this types of models to address the two questions considered in thesis.

The second chapter builds on the expectation-driven business cycle hypothesis, which has a long-standing tradition in macroeconomics. Thus, Pigou argued, in *industrial fluctuations*, that the business cycle was driven by variations in the profit expectations of 'business men'. Other hypothesis of expectations as driving forces of the business and financial cycle are found in the *animal spirits* of Keynes and the *irrational exuberance* of Shiller, among others. More recently, this idea has been modeled through news (anticipated) shocks. This chapter suggests a novel approach for modeling this type of shocks by considering quality-of-capital (QoC) news shocks rather than total factor productivity (TFP) shocks. QoC shocks represent qualitative appreciations (depreciations) of physical capital, which trigger an exogenous change in the productivity of capital and also directly affect the balance sheet of financial intermediaries whose assets are collateralized by that capital. QoC news shocks (differently to TFP news shocks) are connected with financial markets through the credit and expectation channels. More precisely, a QoC news shock affects the production function similarly to a TFP news shock but also acts as an exogenous trigger of asset price dynamics. For example, an anticipated upgrade in physical capital improves production expectations and may immediately impact the balance sheets of financial intermediaries whose assets are backed up by that capital. Similarly, when sector-specific capital is expected to become obsolete, production is expected to fall, and agents may also anticipate the coming drop in capital (asset) value, making the level of debt excessive relative to the stock of capital. In short, the fundamental difference between QoC and TFP news shocks lies in the direct effects on financial variables induced by the former and amplified through the expectation and credit channels. This chapter shows that QoC news shocks are favored by the data when considered together with TFP news shocks in the model. This finding is due to the direct effect of QoC news shocks on the financial markets.

The third chapter of the thesis also contributes to the literature studying the role of expectations in the business cycle. In the previous section, agents were assumed to be fully rational, and consequently, they perfectly understand the transmission mechanism of news shocks. However, The effects of (news) shocks on the economy are hard to predict in reality. Policy makers,economic pundits, and economic agents in general have limited knowledge about the economic effects of news shocks regarding the impact of a new technology, a pandemic-fighting vaccine, an armed conflict, a labor strike, a legislation change in the regulation of a specific market (e.g. a specific policy to reform the labor market), etc. In this scenario, agents have to learn the effects of news shocks. This learning process affects agents' decisions through the expectation channel, thereby shaping the transmission mechanism of news shocks. This chapter deviates from the rational expectations (RE) hypothesis in assessing the role of TFP news shocks as a source of business cycles. This assumption relaxation implies an improvement in the estimated model capability to reproduce the business cycle. The estimation also find that the effects of news shocks on inflation are reversed. Thus, news shocks are deflationary under bounded-rationality rather than inflationary as in the Rational Expectation specification allowing to reconcile the DSGE model with empirical evidence estimated through a VAR model. Finally, the expectational channel of news shock is also found to play a more important role when assuming bounded-rationality.

The forth chapter of the thesis addresses a policy-oriented research question: which is the role of BBM policies in enhancing financial resilience? In pursuit of empirical evidence to understand the role of household indebtedness, a state-dependent panel local projection model is estimated to analyze the dynamics of credit shocks conditioned on household leverage. Notably, the findings reveal a noteworthy relationship between higher levels of household indebtedness and the amplification of the identified credit shock. This insight suggests that households carrying elevated levels of debt may serve as amplifiers, exacerbating the impact of credit shocks on overall financial stability. The empirical evidence thus underscores the importance of considering BBM as an instrument to constrain household leverage, containing the amplification channel of financial shocks.

Building upon the empirical insights obtained, I further develop a non-linear Dynamic Stochastic General Equilibrium (DSGE) model that intricately captures the interactions among savers, borrowers, and banks. Specifically, the model distinguishes between savers and borrowers, with the latter being subject to a collateral constraint. In this framework, borrowers use their housing value as collateral, compelling them to make abrupt adjustments in both consumption and housing purchases in response to any shocks affecting the value of their housing. Consequently, higher levels of indebtedness lead to more substantial adjustments, amplifying the impact of shocks. The credit supply within this model is intermediated by banks. Banks receive deposits from savers and extend loans to both households and firms. Savers deposit an amount of savings that prevents banks from diverting their assets, reflecting the inherent moral hazard issue. During periods of financial distress, when banks exhibit heightened leverage, deposits become scarce. Consequently, banks are compelled to increase lending rates above the risk-free rate, creating a lending spread. Importantly, the two described frictions, namely the collateral constraint on borrowers and the moral hazard issue faced by banks amplify each other. The heightened deleverage of households, particularly when indebtedness is high, negatively impacts the balance sheets of banks. Simultaneously, the increase in lending rates triggers financial distress in borrower households. This intricate interplay of frictions enables a comprehensive assessment of the implications of Borrower-Based Macroprudential (BBM) policies for financial resilience on both sides of the credit channel.

The main findings of the paper are fourfold. First, empirical evidence is found that household indebtedness amplifies financial shocks, implying that BBM policies are well-suited to increase financial resilience. Second, a non-linear DSGE model with a collateral constraint and constrained banks is developed, resembling the empirical findings and serving as a laboratory to study the costs and benefits of activating BBM policies. This model shows that tighter BBMs increase financial resilience by reducing household indebtedness. Less leveraged households reduce the amplification driven by the collateral channel and the feedback effect of constrained banks, whose assets are less depreciated. This implies that credit supply shocks are better accommodated by both households and banks. Moreover, shocks originating in the housing markets are contained, reducing their impact on the balance sheets of the banks and consequently reducing systemic risk since the transmission of the shock to the rest of the economy is highly reduced. The third result relies on the interaction of unconventional monetary policies and BBM policies. It is found that the effects of asset purchase programs are reduced when BBM policies are activated. This is due to the fact that BBMs reduce the amplification driven by financial frictions, and since QE aims to reduce the effects driven by financial distress, milder financial frictions imply milder transmission of QE. Finally, it is found that the activation cost of BBM policies is remarkably higher when activated under financial distress. However, this higher cost of activation can be reduced by smoother activation that allows a smoother reduction in credit and consequently a smaller impact on banks' balance sheets.

In sum, this thesis studies the characterization of expectation in structural models and the role of BBM policies containing the effects of financial distress. Both questions are addressed through the prism of DSGE models, that has been proved to be a powerful tool for explaining macroeconomic dynamics and assessing economic policy in the first chapter.

Chapter 2

Interpreting Structural Shocks and Assessing Their Historical Importance

2.1 Introduction

New Keynesian DSGE models are currently widely used to explain macroeconomic dynamics and assessing economic policy. They are often considered to be the workhorses of modern macroeconomics.[1] One of the main criticisms is the explanation of aggregate fluctuations driven by exogenous shocks: All events that affect macroeconomic variables that are not explicitly modeled are captured by exogenous shocks in these models. In principle, this can be a problem when it comes to explaining what shocks are really capturing. Then, further efforts are needed to understand what estimated shocks from DSGE models are truly capturing: Structural shocks (e.g. oil shocks, legislation changes, monetary policy shifts) that match recognizable economic events rather than measurement errors that allow the model to fit the data.

This paper evaluates the relative importance of alternative structural shocks during the periods surrounding three major US recessions by using the medium-scale DSGE model of Smets and

[1] Nevertheless, the adequacy of DSGE models has been regarded with skepticism in recent times. Romer (2016) and Stiglitz (2018) have recently set out a frontal critique of macroeconomics based on these models along several dimensions. Reacting to these critiques, Christiano et al. (2018) defend the use of DSGE models as a leading tool for making assessments, in an open and transparent manner, on the net effect of forces operating on different parts of the economy. In the same vein, Reis (2018) provides a critical assessment of the state of macroeconomics by responding to some of the negative views on what is the trouble with macroeconomics stated in Stiglitz (2018), among others.

Wouters (2007) augmented with the financial accelerator of Bernanke et al. (1999).[2] As such, this paper can be viewed as a test of the standard New-Keynesian DSGE model with financial accelerator in closed economies in assessing its ability to characterize different economic episodes. We consider this benchmark specification since we want to keep the model as standard as possible and versions of this model have been extensively used in the related literature.[3,4] Thus, we consider the Great Depression, whose cause has usually been associated with a mixture of financial shocks and wrongly conducted monetary policy (Christiano et al., 2003); the Stagflation, which has been widely interpreted as a consequence of the oil supply quotas introduced by the OPEC cartel as discussed in intermediate macroeconomics textbooks (e.g. Abel and Bernanke, 1998, p. 433) and in the context of DSGE models (Smets and Wouters, 2007); and the Great Recession, which is usually viewed as a crisis driven mainly by financial shocks (Christiano et al., 2014). We consider these three periods for two main reasons. First, each of these periods includes a major US recession.[5] Second, these three periods have been widely studied using alternative models and econometric approaches, and some consensus about the sources causing each recession has been achieved. This consensus can be then used as an important piece of evidence for an external validity test of the DSGE model considered.

We show that the estimated DSGE model with financial frictions provides a close link between structural shock realizations and their dynamics effects with well-known historical events reported in the literature. Thus, the identification of the nominal and real rigidities in addition to the identification of structural shock realizations for each quarter allows us to derive a historical variance decomposition of real output that turns out to be rather precise in explaining the fluctuations of the selected periods featuring major recessions. We find that the shocks that mainly caused the Great Depression are (i) the risk premium shock capturing the 1929 stock market crash and the

[2]Del Negro and Schorfheide (2013) show that this DSGE model with this type of financial frictions would have done a much better job forecasting the dynamics of real GDP growth and inflation during the Great Recession than the DSGE model without financial frictions.

[3]See, among others, Christiano et al. (2003) for assessing the Friedman-Schwartz hypothesis that a more accommodative monetary policy could have mitigated the severity of the Great Depression; Christiano et al. (2014) for analyzing the importance of risk shocks in the Great Recession; De Graeve (2008) for obtaining a measure of the external finance premium; Villa (2016) for evaluating alternative approaches of incorporating financial frictions in a DSGE model; and Rychalovska et al. (2016) for studying how bounded rationality modify the implications of financial frictions for the real economy.

[4]In order to assess the robustness of the empirical findings, we have also estimated the alternative specification suggested in Gertler and Karadi (2011) for augmenting the DSGE model with financial frictions. Our estimation results from the two alternative specifications show the robust ability of the estimated structural shocks to match recognizable economics events.

[5]We do not consider the current recession driven by Covid-19 because our goal is to study samples featuring a major recession, but where the samples also include the period prior to a recession as well as its aftermath. However, the aftermath of the Coronavirus recession will take place hopefully in the near future.

consequent financial turmoil; (ii) monetary policy shocks representing shifts in (an inappropriate monetary) policy; and (iii) the wage and price markup shocks associated with important changes in legislation which, for instance, allowed firms to reach collusive price agreements (the 1933 NIRA Act), and allowed workers to organize themselves into unions independently from their employers (the 1935 Wagner Act). These results are in line with several studies like Romer (1990) and White (1990) who point out the financial instability as crucial in this huge recession, Christiano et al. (2003) who argue that a more accommodative monetary policy could have mitigated the Great Depression, and Weinstein (1980) and Cole and Ohanian (2004) who suggest that the legislation changes in the labor and good markets (i.e. New Deal policies) played an important role in the weak recovery during the Great Depression.[6]

The estimated price markup shock identifies the oil crisis as the main driving force of the Stagflation. Nevertheless, the overall increase in wages may also played an important role in this recession. Thus, there was resilience to the cutting of real wages of unskilled workers through changes in the minimum wage laws. Our findings are similar to those of Bernanke et al. (1997), Hunt (2006), and references therein, who point out the importance of cost push shocks. Moreover, there was an increase in the wage gap between skilled and unskilled workers as a result of a shift in demand for skilled workers due to the adoption, among others, of new energy-saver technologies.

The estimated DSGE model identifies two shocks as the main causes for the Great Recession: (i) The monetary policy shock that captures the expansive monetary policy conducted by the Fed at the beginning of the 2000s; and (ii) the negative risk premium shock that captures the undervaluation of financial risk up to 2008, and the positive realizations of this shock capturing the pessimism that suddenly surrounded the whole economy after the subprime lending crisis. These results are in line with Christiano et al. (2014), Christiano et al. (2015), among others, by highlighting the role of financial shocks in the Great Recession.

Apart from the specific shocks hitting the economy in each recession, our estimation results show that the persistence of a few shocks are rather similar across recession periods. Thus, the high persistence of risk premium shocks is similar across the three recessions due to the boom and bust of the financial markets that characterized each of these periods.[7] In contrast, the high persistence

[6] Christiano et al. (2003) also emphasize the role played by a shock that rose the market power of workers in the slowness of the recovery from the Great Depression.

[7] Certainly, the interpretation of booms and crashes as financial shocks in a DSGE model it is sort of a shortcut to keep us from having to model how learning and changing beliefs may result in booms and busts as suggested in Branch and Evans (2011, 2013). Moreover, there is a myriad of ways suggested in the literature to explain booms and crashes, and deciding which is one of them should be considered in an estimated DSGE model is at least challenging. Thus, Dong et al. (2020) suggest a dynamic New-Keynesian model where monetary policy determines the conditions for the existence of a rational bubble. As yet another example, Dong and Xu (2020) suggest that excessive credit

of the price markup shock is a distinctive feature of the Stagflation capturing the recurrent oil price increases introduced by the OPEC cartel.

Real and nominal rigidities also play an important role in the transmission of shocks and our study enables the different sources of rigidity featured in each recession period to be identified. Several research articles have shown that the rigidities considered in New Keynesian models are critical for explaining these three recessions. Eichengreen and Sachs (1985), Bernanke and Carey (1996), and Bordo et al. (2000) state that wage rigidity was unusually high during the Great Depression and played a crucial role in its aftermath. Other researchers claim that financial frictions are the main cause of both the Great Depression (Kobayashi, 2004) and the Great Recession (Christiano et al., 2015; Huo and Ríos-Rull, 2016). Moreover, nominal rigidities are crucial for determining the transmission of monetary policy shifts to the real side of the economy and, consequently, assessing the extent to which these rigidities could have mitigated or worsened the effects of negative disturbances during these recessions, for instance, the negative oil shocks during the Stagflation. The estimated DSGE model shows that wage stickiness was not especially high during the Great Depression in comparison with the other two recessions, but what partially captures the sluggishness of wages is the moderate persistence of wage markup shocks in line with the findings reported in Christiano et al. (2003). We also find substantial financial frictions during all three periods studied.

The structure of the paper is as follows. Section 2 briefly describes the medium-scale DSGE model with financial frictions. Section 3 describes the data set and the prior distributions of the estimated parameters used in the Bayesian estimation procedure. Section 4 discusses the model's fit based on second-moment statistics, the estimation results based on the estimated posterior distribution of the parameters, and the unconditional variance decomposition. Section 5 discusses the historical variance decomposition of output in order to link the estimated structural shocks with specific economic events and assess their relative importance across US recessions. Section 6 study the implications of extending the DSGE model with a fiscal building block. Section 7 concludes.

2.2 The model

This paper considers a medium-scale DSGE model with financial frictions. The model includes several nominal and real rigidities that together with various persistent exogenous shocks enable us to reproduce the main features of the US business cycle. The model is similar to the well-known New Keynesian DSGE models suggested by Christiano et al. (2005) and Smets and Wouters (2007) and is

creation by a frictional banking sector may result in excessive investment and then endogenous boom-bust cycles.

augmented with the financial accelerator of Bernanke et al. (1999), henceforth BGG model. Versions of this DSGE model with BGG financial frictions have been studied, among others, by Christiano et al. (2003, 2014),De Graeve (2008), Rychalovska (2016) Rychalovska (2016), Villa (2016), and Rychalovska et al. (2016).

This section provides a brief description of the model.[8] The demand side of the model economy is formed by households which choose consumer spending and hours worked and hold riskless assets, bank deposits, and government bonds. The utility reported by consumer spending is relative to a time-varying external habit variable. Hours worked are homogeneously supplied by households to an intermediate labor union. This labor union differentiates the labor and supplies it to labor packers, who subsequently sell it to the intermediate goods production sector. The intermediate goods firms use their production inputs (labor and capital) and sell a differentiated good as an input to the final sector, which closes the circle by selling a homogeneous good to households in a perfectly competitive market. Both the intermediate goods sector and the labor union supply differentiated goods, so they are assumed to have some degree of market power. Moreover, both wage and price stickiness are modeled à la **?**. In addition to these nominal rigidities, prices and wages that are not re-optimized are indexed to past inflation realizations. Monetary policy is simply characterize with a Taylor rule where the short-term nominal interest rate set by the central banker reacts to inflation, changes in inflation, output gap, and output gap growth. The output gap is defined as the difference between (the log of) output determined in the economy featuring price-wage rigidity and the one determined in a fully-flexible economy.[9]

The model is further enriched by including an endogenous financial sector. More precisely, we consider the BGG financial accelerator. The financial sector includes entrepreneurs, capital good producers and financial intermediaries. A fraction of households comprises entrepreneurs that own the stock of capital and choose the degree of utilization. The entrepreneurs buy capital from the capital producers who make the investment decision. Entrepreneurs fund capital acquisition using their own net worth and by borrowing external funds from financial intermediaries. The cost of funding is compounded by the sum of the risk-free interest rate and a risk premium that depends on the entrepreneurial leverage ratio. This premium is justified by the existence of an idiosyncratic shock that affects the capital holdings and the return on capital holdings of each entrepreneur. Financial intermediaries (i.e. banks) have to pay a monitoring cost to infer the realized return (i.e.

[8] The appendix describes the model in more detail and the log-linearized equations that characterize the equilibrium.

[9] Readers may question the use of a Taylor rule during the 1920's and 1930's when the Gold Standard was operational. Nevertheless, Orphanides (2003) finds that the interest rate rule could be well characterized by a Taylor rule during the 1920's. Moreover, Taylor (1999) claims that the short-term nominal interest rate reacted to changes in output and inflation during the Gold Standard period.

costly state verification) and that cost is passed on to entrepreneurs. Moreover, entrepreneurs face a survival probability that captures both the creation and the closure of firms. The survival probability also avoids the possibility of entrepreneurs becoming rich enough to self-finance their own ventures. The survival probability is assumed to be constant, so the number of entrepreneurs is also constant. The entrepreneurs' net worth comes from the profits accumulated through the investment projects that they carried out in the previous period.

Financial intermediaries are characterized by a representative perfectly competitive bank. This representative bank funds entrepreneurs by issuing deposit liabilities to households, which pay a risk-free interest rate. Hence, financial frictions are assumed to be credit demand frictions. Such financial frictions imply that the variability of the assets price affects the financial position of entrepreneurs, and consequently their investment decisions. Therefore, these investment decisions are highly affected by asset prices and the external financial premium.

We also consider an alternative DSGE model augmented with the type of financial frictions suggested by Gertler and Karadi (2011), henceforth GK approach, in order to check for robusteness. This alternative approach of incorporating financial frictions in medium-scale DSGE models is also becoming popular (e.g. Villa, 2016; Gelain and Ilbas, 2017; Görtz and Tsoukalas, 2017). The two estimated models incorporating financial frictions share the DSGE framework of Smets and Wouters (2007) by considering an economy populated by household, retailers, final good firms, intermediate goods firms, capital producers, labor unions, labor packers, and the central banker, but the DSGE model with financial frictions à la GK incorporates financial intermediaries (bankers) in a different way. More precisely, this alternative model with financial frictions assumes that within each household there are, in fixed proportions, two type of agents: workers and bankers. The model assumes that (i) each banker has a finite horizon in order to avoid the possibility of full self-financing, (ii) each banker stays as a banker the next period with a fixed probability, which is independent of history (this assumption implies that every period a fixed proportion of bankers exit and become workers, and similarly, a number of workers become bankers, so the relative proportions of workers and bankers remain constant), (iii) the household provides a new banker with a start-up transfer, which is a small fraction of total assets, and (iv) the intermediate goods firms finance their capital acquisitions each period by obtaining funds from a banker. Although there are no financial frictions in this activity, there is a moral hazard problem between bankers and households because the former can choose to divert a fraction of available funds from the bank project. Hence, an incentive compatibility constraint must hold in order to make households willing to deposit money in the bank. This feature implies that the assets a banker can acquire depend positively on her net worth. Villa (2016) provides further discussion on the two models with financial frictions, but focuses on the

Great Moderation period in her empirical analysis. In contrast, this paper studies major recessions where financial frictions may play an important role.

2.3 Description of data and prior distributions

As in the related DSGE literature, we follow a Bayesian approach to estimate the DSGE model for the three sample periods considered. The length of those three periods is around 18 years of quarterly data. For each period, the sample considers the boom, recession and recovery phases. More precisely, the Great Depression sample considers the period 1923:1-1940:4,[10] the Stagflation sample covers 1960:1-1979:3, and the Great Recession sample considers 2001:3-2017:4. The data set includes the real per capita output, consumption, investment, hours worked, wages, inflation, and nominal interest rate as in Smets and Wouters (2007). In addition, we also consider financial data for identifying financial market parameters and financial shocks. As a measure of the interest rate spread, we consider the spread between the Moody's Baa and Aaa Corporate Bond yields. Furthermore, as an indicator of the value of equity we consider the Standard & Poors (S&P) 500 for the Great Recession and Stagflation periods.[11] Since the two financial variables in the model have no straightforward observable counterpart, we allow for i.i.d. measurement errors between the observable variables used in the estimation and their counterparts in the model.

For the periods including the Stagflation and the Great Recession, time series data are taken from the U.S. Bureau of Economic Analysis and the U.S. Bureau of Labor Statistics. However, quarterly data on a few time series for the Great Depression period are not available in these databases. Therefore, GNP, consumption and investment time series are taken from the data set provided by Balke and Gordon (1986), and the GNP deflator is taken from the National Bureau of Economic Research's Macro History database.[12] To express the data in per capita terms, we compute quarterly population data by interpolating the annual data provided by Chari et al. (2002). The nominal interest rate time series is taken from the NBER data set. Hourly earnings in manufacturing are taken from Hanes (1996), whereas hours worked are taken from Chari et al. (2002). In order to facilitate comparison across sample periods, we linearly detrend the non-stationary time series

[10] Although the WWII started by Germany's invasion of Poland in September 1939, the US did not enter the war until after the Japanese attacked the US fleet in Pearl Harbor in December 1941.

[11] The S&P500 index is not available for the Great Depression period. Therefore, we consider Shiller (2000) estimates for this index so as to use a set of observables similar to that used for the other two periods studied.

[12] At the website https://www.nber.org/research/data/tables-american-business-cycle. As suggested to us by a referee, alternative data sets exist such those collected by Barro and UrsÃºa (https://scholar.harvard.edu/barro/publications/barro-ursua-macroeconomic-data) and Piketty and Zucman (https://gabriel-zucman.eu/capitalisback/), but these alternative data sets only contain annual data.

(output, consumption, investment, real wages, and the S&P500 index) for the the three sample periods.[13] In regards of the period including the Great Recession, we consider the shadow nominal interest rate suggested by Wu and Xia (2016) to deal with the zero-lower-bound issue that affects it. The shadow rate corresponds to the federal funds rate when the zero-lower-bound is not binding, but it is negative to account for unconventional policy tools implemented when the federal funds rate is close to the zero lower bound (roughly from 2009:1 to 2015:4). Recent papers (e.g. Wu and Zhang, 2019; Mouabbi and Sahuc, 2019; Aguirre and Vázquez, 2020) use the shadow rate as a replacement for the federal funds rate in estimating New-Keynesian models.

Figures 1-3 show the set of observables from the Great Depression, Stagflation and Great Recession, respectively.[14] These figures shed light on the main differences across the three major US recessions. In particular, by looking at the different scale of the vertical axis, we observe that the boom and the bust associated with Great Depression are much larger than the ones associated with the other two recessions.

Regarding the Great Depression period (Figure 1), a huge drop in investment during the 1930's is observed, which is much higher than the drop in consumption. Moreover, there is a remarkable slump in labor which was not overcome during the following years. Prices also dropped during this period, identifying this as a demand-side recession. By contrast, the Stagflation (Figure 2) features a scenario of increasing inflation, widely interpreted as a consequence of the oil supply quotas introduced by the OPEC cartel (e.g. Abel and Bernanke, 1998, p. 433), and a remarkable output drop.[15] Finally, the Great Recession (Figure 3) also features a deep economic bust. The drop in the S&P500 indexes during all the recessions is also noteworthy. A loss of confidence in financial markets, captured by the increase in the interest rate spread, is also common to all three major recessions studied. This further motivates the inclusion of financial frictions in the DSGE models considered.

[13] We further focus on the linearly-detrended time series instead of considering the growth rates of non-stationary variables usually used in the related literature (e.g. Smets and Wouters, 2007) because growth rates of non-stationary variables mainly isolate high-frequency components of time series, and may thus ignore important components of the business cycle.

[14] Output, investment, consumption, wage and S&P500 are expressed in real terms and are linearly detrended. Inflation, nominal interest rate, and interest rate spread are expressed in quarterly rates and are demeaned. The log of hours worked is also demeaned.

[15] This traditional view of the Stagflation has been challenged by (Barsky and Kilian, 2002). They argue that the Stagflation of the 1970s could have been avoided to a large extent, should the Fed not implemented the major monetary expansions in the early 1970's. The discussions of Olivier Blanchard and Allan Blinder on Barsky and Killian's article—which are published in the same volume of the NBER Macroeconomics Annual, 2001— critize Barsky and Killian's monetary explanation of the sources of the Stagflation on several grounds. See also the comments and remarks raised by a few prominent macroeconomists, which were published in the same volume.

Figure 2.1: Great Depression data (1923:1-1940:4)

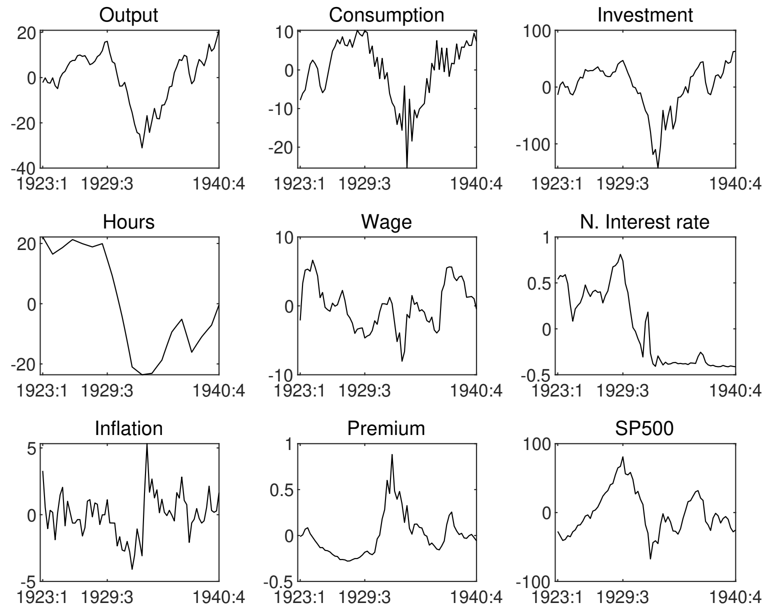


Figure 2.2: Stagflation data (1960:1-1979:3)

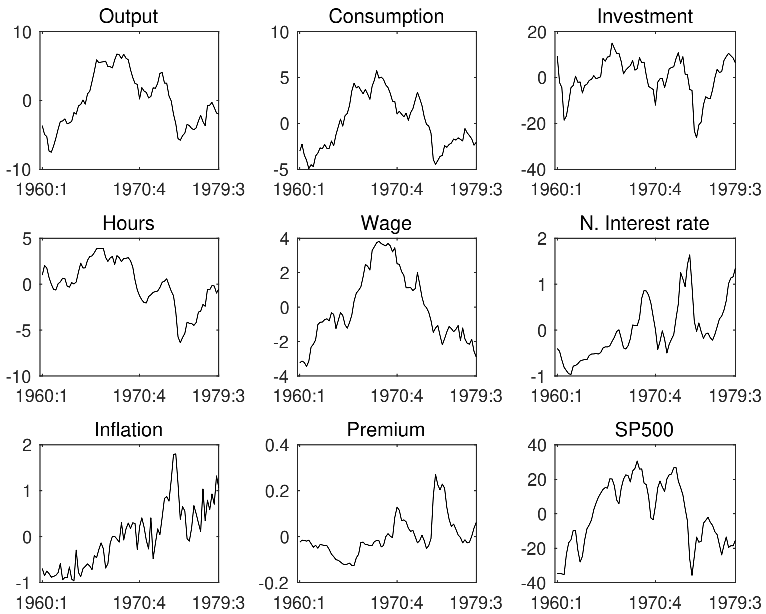
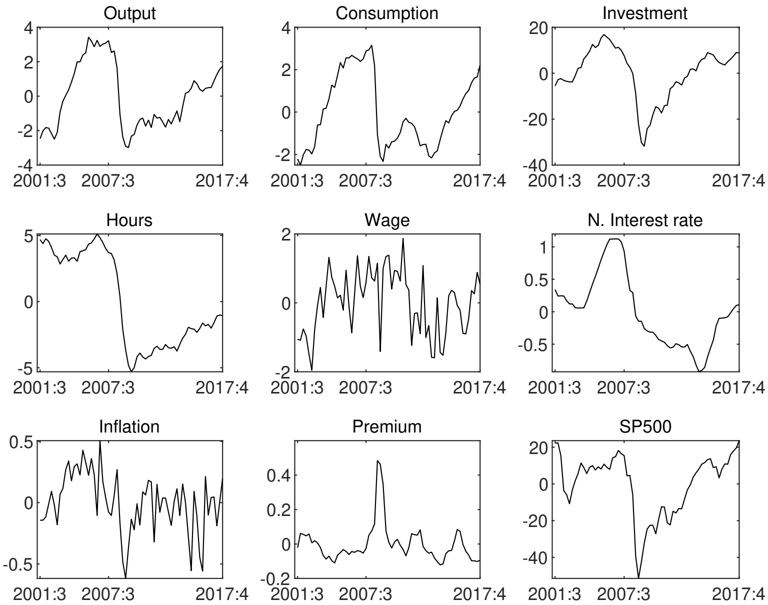


Figure 2.3: Great Recession data (2001:3-2017:4)



We choose the set of prior distributions considered in Smets and Wouters (2007). Moreover, the parameters related to the financial accelerator are estimated using uninformative priors in line with those used in De Graeve (2008). A detailed description of those prior distributions can be found in those papers. Certain parameters that govern the long-run path are also calibrated according to De Graeve (2008). The discount factor β is 0.99, implying a quarterly real interest rate of 1%, the wage markup λ_w is assumed to be 0.5, the capital depreciation rate τ is 0.025, and the capital share in production α is 0.24, like in De Graeve (2008).[16]

In addition to this standard set of prior distributions, we follow Christiano et al. (2011) by considering endogenous priors formed as the product of the former priors and the likelihood of a set of sample statistics given by the standard deviations of the observed variables. As pointed out by Christiano et al. (2011), this strategy overcomes the common problem of overpredicting the volatility implied by the model. Moreover, the use of endogenous priors allows us to use both a common set of priors for the three recession periods studied and a different set of prior volatilities for each recession.

[16] A reader may view the value chosen for the capital share, α, as rather small. Nevertheless, this value is in line with the estimates reported in the related DSGE literature (among others, the posterior mean of α is 0.19 in Smets and Wouters (2007), and 0.22 in Gelain and Ilbas (2017)). Moreover, Schmitt-Grohé and Uribe (2012) also calibrate α=0.225 in a DSGE model where there is a fixed factor of production that introduces decreasing returns to scale in the variable factors (capital and labor) of production.

2.4 Estimation Results

This section is split into two subsections. The first analyzes the fit of the model by assessing model's ability in reproducing the second moments of the observed variables during each period. The aim of this exercise is to provide evidence of the strength of a DSGE model with financial frictions in capturing economic events highlighted in the literature as important drivers of aggregate fluctuations, which helps to shed light on the structural shocks featuring DSGE models. The second subsection discusses parameter estimates and the variance decomposition in order to uncover what were the main drivers of each recession.

2.4.1 Model fit

This section compares the theoretical second moments implied by the DSGE model with those obtained from actual data. Table 1 shows three theoretical second moment statistics: the standard deviation, the contemporaneous correlation of each observable variable with output and the first-order autocorrelation coefficient together with those computed for actual data.

The first panel of Table 1 shows the standard deviation of each variable. We find that most of the standard deviation statistics from actual data are rather close to the corresponding theoretical moment. Since the three sample periods are characterized by large shocks, the model proves to be useful in capturing differences in volatility across recessions. The second panel of this table shows the comovement of the observed variables with output. In most cases, the model does a good job in matching the correlations with output computed with actual data. Nevertheless, the model has trouble in replicating the comovement of output with both inflation and the nominal interest rate during the Stagflation period. While our estimation procedure imposes determinacy, Clarida, Gali, and Gertler (1999), Lubik and Schorfheide (2004) and Boivin and Giannoni (2006) suggest that monetary policy was not successful at ruling nonfundamental fluctuations driven by multiple equilibria during the Stagflation period. In contrast many articles (Bernanke and Mihov, 1998; Cogley and Sargent, 2005; Sims and Zha, 2006, among others) find little evidence supporting a drastic change in the US monetary policy after the Stagflation period. In spite of whether indeterminacy is an issue or not, our estimation results shown below suggest that the Fed response to inflation was, perhaps, too lax in fighting inflation by reacting strongly to output-gap growth fluctuations. Moreover, the model has trouble in reproducing the strong negative correlation of the spread with ouput during the Great Depression as well as the moderate/strong positive correlation between net worth and output during the three recession periods. Finally, the lower panel of Table 1 shows the first-order autocorrelation of the observable variables. In general, the model is able to reproduce the

Table 2.1: Theoretical second moments

	Great Depression		Stagflation		Great Recession	
Standard Deviation						
	Actual Data	Model	Actual Data	Model	Actual Data	Model
Output	11.75	13.61	3.96	3.56	1.88	1.80
Consumption	7.68	8.95	2.93	2.81	1.71	1.99
Investment	42.97	49.78	8.60	10.65	11.31	11.81
Labor	16.62	14.20	2.54	2.23	3.53	3.31
Inflation	1.61	1.73	0.68	0.77	0.24	0.27
Wage	3.27	4.06	2.07	2.01	0.92	1.09
Interest rate	0.41	0.41	0.62	0.72	0.41	0.54
Spread	0.23	0.23	0.09	0.10	0.11	0.16
Net worth	31.55	19.70	19.54	12.32	20.03	19.64
Correlation with output						
	Actual Data	Model	Actual Data	Model	Actual Data	Model
Output	1	1	1	1	1	1
Consumption	0.86	0.73	0.97	0.73	0.95	0.73
Investment	0.96	0.92	0.69	0.76	0.82	0.60
Labor	0.62	0.81	0.67	0.73	0.54	0.55
Inflation	0.14	0.10	0.03	-0.21	0.46	40
Wage	0.15	0.41	0.83	0.51	0.27	0.30
Interest rate	0.38	0.07	0.26	-0.30	0.75	0.40
Spread	-0.75	-0.20	-0.35	-0.10	-0.36	-0.39
Net worth	0.53	0.27	0.83	0.25	0.54	0.38
Autocorrelation of order 1						
	Actual Data	Model	Actual Data	Model	Actual Data	Model
Output	0.93	0.89	0.96	0.93	0.93	0.85
Consumption	0.75	0.82	0.95	0.95	0.92	0.95
Investment	0.90	0.90	0.85	0.92	0.95	0.98
Labor	0.98	0.74	0.96	0.88	0.97	0.55
Inflation	0.54	0.54	0.85	0.81	0.47	0.54
Wage	0.86	0.90	0.95	0.96	0.50	0.84
Interest rate	0.94	0.83	0.90	0.89	0.97	0.79
Spread	0.89	0.90	0.92	0.85	0.81	0.89
Net worth	0.92	0.88	0.92	0.93	0.91	0.96

persistence of actual data rather accurately. There are a few exceptions though. Thus, the model falls short in matching labor persistence and overpredicts real wage persistence during the Great Recession.

With these few caveats in mind, we can conclude that overall the standard DSGE does a reasonably good job in replicating the second moment statistics featuring the actual business cycle across recession periods. This finding is quite remarkable since the US economy was hit by rather severe shocks during these specific periods. In the following sections, we assess the main causes behind each crisis.

2.4.2 What are the main driving forces behind each crisis?

This question is addressed in three steps. First, we discuss the parameter estimates, focusing especially on the parameters characterizing both endogenous and exogenous persistence. Second, an unconditional variance decomposition is carried out in order to provide a general overview of the role of each shock in the economy. Finally, a quarter-to quarter variance decomposition of output is discussed below in Section 5, which helps to grasp the nature of shocks driving the large aggregate fluctuations featured in the three major US economic crises.

Parameter estimates

This section discusses the posterior estimates of the structural and shock process parameters for the three different periods.[17] Table 2 shows the posterior estimates together with their corresponding 90% highest posterior density intervals (HPDI) in parentheses. The first three columns in these tables show the notation, the description, and the prior distribution assumed for each parameter estimated. The remaining three columns show the posterior mean estimates, together with their corresponding 90% HPDI, obtained from the baseline DSGE model with financial frictions à la BGG for the periods featuring in the Great Depression, the Stagflation, and the Great Recession, respectively.

The posterior estimates of the structural parameters show certain discrepancies across recession periods, but still it is a quite remarkable finding that their corresponding posterior density intervals largely overlap across recession periods with a few exceptions as discussed next.[18]

[17] An appendix, available from the authors upon request, shows identification tests statistics following the methodology suggested by Iskrev (2010). Identification tests results show that all parameters are identified.

[18] While the large overlap between estimated intervals are due in some cases to the large size of them, it is also true that the size of these intervals are similar to those reported in the literature (e.g. Smets and Wouters, 2007) and those estimated for the Great moderation period (1984-2007). The latter are not presented here for space reasons, but are also available upon request from the authors.

The first four parameters in Table 2 determine the effects of the financial accelerator. More precisely, higher values of these four parameters mean greater effects of the financial frictions on the economy.[19] Our estimates of the elasticity of external finance premium, ϵ, are the same across recessions (0.012). These values are close to the estimated value of 0.0186 reported by Rychalovska (2016) for the whole post-WWII period (1954:1–2008:3) without considering financial data as observables. Moreover, the estimate reported in Merola (2014), which also considers the spread between Baa and Aaa bond yields as observable, estimates a value of 0.028 for the period 1967:1-2012:4, which is also close to the estimates obtained in this paper. However, these values are significantly lower than the 0.08 considered by Bernanke et al. (1999) in their simulations (this calibration value is based on realistic values of bankruptcy rates and monitoring costs). De Graeve (2008) and Villa (2016), who do not use financial data, also get higher values (0.1047 and 0.05) for the periods 1954:1-2004:4 and 1983:1-2008:3, respectively. This comparison across papers in the related literature suggests that the consideration of financial data as well as the sample period are important for the identification of the elasticity of external finance premium. Furthermore, our low estimates of this parameter may be due to the fact that we consider sample periods where the uncertainty in the financial markets is unusually high, so banks were issuing credit at higher interest rates in these periods of distress than under normal economic conditions. Both, the investment adjustment cost parameter, φ, and the elasticity of capital utilization, ψ, show important differences across recessions. Thus, the investment adjustment cost parameter is higher in recent recessions, especially during the Great Recession (7.02), whereas the elasticity of capital utilization is higher in the Great Depression (0.71) than in the other two recessions (roughly around 0.15) .

The estimate of the habit persistence parameter, h, for the Great Depression is much lower (0.13) than the estimates obtained for the other two recession periods (0.58 and 0.66), which are closer to those reported in the literature (e.g. Smets and Wouters, 2007, report a posterior estimate of 0.7).

Turning to the parameters featuring nominal rigidities, we find that the stickiness of wages, ξ_w, is not especially high during the Great Depression. This finding is somewhat in contrast with those of several economists (e.g. Eichengreen and Sachs, 1985; Bernanke and Carey, 1996; Bordo et al., 2000) about the role of wage stickiness in the Great Depression and the money non-neutrality implication. Our estimates suggest that nominal wages were rigid to some extent, but that rigidity was not especially high during the Great Depression in comparison with the other two recession periods. The main reason for the contemporaneous drops in employment and rigid nominal wages is found to be the moderate persistence of the wage markup shock (0.41) capturing labor market

[19] The consideration of financial data makes for a better identification of these parameters, especially the elasticity of the external finance premium.

legislation changes as further discussed below. Regarding price stickiness, we find a low Calvo's lottery parameter, ξ_p, estimate for the Stagflation period (0.67) due to the high rates of inflation, as expected. This estimate is lower than the estimates found for the other two recessions (around 0.83) featured for (near) deflationary episodes.

Alternative values of the coefficients of the Taylor rule suggest that the conducted monetary policy varies across periods. This is in line with Benchimol and Fourçans (2019) who investigate in more detail which central bank's rules are most in line with the historical data. We find that the main difference across recessions is related to the interest rate smoother parameter, which is much lower (0.81) in the Stagflation and Great Recession periods than in the Great Depression period (0.97). This suggests that the nominal interest rate was reacting more to the economic outlook during the two most recent recessions studied. In the same vein, we also observe that the Fed was more concerned about output growth stabilization during the Stagflation and the Great Recession than during the Great Depression.[20] The estimates of policy parameters of the Stagflation period are somewhat in line with economic wisdom of the time. Thus, expansive monetary policies were seen as useful to restore any drop in output and employment. Indeed, the Fed responses might be viewed as propitiating a scenario in which monetary policy was not fighting inflation aggressively enough by trying to stabilize output gap growth, which led to a two-digit inflation scenario.[21]

Table 2 also shows the estimated values of the parameters associated with the shock processes. The main discrepancies across recessions arise in the persistence of the productivity shock, wage and price markup shocks. Thus, productivity shocks are more persistent during the Stagflation period likely capturing the introduction of energy saving technologies after the recurrent oil crises. It is also noteworthy that although the stickiness of wages is not as high as found in other studies of the Great Depression, the persistence of the wage markup shock is moderately high during this period. Thus, wage stickiness might be due not to the formation of wages but rather to the persistence of wage markup shocks capturing labor market legislation changes which had an important role during this period as further discussed below. As expected, the persistence of the price markup shock that

[20] This concern for output stabilization during the Stagflation is in line with the empirical findings of Smets and Wouters (2007) based on a DSGE model without financial frictions, and Orphanides (2003) based on the estimation of a Taylor rule using real-time data.

[21] We have explored alternative modeling possibilities, such as a Taylor rule that reacts to the money demand—as in Canova and Ferroni (2012) and Casares and Vázquez (2018)— finding similar results to those presented in this paper (including MZM time series as an observable variable in the Stagflation and the Great Recession samples, and M1 in the Great Depression sample). Since the only difference found is a relatively small increase in the standard deviation of the monetary policy shock, pointing out the worse fit of that Taylor rule, we have advocated for a simple policy rule in order to keep the model as parsimonious as possible. Results from this alternative specification are available upon request from to the authors.

Table 2.2: Estimated structural parameters

Parameter	Description	Prior Distribution		Great Depression	Stagflation	Great Recession
		Type	Mean/Std	1923:1-1940:4	1960:1-1979:3	2001:3-2017:4
R^k	Steady state return to capital	Normal	1.015/0.002	1.010 [1.005 - 1.012]	1.016 [1.013 - 1.019]	1.007 [1.004 - 1.010]
K/N	SS capital to net worth ratio	Normal	2.5/0.25	1.47 [1.24 - 1.69]	1.55 [1.2365 - 1.8422]	2.13 [1.74 - 2.50]
γ	Survival probability	Beta	0.95/0.02	0.91 [0.88 - 0.94]	0.92 [0.90 - 0.93]	0.97 [0.96 - 0.98]
ϵ	Elasticity of external finance premium	Normal	0.05/0.02	0.012 [0.009 - 0.015]	0.012 [0.009 - 0.015]	0.012 [0.007 0.018]
φ	Investment adjustment cost	Normal	4/1.5	1.17 [0.78 - 1.57]	4.17 [3.10 - 5.21]	7.02 [4.96 - 9.08]
h	Habit formation	Normal	0.7/0.1	0.13 [0.10 - 0.17]	0.58 [0.50 - 0.67]	0.66 [0.57 - 0.75]
ψ	Elasticity of capital utilization	Gamma	0.2/0.075	0.71 [0.48 - 0.95]	0.17 [0.08 - 0.27]	0.11 [0.05 - 0.17]
ϕ	Fixed cost	Normal	1.25/0.125	1.38 [1.26 - 1.49]	1.48 [1.36 - 1.59]	1.30 [1.13 - 1.46]
σ_l	Elasticity of labor supply	Normal	2/0.75	1.76 [0.80 - 2.71]	1.98 [1.02 - 2.89]	2.57 [1.76 - 3.36]
ξ_w	Calvo Lottery for wage	Beta	0.5/0.1	0.79 [0.75 - 0.83]	0.77 [0.69 - 0.84]	0.73 [0.68 - 0.77]
ξ_p	Calvo Lottery for prices	Beta	0.5/0.1	0.82 [0.78 - 0.86]	0.67 [0.61 - 0.74]	0.84 [0.82 - 0.86]
γ_w	Indexation of past inflation in wages	Beta	0.5/0.15	0.80 [0.70 - 0.91]	0.58 [0.41 - 0.76]	0.34 [0.14 - 0.52]
γ_p	Indexation of past inflation in NKPC	Beta	0.5/0.15	0.25 [0.11 - 0.38]	0.33 [0.17 - 0.49]	0.23 [0.11 - 0.34]
ρ	Interest rate smoother	Gamma	0.75/0.1	0.97 [0.96 - 0.98]	0.81 [0.77 - 0.86]	0.81 [0.77 - 0.85]
r_π	Response to inflation	Normal	1.5/0.1	1.45 [1.29 - 1.61]	1.52 [1.36 - 1.67]	1.53 [1.38 - 1.68]
$r_{\Delta\pi}$	Response to change in inflation	Gamma	0.3/0.1	0.03 [0.01 - 0.03]	0.14 [0.08 - 0.21]	0.17 [0.06 - 0.17]
r_y	Response to output gap	Gamma	0.125/0.05	0.12 [0.07 - 0.16]	0.10 [0.06 - 0.13]	0.10 [0.07 - 0.12]
$r_{\Delta y}$	Response to output gap growth	Gamma	0.063/0.05	0.02 [0.01 - 0.02]	0.13 [0.09 - 0.16]	0.09 [0.06 - 0.12]
ρ_a	Persistence produtivity shock	Beta	0.5/0.2	0.61 [0.52 - 0.70]	0.84 [0.80 - 0.88]	0.43 [0.32 - 0.55]
ρ_b	Persistence risk premium shock	Beta	0.5/0.2	0.66 [0.55 - 0.79]	0.74 [0.65 - 0.83]	0.68 [0.58 - 0.78]
ρ_i	Persistence investment shock	Beta	0.5/0.2	0.30 [0.13 - 0.48]	0.10 [0.02 - 0.16]	0.16 [0.05 - 0.26]
ρ_w	Persistence wage markup shock	Beta	0.5/0.2	0.41 [0.28 - 0.54]	0.48 [0.29 - 0.68]	0.02 [0.00 - 0.04]
ρ_p	Persistence price markup shock	Beta	0.5/0.2	0.30 [0.15 - 0.45]	0.86 [0.80 - 0.92]	0.17 [0.05 - 0.28]
ρ_{nw}	Persistence net worth shock	Beta	0.5/0.2	0.33 [0.10 - 0.56]	0.54 [0.37 - 0.71]	0.32 [0.11 - 0.52]
σ_a	Std. productivity shock	Gamma	0.25/0.2	5.78 [4.52 - 7.01]	0.59 [0.50 - 0.68]	2.41 [2.11 - 2.70]
σ_b	Std. risk premium shock	Gamma	0.25/0.2	2.07 [1.38 - 2.74]	0.67 [0.39 - 0.94]	0.60 [0.33 - 0.87]
σ_i	Std. investment shock	Gamma	0.25/0.2	8.42 [6.61 - 10.04]	2.00 [1.74 - 2.26]	1.04 [0.84 - 1.23]
σ_r	Std. monetary policy shock	Gamma	0.25/0.2	0.13 [0.12 - 0.15]	0.19 [1.74 - 2.26]	0.13 [0.11 - 0.16]
σ_p	Std. price markup shock	Gamma	0.25/0.2	0.84 [0.66 - 1.02]	0.13 [0.10 - 0.17]	0.13 [0.11 - 0.16]
σ_w	Std.wage markup shock	Gamma	0.25/0.2	0.43 [0.34 - 0.53]	0.15 [0.11 - 0.19]	0.33 [0.30 - 0.36]
σ_{nw}	Std. net worth shock	Gamma	0.25/0.2	4.37 [3.58 - 5.02]	1.33 [0.73 - 1.88]	2.32 [0.86 - 3.66]

likely captures the strong effects of the oil crisis is very important during the Stagflation. Finally, it is worth mentioning the differences in the standard deviations of the shocks between the Great Depression and the other two recessions. This may indicate that the deep recession experienced during the 1930's could have been caused and aggravated by remarkably large shocks.

Our results show that, although many of the estimations of structural parameters are rather robust across the sample periods, the same standard DSGE model is able to capture important differences across the three main crises of the last century in terms of both parameter rigidities and the contributions of each shock throughout the business cycle. In order to interpret these changes in shock parameters, the rest of the paper focuses on the role of the shocks in more detail.

Unconditional variance decomposition

The variance decomposition of the key aggregate variables sheds light on the causes of each recession and provide an overview of fluctuation causes for each variable. Table 3 shows the unconditional variance decomposition for the Great Depression, the Stagflation and the Great Recession from top to bottom. The analysis of the variance decomposition shows both similarities and differences across recession periods.

Risk premium, productivity and investment specific shocks are major drivers of output fluctuations in the three recession periods analyzed, but output fluctuations are also explained by different shocks in addition to the former three. Thus, monetary shocks explain 20% of output fluctuations during the Great Depression. Moreover, price and wage mark up shocks explain a sizable proportion of output fluctuations during the Stagflation period (25% and 13% respectively). Indeed, the important role of price and wage markup shocks in explaining fluctuations across variables is a distinctive feature of the Stagflation period, capturing the effects of the oil supply interruption and the resistance of cutting wages. In contrast, net worth shocks play an important role in explaining aggregate fluctuations in the Great Recession period (they explain 41% and 61% of consumption and investment fluctuations) while their importance in explaining real variable fluctuations is rather small in the other two recessions. To a lesser extent, monetary policy shocks play a role in explaining aggregate fluctuations in the Great Depression (they explain 20% of output and consumption fluctuations and around 15% of investment and labor variability) while their importance is much smaller in the other two recessions. These results indicate that the estimated model is able to distinguish the different features that characterize each period and properly identifies the relative importance of structural shocks that drove these recessions.

In the following section, we analyze in detail each episode and connect the estimated shocks with the historical economic evidence through a historical variance decomposition of output. In that analysis special attention is given to the link of the estimated persistence of shocks with the long lasting effects of some specific economic changes.

2.5 Historical variance decomposition of output

This section analyzes what specific shocks cause each recession by analyzing the historical quarter-to-quarter variance decomposition of output. This analysis shows the cumulative effect of a given structural shock on output in each quarter. Figures 4-6 show the historical variance decomposition of detrended output for the three recessions. Each figure contains two graphs. The upper graph shows the historical variance decomposition of output obtained from the baseline model with BGG

Table 2.3: Variance decomposition

Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth
Great Depression									
Productivity	16	19	15	29	13	17	35	9	1
Risk premium	30	40	14	26	2	2	33	2	18
Investment	20	8	45	18	1	4	9	16	2
Price markup	10	7	8	8	63	32	7	3	1
Wage markup	4	5	3	3	8	34	8	2	1
Monetary	20	20	14	16	8	10	10	6	2
Net worth	0	1	2	0	0	0	59	62	75
Stagflation									
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth
Productivity	19	22	14	11	15	18	18	4	2
Risk premium	23	29	8	28	8	1	45	2	11
Investment	14	12	47	18	1	1	4	18	1
Price markup	25	14	12	17	49	69	16	3	1
Wage markup	13	15	11	20	24	11	11	30	1
Monetary	5	5	2	6	3	0	6	0	2
Net worth	1	2	7	1	0	0	0	68	83
Great Recession									
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth
Productivity	13	7	5	85	27	2	63	3	4
Risk premium	44	28	14	7	9	9	18	11	15
Investment	20	16	17	4	2	4	2	8	1
Price markup	2	1	0	0	41	10	2	0	0
Wage markup	3	3	1	1	13	67	2	0	0
Monetary	9	4	2	1	4	3	8	1	2
Net worth	8	41	61	2	2	5	4	77	77

financial frictions, whereas the bottom graph shows the historical variance decomposition of output for the model with GK financial frictions in order to check for robustness. In each graph, the black line shows the actual detrended output and the bars show the contribution of each shock to the deviation of output from its (log-linear) trend in a given quarter. Thus, adding up the bars gives the actual (log-linear) detrended output. Moreover, the figures associate the changes in the relative importance of structural shocks with specific economic events. Hence, this analysis enables us to link the relative importance of the estimated shocks with the narrative historical evidence and assess whether the model is able to provide a sound interpretation of each of these three different recessions. Similar to Figures 1-3, a quick look at the different scale of the vertical axis in Figures 4-6 shows that the output fluctuations (and then the size of the shocks) associated with the Great Depression are much larger than the ones associated with the other two recessions.

The Great Depression

The first sample runs from 1923:1 until 1940:4. The sample considers the boom of the 1920's, the 1929 crash, and the Great Depression. Figure 4 shows the historical variance decomposition of output obtained from the DSGE model with the two approaches followed for including financial frictions (BGG and GK). Focusing on the upper graph, it can be observed that the exogenous risk premium shock also plays a crucial role in the boom of the 1920's. In the model with BGG frictions, financial shocks reflect reductions in the cost of external funds. Therefore, investment becomes more attractive for entrepreneurs during this decade. The model captures the financial optimism of the decade. As discussed in White (1990), investors aiming at gaining future dividends believed that the positive trend of the stock market was going to last for a long time. Moreover, White (1990) blames news of an upcoming recession and the rise in the nominal interest rate for the change in stockholders' expectations at the end of the decade that triggered the 1929 crash. The estimated historical decomposition captures well how negative realizations of the risk premium shock (which had a positive effect on output) turned into positive realizations of risk premium shocks leading to a large output drop with the 1929 crash. This risk premium shock captures how the model reproduces the expectation changes from financial optimism to high uncertainty. Romer (1990) argues that after the stock market crash the high volatility of stock prices (more than twice as great than ever recorded before) generated tremendous uncertainty among investors. The estimated DSGE model is able to capture this financial uncertainty through the positive realizations of the risk premium shock that prolonged the Great Depression.[22]

[22]The positive realizations of the wage markup shock in the late 1920's and early 1930's, which were persistent

The model does not allow us to clarify the link between the rise in nominal interest rates and the change in expectations captured by the risk premium shock, but it does show —as Christiano et al. (2003) suggest— that monetary policy was conducted in a way that magnified the severity of the recession. In the early 1930's, while the economy was collapsing and the unemployment was rapidly increasing, the Federal Reserve applied an unprecedented increase in the nominal interest rate (to a level that was not reached again until the 1980's). In particular, the US government was concerned in 1931 about the possible outflow of capital to overseas markets, so they increased the interest rate in an unprecedented way. These risk premium and monetary policy shocks substantially contributed to the large drop in output turning the initial contraction into the Great Depression. They are captured well by the estimated DSGE model as Figure 4 shows. Nevertheless, along with the implementation of the First New Deal (1933-1934), the Federal Reserve and the Roosevelt government announced a new objective of monetary policy: âMonetary policy will help to restore economic growthâ. As a result, the negative effects of monetary policy shocks in the quarter-to-quarter variance decomposition of output are observed to vanish, meaning that the monetary policy conducted is captured well by the Taylor rule. Once these shocks fade out, and consequently interest rates decrease, an increase in output is observed.

As a part of the First New Deal, the US authorities reformed the market economy by passing the National Industrial Recovery Act (NIRA) in 1933. This act was intended to fight against deflationary pressure and trigger an increase in economic activity. However, as part of the Second New Deal, the National Labor Act (Wagner Act) of 1935 empowered labor unions, implemented minimum wages, and shortened the working week. As Prescott (1999) claims, this change in legislation meant that the drop in labor was not recovered and hours worked stayed low. In addition, the NIRA also allowed firms to reach collusive price agreements to prevent the bankruptcy of the increasing number of firms that were unable to cut prices. These important changes in legislation resulted in an increase in the price markup. The effects of this increase in market power of labor unions (in the labor market) and firms (in the goods market) on output are captured by the estimated model through positive, persistent wage and price markup shocks that pushed down output and produced a slow US economic

during this period, were also a (minor) determinant of output fluctuations. These shocks capture the incorporation into the labor force of new workers willing to work for low pay. The 1920's was the last decade of mass immigration flows (the peak inflow of immigrants was reached in 1930) from Southern and Eastern Europe in pursuit of the prosperity that the US was promising (i.e. the American Dream). In addition, African Americans from the rural south were moving to major central and northeastern cities seeking better jobs and escaping from segregation laws and institutionalized discrimination. These two persistent factors together with the increasing participation of women in the labor market resulted in a persistent reduction of wages, as captured by the positive effect of wage markup shocks on output.

recovery as Figure 4 shows. These results obtained in a DSGE framework are in line with the findings in Weinstein (1980) and Cole and Ohanian (2004) using different approaches. In particular, they find that the collusive price agreement triggered significant wage and price increases.[23]

Interestingly, the historical variance decomposition obtained using the DSGE model with GK financial frictions (bottom graph in Figure 4) is rather similar to the one obtained from the baseline model with BGG financial frictions, indicating the robustness of the relative importance of structural shocks and their interpretation to the approach used to introduce financial frictions in the DSGE model. There is an important difference though. The importance of most shocks in explaining output fluctuations largely decreases in the pre-crisis period and the recovery phase in the model with GK frictions, with the exception of the risk premium shocks that play a crucial role in the two specifications.

To sum up, this crisis was caused by a whole variety of persistent shocks with different sources, including a financial crash, monetary policy shifts, and recurrent financial turmoils as well as important changes in legislation which by nature had long lasting effects across markets. The estimated DSGE model is able to link the persistent of these shocks with these specific economic sources.

The Stagflation

After the rapid growth era of the 1960's and early 1970's the US economy suffered a crisis with unprecedented features, known as the Stagflation. Its historical variance decomposition is shown in Figure 5 for the two alternative ways of introducing financial frictions considered in this paper.

This period features accelerating inflation. The main cause leading to two-digit inflation rates was the so-called oil crisis as discussed in intermediate macroeconomics textbooks (e.g. Abel and Bernanke, 1998, p. 433). During this period the US was one of the world's main oil producers. However, due to the fast development of the automobile industry, among other reasons, oil consumption far exceeded oil production. This scenario empowered a new oil cartel (OPEC), which became the main oil supplier of the US, Europe, and Japan. As a response to the political support

[23] Cole and Ohanian (2004) suggest a model of the bargaining process between workers and firms that occurred with the New Deal cartelization policies, and incorporate that model within a dynamic general equilibrium model. In line with our interpretation of the estimated structural shocks, they argue that the collusive price agreements propitiated by New Deal policies are a significant factor explaining the post-1933 Depression. Moreover, Cole and Ohanian (2004) argue that the main depressing factor of New Deal policies was not collusion itself, but rather the connection between price collusion and the high wages implied by the raising of labor bargaining power. In the same vein, Christiano et al. (2003) highlights the role played by a shock that increased the market power of workers in explaining the long duration of the Great Depression.

of the US and western European countries for Israel's foreign policy in the Middle East, OPEC (led by Middle-East oil exporting countries) cut off oil supplies in 1973. Demand for oil is extremely inelastic in the short-medium run, so the oil price dramatically increased, resulting in a persistent increase in the production costs in almost all sectors of the economy. In particular, recurrent oil price shocks triggered a wage-price spiral. The upper graph of Figure 5 shows how these cost-push shocks are captured in a timely fashion by the estimated price and wage markup shocks in the estimated DSGE model with BGG financial frictions, pushing output down strongly, which postulates them as the main drivers of this recession. The important role played by markup shocks in this period is in line with the findings in the related literature. For instance, Smets and Wouters (2007) points out that the recession of 1974 was mainly driven by markup shocks related to the oil crisis.

Up to that time, the US economy was characterized by the so-called Phillips curve. High levels of inflation were viewed as contemporary of high levels of employment and output, and vice versa. Thus, there was a widespread belief that high inflation was caused by high employment rates, which triggered wage increases, and that rise was passed through to prices. This interaction led to the wide acceptance of the ideas put forward by Keynesians (Keynes, 1936; Hicks, 1937; Modigliani, 1944). Indeed, conservative president Nixon would even go so far as to say that "now, we are all Keynesians". In this vein, several studies suggest that the monetary policy implemented during the period played a crucial role in the Stagflation (e.g. Bernanke et al., 1997; Hunt, 2006). In particular, (Hunt, 2006) suggests that oil shocks alone could have not generated that sharp increase in inflation and the drop in economic activity, but the overestimation of the output gap by the monetary authority and a reluctance to reduce wages were fundamental ingredients of this recession. Our estimates somewhat support this hypothesis. The parameter estimates show that the Fed was especially concerned about stabilizing the output gap during the period as shown by the relative low value of the inertial parameter, ρ, which shows that the Fed was more prone to respond to the economic outlook, together with a relative high response of the nominal interest rate to output gap growth in this period. This policy strategy might have led to an unstable scenario in which monetary policy do not strongly fight against inflation triggered by the cost push shocks (oil crisis) as those realized at that time and worsen the situation since people expectations about future inflation may become self-fulfilling (Lubik and Schorfheide, 2004). This strategy did not change until the late 1979 (just at the end of our sample period), when Fed chairman Paul Volcker committed to fight high inflation rates. Moreover, the resistance of workers to cuts in real wages through high inflation rates is also captured by the model through the persistent wage markup shocks, which substantially increased wages. Thus, the model shows that both accommodative monetary policy and increasing wages contributed along with huge oil price increases to the stagflation of the 1970's.

It also important to notice that the historical variance decomposition of output provided by the model also captures the financial boom that characterized the 1960's. The risk premium shock explains a sizable share of the output boost of the 1960's. This financial boom was due to attractive new possibilities of investment, since promising technology was introduced into the economy (e.g. consumer electronics and incipient computer technology). Shiller (2000) argues that this period is an example of high optimism where the idea that the stock market was the best investment was widespread. Nevertheless, the financial market collapsed during the 1970's due to uncertainty and the increase in production costs triggered by the rise in oil prices. The financial crisis worsened the output drop triggered mainly by the cut in oil supplies.

In addition to the factor mentioned above, the productivity shocks captured by the model during the 1970's might be identifying the fact that Japan and European countries were emerging from their post-WWII reconstruction efforts, showing a great deal of competitiveness. Therefore, the international markets pressured US import-competing sectors, forcing them to improve their productivity. For instance, General Motors, Ford, and Chrysler accounted for 89.6% of the automobile industry in 1966, but in the following three years automobile imports grew at an average rate of 84% per annum.[24] Indeed, imports and exports measured as a proportion of GDP rose from 10% to 20% between 1969 and 1980.

Like the Great Depression, the Stagflation period was a recession triggered by a variety of persistent shocks, which this standard DSGE model, using two alternative ways of modeling financial frictions, has proved able to robustly link them with a recurrent increase in oil prices and the price-wage inflation spiral lasting over the whole period.[25]

The Great Recession

Figure 6 shows the historical variance decomposition of output for the the Great Recession period obtained from the two approaches considered to introduce financial frictions. This variance decomposition clearly identifies this recession period as driven by the risk premium shock. Then, the explanation of this recession provided by the baseline DSGE model is in line with other findings based on specific models developed for this period. For example, Christiano et al. (2015) build a DSGE model that can account for the features of the Great Recession, finding that a large proportion

[24] Foreign Automobile Sales in the United States. Federal Reserve Bank of St. Louis. November 1, 1970. Retrieved July 1, 2016.

[25] Notice that the estimated model with the GK approach has some difficulties in capturing the role of some shocks (e.g. wage markup shocks) during the Stagflation period since it allocates a relative large weight to the initial values in the the historical variance decomposition.

of aggregate fluctuations are due to financial shocks.

The historical variance decomposition also shows that the Fed was carrying out an expansive monetary policy in the early 2000's. More precisely, there was a systematic reduction in interest rates after 9/11 with the intention of preventing a recession. This expansive monetary policy provided a massive amount of funds to financial intermediaries. Consequently, banks were able to fund an artificially high number of entrepreneurial projects, which meant that they were underestimating the high risk associated with a large proportion of those projects. The estimated DSGE model captures this scenario through negative risk premium shocks that raise output up to 2007. On top of this, an extremely large flow of credit was directed to investment in the real-estate sector, which worked against the basic principle of hedging against risk in banks and financial intermediaries through a diversified portfolio. The real-estate sector was perceived at the time as a safe investment and increases in real-estate prices were perceived as sustainable. This scenario, where the real-estate sector was booming, is captured well through the risk premium and investment shocks.

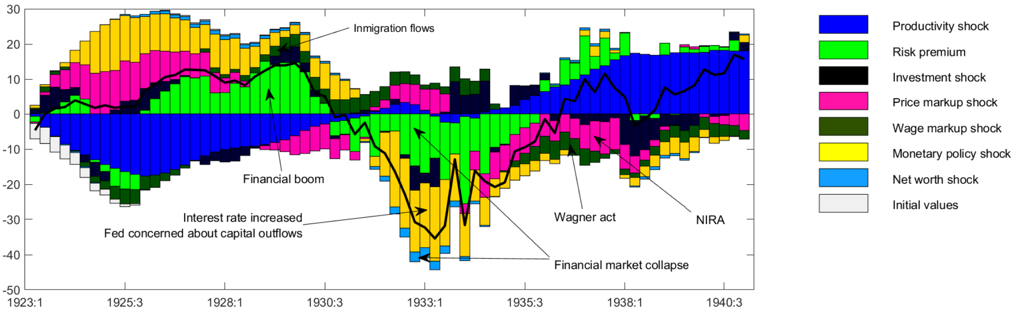
The real-estate bust after 2007 caused a sharp, lengthy drop in output. Entrepreneurs behind risky projects funded by artificially low interest rates began to default. Hence, financial intermediaries realized that risk was undervalued and they rapidly changed their beliefs, but this time became especially skeptical. This sudden shift in beliefs is captured in the estimated model through positive realizations of the risk premium shock, which result in a dramatic fall in output. Moreover, both defaults and credit restrictions decreased demand for housing investment, which was seen before the crisis as a perfectly safe investment. This shift in beliefs about the real-estate sector is also captured in the estimated model through both an investment and a financial shock—in this case entailing negative realizations of the investment and net worth shocks. This large fall in net worth valuation resulting from the real-estate bust led to an increase in the leverage ratio and consequently made external funding even more expensive, worsening the economic outlook. In sum, an expansive monetary policy by the Fed and an increase in credit flow that was intended to finance a (wrongly perceived) risk-free real-estate sector created a housing boom that became unsustainable in 2007. Its bursting gave rise to the Great Recession.[26] Then, we can conclude that the standard DSGE model under the two approaches considered to introduce financial frictions is able to provide a sound description of the period surrounding the Great Recession in line with the historical evidence and other studies findings.[27]

[26]This interpretation is in line with Miao et al. (2015) that identify a stock market boom caused by the housing bubble of the 2000s, and the subsequent Great Recession, in an estimated real-business-cycle-DSGE model with stock market bubbles.

[27]Interestingly, the model with BGG frictions highlights the importance of negative investment shocks during the Great Recession that are somewhat downplayed by the GK approach.

Figure 2.4: Historical Variance Decomposition of Output in the Great Depression

BGG financial sector



GK financial sector

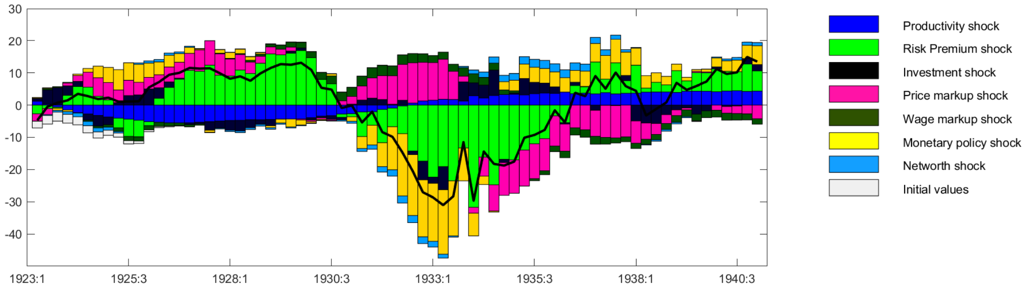
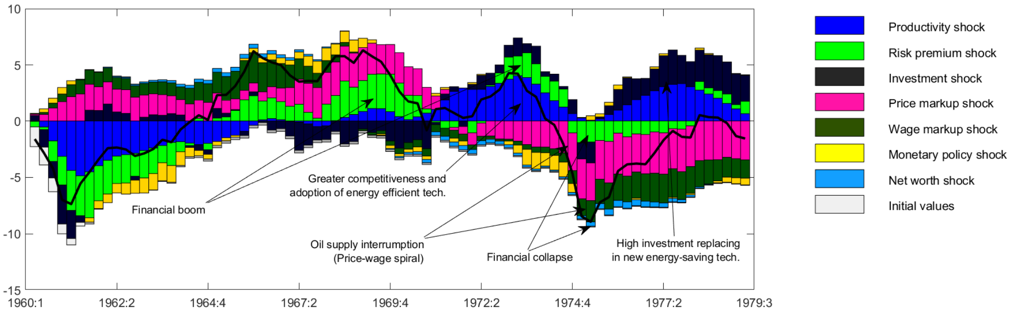


Figure 2.5: Historical Variance Decomposition of Output in the Stagflation

BGG financial sector



GK financial sector

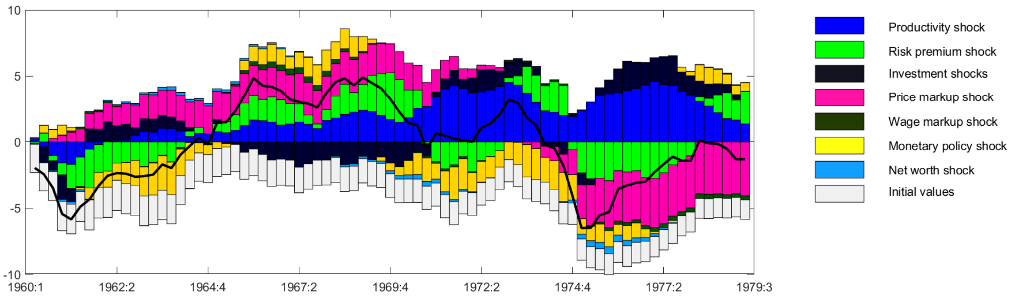
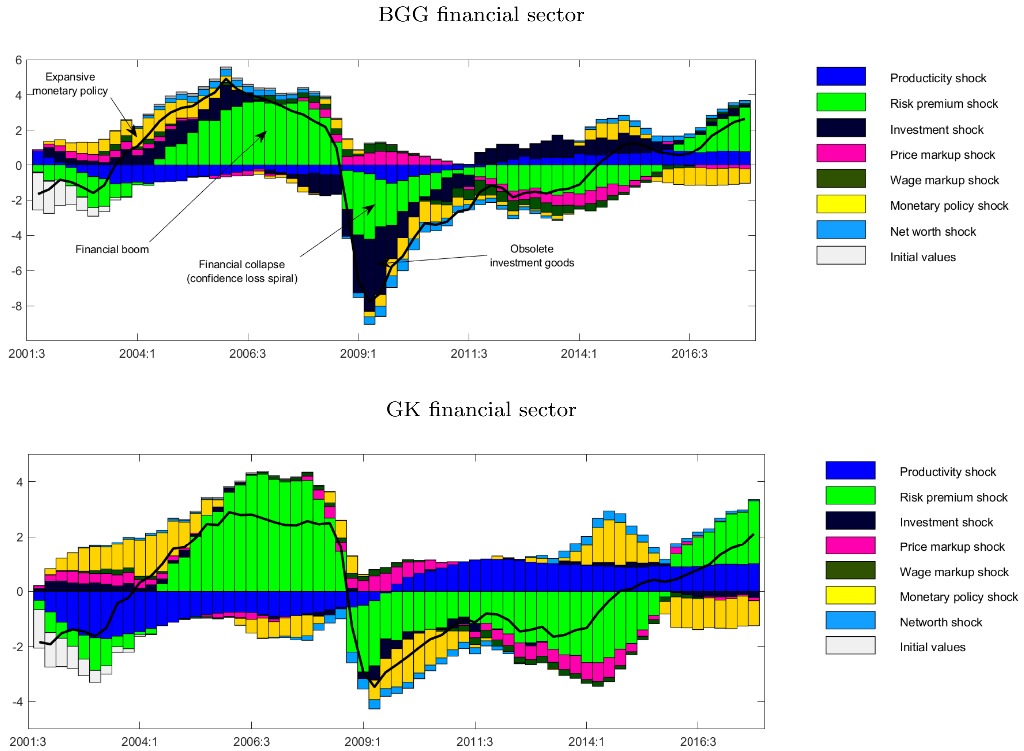


Figure 2.6: Historical Variance Decomposition of Output in the Great Recession



2.6 Robustness analysis

As discussed above, we attempt to consider a parsimonious model to assess its ability to characterize rather different recessions with alternative sources of fluctuations. In this section, however, we include some additional building blocks to assess whether the sound description provided by the baseline model remains robust across recessions. In particular, we assess robustness across three dimensions. First, we consider a fiscal building block. Second, we include money in the model to assess the relative importance of monetary shocks. Finally, we estimate the baseline model over the whole sample (i.e. 1923:1-2017:4) in the spirit of Auray and Eyquem (2019) by considering as missing data the time series points associated with the WWII period and its immediate aftermath.

2.6.1 Fiscal Building Block

The baseline model does not consider a fiscal building block in order to remain as parsimonious as possible. However, it is important to examine whether the estimation results (and more specifically, the identification of structural shocks) are robust to the inclusion of a fiscal building block. To that end, we consider that government spending is financed by lump-sum taxes on households. Following

Leeper et al. (2010) and Born et al. (2013), we consider that aggregate taxes are endogenous and follows a simple rule where taxes react to the log of the government debt in real terms, $log\left(\frac{B_t}{P_t}/\frac{B}{P}\right)$, to ensure stability:

$$T_t = (1-\rho^T)T + \rho^T T_{t-1} + \phi^{TB} log\left(\frac{B_t}{P_t}/\frac{B}{P}\right),$$

where T_t are the lump-sum taxes at time t, $\rho^T$is the autoregressive parameter that captures the sluggishness of aggregate taxes, T is the average tax, and $\phi^{TB}$is the feedback semi-elasticity.

In addition, we also consider a simple rule to describe government spending dynamics.[28] We assume that government spending shows a degree of persistence captured by the parameter ρ^G, and that government spending reacts to the level of current real debt, and to the log-deviation of output from its steady state, $log(Y_t/Y)$, to account for its relation with the business cycle. Moreover, we add a disturbance ϵ^G to complete the spending rule:

$$log\left(\frac{G_t}{G}\right) = \rho^G log\left(\frac{G_{t-1}}{G}\right) + \phi^{GB} log\left(\frac{B_t}{P_t}/\frac{B}{P}\right) + \phi^{GY} log\left(Y_t/Y\right) + \epsilon_t^G.$$

The government budget constraint implies the following law of motion of the debt:

$$B_{t+1} = R_t B_t + G_t - T_t,$$

and the resource constraint of the economy is now represented by the following equation:

$$Y = C_t + I_t + G_t + C_t^{util} + C_t^{bankru}.$$

We add an additional observable in the estimation procedure in order to identify government spending dynamics. More precisely, we consider US total government expenditures to assess the relative importance of government spending shocks in explaining aggregate fluctuations.

Table 4 shows the variance decomposition of the three recessions considered. On the one hand, we find that the effects of the government spending shocks are almost negligible in explaining the aggregate observable fluctuations during the Great Depression and the Stagflation. These shocks only play an important role in explaining government spending fluctuations. As a result, the baseline model seems to be a reasonable benchmark for characterizing the main features of these two recessions. Moreover, the historical variance decomposition of output (shown in an appendix not intended for publication) shows a roughly equivalent description of both recessions with regard to their silent-fiscal-side counterpart shown above (Figures 4-5).

[28] Government spending may be though of as entering the household utility function as suggested in Born et al. (2013)

On the other hand, the fiscal shock plays a role during the Great Recession, but its contribution is small.[29,30] Figure 7 shows the historical variance decomposition of output when the fiscal building block is taken into account. It is noticeable that fiscal policy plays a role at the beginning of the recession by attempting to smooth the sharp drop in output, as well as in the recovery phase when the government budget must be adjusted, slowing the recovery. In any case, the inclusion of the fiscal building block does not alter the assessment on the main determinants of each recession.

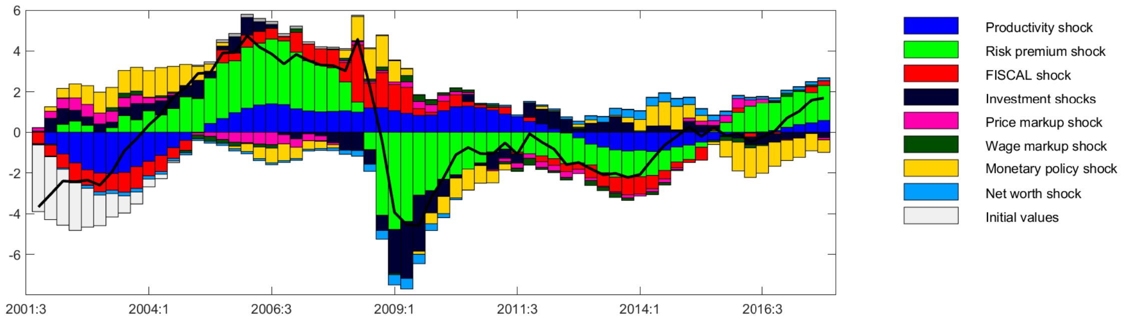
Table 2.4: Variance decomposition with a fiscal building block

Great Depression										
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth	Gov. Spending
FISCAL	1	1	1	1	1	0	5	1	0	84
Productivity	13	12	12	16	8	15	14	8	1	2
Risk premium	30	47	15	32	10	3	32	3	16	5
Investment	19	9	41	18	2	4	6	17	2	1
Price markup	5	6	3	3	54	30	7	2	0	2
Wage markup	4	7	2	1	10	36	13	2	1	2
Monetary	28	18	24	27	16	12	23	10	4	5
Net worth	1	1	1	0	0	0	1	57	76	0
Stagflation										
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth	Gov. Spending
FISCAL	1	3	1	7	0	0	1	0	0	48
Productivity	26	27	16	11	21	31	29	1	1	14
Risk premium	16	24	6	23	11	0	52	1	2	14
Investment	18	13	52	22	0	4	2	7	1	6
Price markup	25	17	11	19	50	57	14	1	1	9
Wage markup	9	10	6	12	15	6	6	0	0	4
Monetary	5	6	2	5	1	0	5	0	1	3
Net worth	1	2	7	1	0	0	0	91	96	1
Great Recession										
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth	Gov. Spending
FISCAL	11	12	2	18	3	0	1	1	1	32
Productivity	10	11	9	22	9	10	7	2	3	11
Risk premium	44	44	23	24	19	4	75	15	28	25
Investment	14	5	28	7	1	3	1	13	2	10
Price markup	1	1	1	1	40	11	2	0	1	1
Wage markup	3	4	3	5	19	68	3	1	0	4
Monetary	14	11	10	19	8	2	10	4	8	14
Net worth	3	11	23	4	1	2	1	62	57	3

[29] Other studies also find that *fiscal policy shocks contribute little to the cyclical variability of aggregate non-policy variables* (Leeper, Plante, and Traum, 2010, foonote #15) .

[30] We also observe that incorporating a fiscal building block into the DSGE model somewhat reshapes the relative importance of a few shocks. Thus, it largely reduces the importance of net worth shocks in explaining consumption and investment fluctuations in the Great Recession period, while increasing the importance of risk premium shocks.

Figure 2.7: Historical variance decomposition of the Great Recession - with fiscal side



2.6.2 Including money

In this section we analyze whether the introduction of an explicit money market affects the sound description of the structural shocks provided by the cash-less baseline model across recessions. More precisely, we incorporate a microfounded demand of money by considering a money-in-the-utility approach in the household optimization problem. Thus, the representative household utility function and its resource constraint it is defined as follows:

$$E_t \sum_{k=0}^{\infty} \beta^k \left[ln(C_{t+k}(i) - hC_{t+k-1}) - \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l} + \epsilon_t^m \frac{1}{1+\sigma_m} \left(\frac{M_{t+k}(i)}{P_{t+k}} \right)^{1+\sigma_m} \right],$$

$$C_{t+k}(i) + \frac{B_{t+k}(i)}{e^{\epsilon_t^b} R^n_{t+k} P_{t+k}} + \frac{M_{t+k}}{P_{t+k}} - T_{t+k} = \frac{W_{t+k}(i)L_{t+k}(i)}{P_{t+k}} + \frac{B_{t-1+k}(i)}{P_{t+k}} + \frac{D_{t+k}}{P_{t+k}} + \frac{M_{t-1+k}}{P_{t+k}},$$

where M_t represents nominal money balances, and $\epsilon_t^m$is a preference shock on money holdings. The first-order condition with respect to M_t yields a standard money demand equation that establishes that the marginal rate of substitution between money and consumption equals the opportunity cost of holding money. Following recent literature (e.g. Canova and Ferroni, 2012; Casares and Vázquez, 2018) we also extend the baseline model by allowing the policy rule to depend on the growth rate of nominal balances, $(\frac{M_t}{M_{t-1}})$, in order to feature concerns that the Federal Reserve had over monetary aggregates in some recession episodes. Formally, the policy rule is represented by

$$\frac{R_t^n}{R^n} = \left[\frac{R_{t-1}^n}{R^n} \right]^{\rho} \left[\left(\frac{\pi_t}{\pi} \right)^{r_\pi} \left(\frac{Y_t}{Y_t^f} \right)^{r_y} \right]^{1-\rho} \left[\frac{Y_t / Y_t^f}{Y_{t-1}/Y_{t-1}^f} \right]^{r_{\triangle y}} \left[\frac{M_t}{M_{t-1}} \right]^{r_m}.$$

In order to identify the additional preference shock associated with money demand we consider “Money with Zero Maturity” as the observable counterpart of money supply. The Bayesian estimation of the model for the three recession periods is fairly robust to this DSGE model augmented with money. Table 5 shows the variance decomposition of the three alternative periods. It is noticeable that money preference shock plays a negligible role in explaining aggregate fluctuations in any of the three recession periods studied.[31]

Table 2.5: Variance decomposition with money in the DSGE model

Great Depression										
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth	Money
MONEY	0	0	0	0	0	0	4	0	0	95
Productivity	16	18	15	28	12	16	25	8	1	1
Risk premium	25	38	11	22	2	2	32	2	18	2
Investment	21	8	46	19	1	4	8	16	2	0
Price markup	11	8	8	8	67	30	9	3	1	0
Wage markup	4	5	3	4	8	36	8	2	0	0
Monetary	22	22	16	18	9	11	14	6	3	1
Net worth	0	1	2	0	0	0	0	62	76	0
Stagflation										
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth	Money
MONEY	0	0	0	0	0	0	1	0	0	93
Productivity	21	24	15	8	14	17	18	3	2	0
Risk premium	16	21	5	20	9	1	41	1	7	2
Investment	12	11	44	17	1	1	4	17	1	0
Price markup	30	18	14	22	47	71	17	4	1	0
Wage markup	17	20	14	27	27	10	13	4	0	0
Monetary	3	4	1	4	2	0	6	0	2	5
Net worth	0	2	6	1	0	0	1	70	86	0
Great Recession										
Shocks' description	Output	Consumption	Investment	Labor	Inflation	Wage	Interest rate	Spread	Net worth	Money
MONEY	1	1	0	0	0	0	2	0	0	95
Productivity	18	30	7	90	41	1	74	0	2	0
Risk premium	35	30	4	4	4	4	8	1	3	2
Investment	32	22	57	4	2	11	2	6	0	0
Price markup	1	1	0	0	42	7	3	0	0	0
Wage markup	2	2	1	1	10	68	2	0	0	0
Monetary	6	5	1	1	1	2	9	0	1	3
Net worth	5	10	30	1	0	3	1	93	94	0

2.6.3 Whole sample

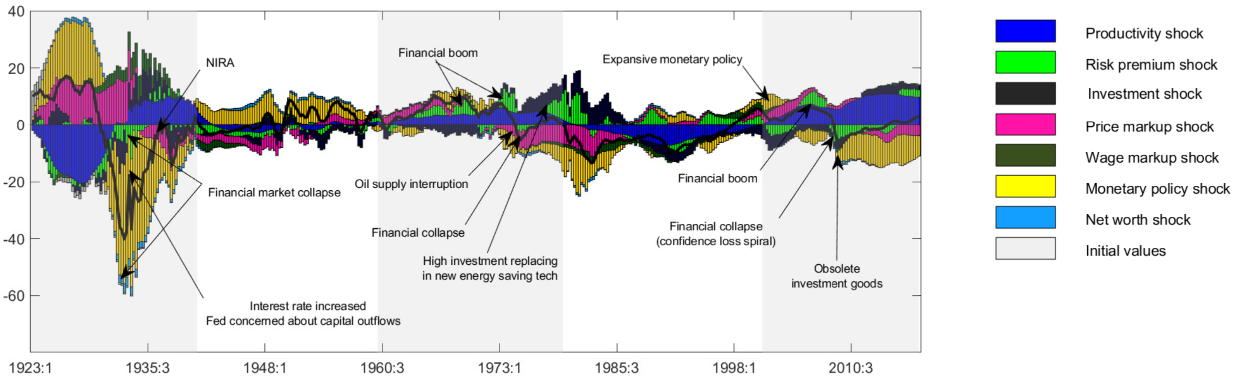
The analysis carried out in this paper is challenging since we consider a single standard DSGE model augmented with financial frictions to assess the sources of aggregate fluctuations across three important, rather different US recessions. We show that the shocks and rigidities implied by the

[31] The historical variance decomposition is also robust to the inclusion of money in the model, which shows a small contribution of the money preference shock to output fluctuations. These results are available upon request.

estimated DSGE model are in line with recognizable economic events as discussed in the related literature analyzing each of these recessions. In this section, we focus again on the baseline DSGE model but this time instead of estimating the three recession separately we consider the whole period from 1923:1 to 2017:3.[32] This is an even more challenging exercise since parameter instability can be an especially important issue when dealing with samples covering a time span of almost 100 years. Thus, standard medium-scale DSGE models are not suitable to cope with switches in both long-term dynamics (e.g. the negative trend of the natural interest rate, population aging, the secular stagnation) and medium-term dynamics (e.g. changes in price and wage rigidity, changes in financial frictions) taking place in such a long sample period. While the approach followed in this paper of analyzing the period surrounding each recession separately allows us to deal with parameter instability in a simple way, it is also important to check the ability of the baseline model to assess the sources of aggregate fluctuations over the whole sample period. Taking into account the shortcoming of dealing with whole sample, we find that the identification of the main sources of fluctuations during the periods surrounding the three deep recessions studied are rather robust when considering this large sample. Figure 8 shows the historical variance decomposition computed considering the baseline model estimated over the period 1923:1-2017:3. The shaded areas correspond to those showed in Figures 4-6. The main picture remains fairly robust with a few discrepancies regarding the relative importance of productivity and monetary policy shocks.

[32] There are some missing data for the aggregate variables in the WWII period. In order to deal with them we treat several observables (output, consumption, investment, labor, wage and inflation) for the period 1940:4-1947:1 as missing observations. In particular, when dealing with a time series exhibiting a trend, we interpolate the missing observations in the period 1940:4-1947:1 with the growth rate observations of the time series before and after this period. Then, after recovering the data in leves we apply a cubic-detrending approach. Then, we remove the interpolated (detrended) data and use the Dynare built-in estimation routine that deals with missing observations treating them as unobserved states and using the Kalman filter to infer their values through the estimation as in Auray and Eyquem (2019).

Figure 2.8: Historical variance decomposition of the whole period



2.7 Conclusions

We estimate a standard medium-scale DSGE model—Christiano et al. (2005), and Smets and Wouters (2007)— augmented with financial frictions à la Bernanke et al. (1999) or alternatively à la Gertler and Karadi (2011), for three different periods, each of which includes a major recession: The Great Depression, the Stagflation and the Great Recession. We find that the estimated DSGE model is able to capture the different features that characterize each recession and shed light on the nature of the shocks that drive the aggregate fluctuations in each period. These results show the strength of DSGE models for the analysis of the business cycle by relating the estimated structural shocks with the historical events driving each economic crisis. Although the DSGE model is not able to provide a precise interpretation of the causes behind each estimated shock, it has proven to be powerful (i) in identifying what shocks played a major role in each recession; and (ii) in relating these shocks to specific events associated in the related literature with a particular recession.

In sum, the DSGE model with financial frictions analyzed in this paper proves to be a good candidate for a core macroeconomic model of the type suggested in Reis (2018) for analyzing aggregate fluctuations. Of course, certain ingredients could be added to this model (and, others could be omitted from it) to analyze specific historical episodes and specific issues, but the important point raised here is that the DSGE models do an overall reasonable good job in explaining the most recent major recessions in the US.

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Chapter 3

On the significance of quality-of-capital news shocks

3.1 Introduction

This paper builds on the expectation-driven business cycle hypothesis, which has a long-standing tradition in macroeconomics. Thus, Pigou (1927) argued that the business cycle was driven by variations in the profit expectations of 'business men'.[1] More recently, Beaudry and Portier (2004) suggest a modeling approach for Pigouâs theory of the business cycle which suggests that *anticipated* (news) shocks are a major source of business cycle fluctuations. Beaudry and Portier (2006) provide further empirical evidence supporting Pigouâs view. They identify two shocks using VAR methods: One drives short-run fluctuations in stock prices and is orthogonal to innovations in total factor productivity (TFP). This shock is closely correlated to a second shock that drives long-run movements in TFP. Moreover, Beaudry and Portier (2006) show that these two shocks anticipate TFP growth by several years. This empirical evidence strongly supports the idea of an expectation-driven business cycle in which the financial sector plays an important role.

This paper suggests a novel approach for modeling the type of news shocks described in Beaudry and Portier (2006) by considering quality-of-capital (QoC) news shocks in the medium-scale DSGE model of Smets and Wouters (2007) augmented with financial frictions à la Gertler and Karadi (2011). Surprise QoC shocks have been considered before in the related literature (e.g. Gertler and

[1] Pigou (1927) also claimed that changes in those expectations were triggered by two âimpulsesâ which have also been considered by recent macroeconomic literature addressing the importance of news shocks: Fundamental impulses, captured by news shocks that end up realizing, and psychological impulses captured by revised and non-realized news.

Karadi, 2011; Gertler et al., 2012; Görtz and Tsoukalas, 2017), but the importance of (anticipated) QoC news shocks in the business cycle has not yet been assessed.[2] This paper contributes to that assessment, which stresses a close link between financial markets and the macroeconomy.

QoC shocks represent qualitative appreciations (depreciations) of physical capital which trigger an exogenous change in the productivity of capital and also directly affect the balance sheet of financial intermediaries whose assets are collateralized by that capital. News shocks to the quality of capital thus have (arguably) a clearer interpretation than TFP news shocks, where the latter are often measured as news shocks to the Solow residual—which interprets any change in output not explained by changes in factor inputs as a change in TFP (?). This clear interpretation of QoC news shocks (relative to TFP news shocks) enables them to be connected with financial markets through the credit and expectation channels. More precisely, a QoC news shock affects the production function in a way similar to a TFP news shock, but it also acts as an exogenous trigger of asset price dynamics. For example, an anticipated upgrade in physical capital improves production expectations and may immediately impact the balance sheets of financial intermediaries whose assets are backed up by that capital. Similarly, when sector-specific capital is expected to become obsolete, production is expected to fall and agents may also anticipate the coming drop in capital (asset) value, making the level of debt excessive relative to the stock of capital.[3] In short, the fundamental difference between QoC and TFP news shocks lies in the direct effects on financial variables induced by the former, which are amplified through the expectation and credit channels. By estimating alternative model specifications, we assess the relative contribution of QoC and TFP news shocks in explaining aggregate fluctuations.

Turning to estimation results, we show that when TFP news shocks and QoC news shocks are both included in the DSGE model the latter become the main driver of aggregate fluctuations while the former play a relatively minor role. This finding is supported by an improvement in model fit. That improvement is especially large for hours, inflation, and the investment growth rate. Thus, the data supports a news shock specification in which news directly affects the credit channel. The estimation results also show three main differences between these two alternative specifications of news shocks: First, the expansionary responses of most real variables (output, investment an labor)

[2] Gertler and Karadi (2011) first refer to them as quality-of-capital shocks, while Merton (1973) and Gertler et al. (2012) also call them asset price shocks. Gertler et al. (2012) provide a sound microfoundation for QoC shocks based on the productivity of capital already installed. This literature views QoC shocks as purely transitory, surprise shocks (i.e. they are described as i.i.d. processes). Our paper retains the assumption of QoC shocks characterized by a stationary process, but we allow for both some degree of persistence and the possibility of shocks being anticipated.

[3] The close link between TFP and financial shocks is also investigated in Moran and Queralto (2018) and Queralto (2020), who emphasize demand driven factors determining medium-term dynamics in TFP. Under their approach, financial shocks affect business innovation activities and consequently future TFP.

at impact are more pronounced in response to a QoC news shock than to a TFP news shock. This is explained by the direct impact of QoC news shocks on the financial side of the economy and, in particular, by the larger fall in the credit spread in response to an expansionary QoC news shock. Second, the short-run response of consumption is much lower for QoC news shocks, and this underscores the transmission of QoC news through the investment/credit channel. Finally, a positive QoC news shock triggers a mild negative response on the part of inflation, which is in contrast to the positive response of inflation to a positive TFP news shock. Interestingly, the deflationary response of QoC news shocks is in line with the deflationary response of TFP news shocks found by Görtz et al. (2021), who use a VAR approach.

We further contribute to the recent literature analyzing news shocks in a DSGE framework by addressing an important question: Does including QoC news shocks truly help to improve the characterization of agents' expectations? This question is important because identifying a news shock must by definition improve the fit of model expectations of forward-looking variables (i.e. the expectation channel). We show that a DSGE model that includes both QoC and TFP news shocks outperforms one that contains only the latter for all observable variables with counterparts reported in the Survey of Professional Forecasters, especially for the growth rate of investment. Including QoC news seems to enhance the importance of the credit channel, thus helping to improve the characterization of investment expectations, among others.

The prominent role of QoC news shocks is further enhanced by the decomposition analysis of news shocks suggested by Sims (2016) to distinguish between pure and realized news shocks.[4] We find that *pure* QoC news shocks are one of the main drivers of aggregate fluctuations. This is somewhat in contrast with Sims (2016), who finds that the empirical significance of TFP news shocks is due to their realized component. In line with Görtz and Tsoukalas (2017), our estimation results highlight the importance of considering a financial sector (which is ignored in the DSGE framework used in Sims, 2016) in order to assess the relative importance of alternative sources of news shocks since financial markets provide useful information that can help in identifying news shocks.

The rest of the paper is structured as follows. Section 2 connects the contribution of this paper to the related literature. Section 3 describes the canonical DSGE model augmented with financial frictions. Section 4 briefly describes the data set, the prior distributions, and the parameters calibrated. Section 5 discusses the estimation results, comparing QoC and TFP news shocks, assesses the importance of and differences in IST news shocks compared to QoC and TFP news shocks, and

[4] More precisely, Sims (2016) proposes a method for distinguishing between the effects of pure news and realized news shocks, with the former seen as the effects at horizons prior to the realization of the news and zero at horizons thereafter, i.e. realized news effects are just the effects of news shocks at horizons after the realization.

examines the relative importance of pure and realized components of QoC news shocks. Section 6 concludes.

3.2 Further related literature

A large body of news literature using DSGE and VAR approaches suggests that the anticipation of future changes in production via financial variables found in Beaudry and Portier (2006) is due to news on TFP. For instance, Beaudry and Lucke (2010) use short- and long-run restrictions to identify TFP news shocks as an important driver of the business cycle. Barsky and Sims (2011) suggest another strategy for identifying TFP news shocks in a VAR framework and also find them to be a significant source of fluctuations. Fujiwara et al. (2011) and Schmitt-Grohé and Uribe (2012) are two seminal papers that incorporate news shocks into a DSGE model. The former identifies TFP news shocks in the US and Japan as an important source of aggregate fluctuations in both countries, but especially in the US. Schmitt-Grohé and Uribe (2012) do not find TFP news shocks to be important.[5] However, Görtz and Tsoukalas (2017) show that findings in Schmitt-Grohé and Uribe (2012) are due to the specific assumptions of their model, such as the lack of transmission channels linking financial markets with real economic activity. In particular, Görtz and Tsoukalas (2017) underlines the importance of considering an endogenous financial sector (such as the one suggested in Gertler and Karadi, 2011) since financial markets convey useful information that can help in identifying TFP news shocks. Thus, they show that when a financial sector is considered TFP news shocks recover their role as the main source of news. Gunn and Johri (2018) use a calibrated model to show that news shocks to future financial returns can create business cycles without recourse to other sources of news. More recently, Görtz et al. (2021) use VAR methods and find that TFP news are highly associated with credit spread indicators and that the dynamics of financial variables are critical for the amplification of TFP news shocks in a two-sector (consumption and investment) DSGE model.

The main contribution of this paper is to stress the direct impact of news on financial markets through QoC news shocks in a DSGE framework which not only induce effects amplified through the credit channel but are also themselves a source of real and financial fluctuations. The main difference between our approach and that in Görtz and Tsoukalas (2017) is that they consider the endogenous financial sector as an important amplifier, whereas we consider a type of news shocks—namely, QoC news shocks— which themselves are a direct source of financial fluctuations. QoC surprise shocks were also introduced in Gertler and Karadi (2011) in a calibrated model to theoretically

[5] They find that other shocks such as news for the wage markup are crucial in explaining the business cycle.

investigate the effects of an exogenous source of variation in asset values. This paper, however, is mainly concerned about the empirical significance of QoC news shocks having a direct impact in the financial sector as well as an anticipated effect on production as a standard TFP news shock has.

Our paper also assesses the relative importance of the investment-specific-technology (IST) news shocks posited in Ben Zeev and Khan (2015) as a major driver of aggregate fluctuations. Further motivation for this assessment can be found in several papers which suggest that IST shocks seem to act as a veil, hiding the response of investment to changes in asset prices (e.g. Kamber et al., 2015; Afrin, 2017; and Görtz and Tsoukalas, 2017). Justiniano et al. (2010) also find evidence that IST shocks are strongly correlated with financial variables such as the interest rate spread. These findings might therefore be viewed as additional evidence reported in the recent literature that IST news shocks may be acting as a veil which may simply capture the risk premium fluctuations that affect the price of capital. Our estimation results confirm this view, as discussed below.

3.3 The model

This paper considers a medium-scale DSGE model with several sources of rigidity and both news and surprise (unanticipated) shocks. The model is similar to the workhorse New Keynesian DSGE model suggested in Smets and Wouters (2007), augmented with the financial frictions suggested by Gertler and Karadi (2011). This model has been widely used in recent macro finance literature (e.g. Sanjani, 2014; Villa, 2016; Afrin, 2017; Gelain and Ilbas, 2017, Görtz and Tsoukalas, 2017).

This section provides a brief overview of the model. The demand side of the model economy is formed by households which choose consumption and hours worked and hold riskless assets such as bank deposits and government bonds. Hours worked are homogeneously supplied by households to an intermediate labor entity that differentiates and supplies labor to labor packers, who subsequently sell labor services to the intermediate goods sector.

Intermediate goods firms choose their production inputs (labor services and effective capital) and sell a differentiated good to the final sector, which sells a homogeneous good to households in a perfectly competitive market. The intermediate goods firms and the labor entity supply differentiated inputs (goods/labor) used in the production of the final consumption good, so they are assumed to have some degree of market power. This assumption also enables nominal rigidities à la Calvo (1983) to be included. Capital services producers acquire physical capital produced by capital-goods producers and assemble it into effective capital, which is rented to intermediate goods firms. Capital services producers finance their acquisition of capital by borrowing funds from financial intermediaries in a perfectly competitive market. Hence, financial frictions are introduced from the credit supply through bank balance sheets as suggested in Gertler and Karadi (2011).[6] Clearly, news on the quality of capital services financed by banks has a direct impact on their balance sheets, which further affects the supply of credit.

The DSGE model with financial frictions considers that banks lend funds, obtained from household deposits, to non-financial firms. They therefore act as intermediaries that assist firms in channeling funds from household deposits to investors. However, banks would like to expand their assets by borrowing additional funds from households indefinitely, since the discounted risk premium that they face is always positive by construction. To restrict their ability to do this, a moral hazard problem is introduced. The banks decide whether to divert a fraction of their assets and transfer them to the households to which they belong. The cost for banks of diverting assets is that the depositor can force them into bankruptcy and recover the remaining fraction of assets. Therefore, households only deposit their savings up to the point where the gain of banks from diverting assets is equal to the gain of not doing so. This incentive constraint introduces a credit supply rigidity.

Next, we describe how two types of news shock are included in the DSGE model and the main differences between them. A brief description of the whole model can be found in the appendix.

Production channel

As is standard in the literature, we consider that intermediate good firms produce goods according to a Cobb-Douglas production function, where the endogenous inputs are capital and labor. This production function is affected by three different shocks. Two of them are the stationary and non-stationary shocks that compound the standard TFP shock, and it is assumed that news arises from the latter. In addition, we consider stationary QoC shocks as in Gertler and Karadi (2011) and Gertler et al. (2012). As explained above, these represent qualitative appreciation (or depreciation) of physical capital, so they trigger exogenous changes in the productivity of capital, affecting the production function in a way very similar to a TFP shock. Formally, the production function is as follows:

$$Y_t = TFP_t \left[(QoC_t) \, K_{t-1} U_t \right]^{\alpha} L_t^{1-\alpha} - A_t \phi_p, \tag{3.1}$$

where $TFP_t = \epsilon_t^a A_t$, ϵ_t^a is the aforesaid transitory TFP shock, A_t is the permanent TFP shock, and its growth rate is denoted by $a_t = ln\left(\frac{A_t}{A_{t-1}}\right)$. QoC_t captures exogenous shocks in the quality of capital, K_{t-1} is capital stock at the beginning of period t, U_t is the capital utilization rate, α is the capital share in production, and ϕ_p is the share of fixed costs involved in production.

Financial channel

[6]This approach of introducing financial frictions contrasts with the approach suggested in Bernanke et al. (1999), which builds on the financial accelerator.

The main difference between a TFP news shock and a QoC news shock is that the latter has an amplifying effect on the price of assets (which in the model is equivalent to the price of capital), so that there is a distinctive, direct impact on the balance sheets of financial intermediaries. The rationale is that the valuation of asset prices by stock investors is highly influenced by incoming information on transitory capital quality upgrades (obsolescence).

Capital services firms purchase physical capital at the end of period t at a price Q_t and sell the undepreciated component to capital good producers at the end of period $t+1$ at a price Q_{t+1}. They also decide capital utilization considering the cost of adjustment and the rate at which they rent the installed capital to the intermediate good firms. Capital services firms also finance their purchases of capital at the end of each period with funds from financial intermediaries, considering that the funding is obtained by issuing claims that are equal to the value of the capital purchased, the price of which is the same ($Q_t S_t = Q_t K_t$). Thus, the profit maximizing problem of these agents is

$$\begin{aligned} &\max_{K_t} \left\{ r^k_{t+1} U_{t+1} K_t \left(QoC_{t+1} \right) - a\left(U_{t+1} \right) K_t \left(QoC_{t+1} \right) + (1-\delta) Q_{t+1} K_t \left(QoC_{t+1} \right) - R^k_{t+1} Q_t S_t \right\} \\ &st. \qquad Q_t S_t = Q_t K_t, \end{aligned}$$

where r^k_t is the rental rate of capital in period t, $a\left(U_t\right)$ is the capital utilization adjustment cost function, and R^k_t is the return of each claim.

The optimal decision obtained from the above problem means that the price of assets (capital) depends *directly* on QoC shocks:

$$Q_t = \frac{r^k_{t+1} U_{t+1} - a\left(U_{t+1}\right) + (1-\delta) Q_{t+1}}{R^k_{t+1}} \left(QoC_{t+1} \right). \tag{3.2}$$

That is, both TFP and QoC shocks affect Q_t through general equilibrium, but QoC shocks also have a direct effect.

Shock processes

The model considers eight types of purely unanticipated (surprise) shock and two shock processes that include both unanticipated and news shock components. The unanticipated shocks are stationary TFP shocks, price and wage markup shocks, monetary policy shocks, preference shocks, net worth shocks, IST shocks, and public spending shocks. Each shock follows an AR(1) process:

$$\epsilon^x_t = \rho^x \epsilon^x_{t-1} + \eta^x_t,$$

where $x = a, p, w, m, b, nw, IST, g$. Nonstationary TFP and QoC shocks have two components: An unanticipated shock and a news shock. The formulation of news shocks follows the seminal paper by Schmitt-Grohé and Uribe (2012):

$$\epsilon_t^z = \rho^z \epsilon_{t-1}^z + \sum_i \eta_{t,t-i}^z,$$

where $z = TFP, QoC$; and $i = 0, 1, 4, 8, 12$. Therefore, $\eta_{t,t-i}^z$ is a z news shock which is expected to realize at time t but is forecast i periods before (i.e. at period $t-i$). For instance, $\eta_{t,t-8}^z$ is a z-innovation realized at time t but anticipated eight periods in advance. Consequently, agents react in advance to future forecast shocks (i.e. agents react to newly obtained information about future shocks even though nothing fundamental has yet changed). More precisely, agents forecast future values of ϵ_{t+k}^z as follows:

$$E_t \epsilon_{t+k}^z = \left(\rho^z\right)^k \epsilon_t^z + \begin{cases} \eta_{t+k,t}^z + \eta_{t+k,t-1}^z + \eta_{t+k,t-4}^z + \eta_{t+k,t-8}^z + \eta_{t+k,t-12}^z, & for\ k = 0, \\ \eta_{t+k,t-1}^z + \eta_{t+k,t-4}^z + \eta_{t+k,t-8}^z + \eta_{t+k,t-12}^z, & for\ k = 1, \\ \eta_{t+k,t-4}^z + \eta_{t+k,t-8}^z + \eta_{t+k,t-12}^z, & for\ 1 < k \leq 4, \\ \eta_{t+k,t-8}^z + \eta_{t+k,t-12}^z, & for\ 4 < k \leq 8, \\ \eta_{t+k,t-12}^z, & for\ 8 < k \leq 12, \\ 0, & for\ k > 12. \end{cases} \tag{3.3}$$

This specification enables agents to revise their expectations about future exogenous shocks, which provides additional flexibility by allowing for anticipated future shocks that fail to materialize. For the purpose of the analysis presented here, we start with a model specification in which QoC news shocks are muted. In a second step we then estimate a model that considers both TFP news shocks and QoC news shocks. In Section 4.5 below IST news shocks are also included to assess their potential role as a source of aggregate fluctuations once QoC news shocks are considered.

3.4 Data and estimation

The estimation procedure for the different model specifications uses US data for nine macroeconomic variables: Output growth, consumption growth, investment growth, wage growth, hours worked, inflation, the nominal interest rate, the spread (risk premium), and the growth rate in the net worth of banks.[7] The set of observables is the same as that in Smets and Wouters (2007), with the addition of the credit spread and the net worth of banks, which seek to provide information about financial reaction to alternative shocks. Financial variables have shown a remarkable power to predict future

[7]The observable for the interest rate spread is the credit spread estimated by Gilchrist and Zakrajšek (2012) and the net worth observable is the total equity capital for US commercial banks used in Görtz and Tsoukalas (2017).

economic activity (e.g. Espinoza et al. 2012; Gilchrist and Zakrajšek, 2012), which in our case may help to distinguish the news component from the unanticipated component of shocks. The predictive power of these variables is due to their flexibility in adjusting more rapidly to shifts in expectation than other (macroeconomic) observables that exhibit a rather high degree of persistence (sluggishness). Moreover, given that the sample period considered in the estimation includes the Great Recession, which started around 2008, we have replaced those values of the Fed funds rate that reach the zero lower bound by the shadow rate constructed by Wu and Xia (2016).[8] The sample considered includes the period 1987q1-2018q4, where the starting quarter is determined by data availability for all the time series considered in the empirical analysis. All the time series used in the estimation procedure are transformed into (log) deviations from their respective means, so the measurement equations are straightforward. Sample means and long-term growth rates are removed because low frequencies may affect the estimation of the business cycle dynamics.[9] The Bayesian estimation procedure follows standard techniques (see, for instance, Fernández-Villaverde, 2010 for a detailed description) and is implemented with the Dynare toolbox.[10]

Calibration and priors

The DSGE model seeks to reproduce business cycle features, so several parameters that govern long-run growth are calibrated due to lack of identifiability. Table 3.1 shows the parameters calibrated and their specific values. The discount factor β is 0.99, which implies a quarterly real interest rate of one percent. Both wage and price markup are assumed to be 0.2. The quarterly depreciation rate is 0.025 and the share of government spending is assumed to be 0.2. The parameters associated with the financial sector, such as the steady-state fraction of funds given to new bankers, and the fraction of funds that bankers may divert are set to hit the following two targets that correspond to the data mean over the sample period: A steady-state (annualized) interest rate spread of 200 basis

[8]Recent papers (e.g. Wu and Zhang, 2019; Mouabbi and Sahuc, 2019; Aguirre and Vázquez, 2020) use the shadow rate instead of the federal funds rate in the estimation of New-Keynesian frameworks. The estimation exercise was also conducted with the Fed funds rate and analogous results were obtained, showing its robustness.

[9]Del Negro et al. (2007) suggest this low frequency misspecification issue and several other papers in the related literature also follow this data treatment (e.g. Christiano et al., 2014; Görtz and Tsoukalas, 2017). For instance, Christiano et al. (2014) argue that they *remove sample means separately from each variable in order to prevent counterfactual implications of the model for the low frequencies from distorting inference in the higher business cycle frequencies that interest us. For example, on average consumption grew faster than GDP in our dataset, while our model predicts that the log of the consumption to GDP ratio is stationary.* Since we are also dealing with a relative small sample in our paper, we face issues similar to those pointed out in Christiano et al. (2014) in properly identifying the low-frequency implications of the model regarding large ratios, so we also follow their approach of removing sample means separately from each variable.

[10]We have run 2 chains of 200,000 replications and performed the Brooks and Gelman (1998) convergence diagnosis tests to ensure convergence.

points, and a steady-state leverage ratio of 5.47. The survival rate parameter, θ, is fixed at 0.96 as in Görtz and Tsoukalas (2017).[11]

The prior distribution of the structural parameters estimated is the same as in Smets and Wouters (2007). The prior distributions of all innovations are also assumed to follow inverse gamma distributions with a mean of 0.1 and a standard deviation of 2.[12]

Table 3.1: Calibration of fixed parameters

Parameters		Calibrated value
Discount factor	β	0.99
Capital depreciation rate	δ_k	0.025
Wage mark-up	ϵ_w	0.2
Price mark-up	ϵ_p	0.2
S.S. goverment spending share	g/y	0.20
Fraction of capital that can be diverted	λ	0.536
Transfer to the entering bankers	ω	0.001
Survival rate of the bankers	θ	0.96

3.5 Estimation results

This section presents the results for the estimation of the DSGE model for the alternative news shock specifications analyzed in this paper. The first model specification mutes QoC news shocks but the second includes them. This exercise of estimating alternative news specifications lets the data determine whether considering a distinctive impact of news shocks on the financial sector as implied by QoC news is a more suitable assumption.

3.5.1 Model fit

The upper panel of Table 3.2 shows the (log) marginal data density (MDD) associated with each model specification of news. The marginal data density is that which is based on the modified

[11] A supplementary appendix describes the calibration approach in more detail. That appendix also reports a sensitivity analysis conducted by estimating the baseline model for the calibration used in Villa (2016), who uses lower values of 4 and 150 basis points for the steady-state leverage ratio and the spread, respectively; and a higher value of 0.972 for the survival rate parameter. The estimation results remain robust for this alternative calibration.

[12] The results are robust to more conservative priors for news shocks, such as those chosen in Christiano et al. (2014), which impose priors so that the variance of the unanticipated component is 50% of the total variance of the shock. The posterior estimates of standard deviations featuring news shocks are much lower than those associated with surprise shocks, which means that the data is informative about the low variability of news shocks relative to other shocks.

harmonic mean estimator (?). Fernández-Villaverde and Rubio-Ramírez (2004) show that the MDD favors the model specification that is closest to the true data generating process. The specification that includes QoC news shocks outperforms the specification that includes only TFP news shocks by almost 60 points. This major improvement in model fit underscores the importance of QoC news shocks.[13] The major improvement found is somewhat in contrast with the small differences in the MDD between the QoC and TFP news shock specifications found in GÃ¶rtz and Tsoukalas (2017). We argue that these contrasting results are mainly due to the different approaches considered in the two papers to introduce QoC news shocks. In our model, a positive QoC news shock triggers an appreciation of the value of assets (capital) and therefore has a positive effect on the credit markets as a whole. In contrast, a sector-specific QoC news shock as in GÃ¶rtz and Tsoukalas (2017) results in a credit reallocation effect. Thus, a positive sector-specific QoC news shock has an expansionary effect on credit in a particular sector, but a recessionary impact on credit in the other sector. Hence, this credit reallocation effect partially offsets, from a quantitative perspective, the shock transmission mechanism that this paper suggests to be the most important for QoC news shocks as discussed below.[14]

To identify the sources of the major improvement in model fit, the middle-left panel of Table 3.2 shows the RMSE-statistics associated with each filtered variable generated by the two specifications studied: (i) The specification including TFP news shocks alone; and (ii) the baseline specification including QoC news shocks in addition to TFP news shocks. The improvement in model fit is observed to be especially large for hours, inflation, and the investment growth rate (the RMSE-statistics decrease by 22.2%, 17.4%, and 11.4% respectively when QoC news shocks are included), but more modest for the rest of the observable variables (the reduction in the RMSE-statistic is less than 10%). This table also contains a column showing the RMSE-statistics of the one-quarter ahead forecast provided by the Survey of Professional Forecasters (SPF) with respect to actual data.[15] Comparing the model-implied RMSE-statistics with those implied by the SPF, we conclude that the model with QoC news shocks outperforms the one that ignores them for all observable variables that have an SPF counterpart, and especially for inflation and the growth rate of investment. In short, these results suggest that the improvement in fit triggered by the inclusion of QoC news shocks is mainly due to their ability to fit macroeconomic variables.

[13]We have also estimated a model including only QoC news shocks and obtained an MDD of -986, suggesting that the exclusion of TFP news shock does not worsen model fit.

[14]However, from a qualitative perspective, our results are in line with GÃ¶rtz and Tsoukalas (2017), who suggest that an endogenous financial sector is key for the proper identification of news shocks, but in addition our results suggest that news shocks that directly affect the credit flow are favored by the data.

[15]This survey is conducted by the Federal Reserve Bank of Philadelphia and is publicly available on their website. The sample period considered for the SPF matches that of the estimation sample.

The middle-right and bottom panels of Table 3.2 show several actual and theoretical second moments derived from the posterior distribution of the estimated parameters (namely the standard deviation, the first-order autocorrelation, and the correlation with output growth for each observable variable obtained from actual data and from the two estimated specifications). The results for the second-moment statistics are in line with those obtained by comparing the log-density across the two news shock specifications: The specification that includes QoC news shocks performs better than the one with TFP news shocks alone in terms of matching most of the second-moment statistics considered with the exception of the correlation between output growth and consumption and investment growth, since the latter specification seems in general to induce too much volatility across observed variables.

Along with the improvement in both model fit and the matching of the second-moment statistics provided by a specification that includes QoC news shocks, we also contribute to the related literature by assessing how QoC news shocks help to shape the expectations of forward-looking variables (i.e. the expectation channel). This is an important assessment because the improvement in model fit must be closely related to the ability of new shocks to characterize model expectations of observed (forward-looking) variables used in the estimation procedure of the DSGE model. The performance of expectations built on news shocks can be further assessed by using external information sources. Thus, the empirical validity of expectations based on news shocks can be assessed by studying their ability to match the forecasts reported in the SPF. The middle-column in the second panel shows the RMSE statistics of the one-quarter-ahead forecasts of the observable variables with respect to the forecasts reported in the SPF. We find that the expectations generated by a model specification that amplifies the effects of the credit channel via QoC news shocks are much closer to SPF forecasts, revealing that this specification is better at capturing actual agentsâ expectations as reported in the SPF.

Table 3.2: Model fit assessment

	TFP	QoC						
Marginal Data Density	-1051.70	-996.05						

	RMSE			RMSE to SPF		Standard deviation		
	TFP	QoC	SPF	TFP	QoC	Actual	TFP	QoC
Output growth	0.58	0.56	0.50	0.19	0.09	0.59	1.08	0.99
Consumption growth	0.57	0.52	0.50	0.79	0.79	0.56	0.97	0.57
Investment growth	1.67	1.48	1.44	0.19	0.09	1.84	3.87	3.40
Hours	0.54	0.42	-	-	-	4.30	4.30	3.20
Wage growth	0.87	0.86	-	-	-	0.86	1.14	0.92
Inflation	0.23	0.19	0.19	0.03	0.02	0.24	0.42	0.33
Spread	0.17	0.16	-	-	-	0.25	0.56	0.43
Interest rate	0.09	0.09	-	-	-	0.79	0.61	0.52
Net worth growth	2.10	2.20	-	-	-	1.53	8.52	6.36

	Autocorrelation			Correl. with output growth		
	Actual	TFP	QoC	Actual	TFP	QoC
Output growth	0.29	0.63	0.38	1	1	1
Consumption growth	0.33	0.74	0.34	0.66	0.67	0.51
Investment growth	0.68	0.64	0.60	0.66	0.66	0.71
Hours	0.99	0.98	0.97	0.21	0.46	0.18
Wage growth	-0.15	0.28	0.14	-0.04	0.41	0.19
Inflation	0.62	0.74	0.71	0.05	0.25	-0.08
Spread	0.89	0.80	0.81	-0.57	-0.43	-0.36
Interest rate	0.98	0.98	0.97	0.13	0.40	0.20
Net worth growth	0.22	-0.05	0.02	0.04	0.30	0.35

3.5.2 Parameter estimates

Table 6.3 shows the prior distribution, the posterior mean, and the 90% higher posterior density interval (between brackets) of the structural parameters and the estimated standard deviations of news shocks. A noteworthy finding is that the estimated persistence of TFP shocks is greatly reduced when QoC shocks are considered. This suggests that the high persistence of TFP shocks is due to the omission of an important source of shocks, in the form of QoC shocks. Moreover, the reduction in persistence of TFP shocks explains their relative lack of importance in the variance decomposition analysis carried out below when QoC shocks are included in the DSGE model. Interestingly, the structural parameter estimates are rather robust across the alternative specifications of the DSGE model with news shocks, but there are a few noticeable differences. Thus, habit formation and the response of the nominal interest rate to output are estimated as larger under the specification that includes QoC new shocks. By contrast, the elasticity of capital utilization adjustment cost and, as highlighted above, the persistence of TFP shocks decrease greatly in this baseline specification with QoC news shocks.

Table 3.3: Selected parameter estimates

Parameter	Prior distribution		Posterior Mean	
	Type	Mean/Std	TFP	QoC
Structural parameters				
Investment adjustment cost	Normal	4/1.5	1.19 [0.71,1.64]	0.74 [0.47,0.98]
Habit formation	Normal	0.7/0.1	0.68 [0.62,0.74]	0.94 [0.90,0.98]
Calvo probability for wages	Beta	0.5/0.1	0.77 [0.70,0.85]	0.79 [0.72,0.86]
Elasticity of labor supply	Normal	2/0.5	1.09 [0.25,1.88]	1.69 [0.91,2.40]
Calvo probability for prices	Beta	0.5/0.1	0.94 [0.93,0.95]	0.94 [0.93,0.95]
Indexation of past inflation in wages	Beta	0.5/0.15	0.38 [0.15,0.60]	0.21 [0.08,0.33]
Indexation of past inflation in inflation	Beta	0.5/0.15	0.21 [0.07,0.34]	0.19 [0.07,0.30]
Utilization adjustment cost	Gamma	0.5/0.15	0.95 [0.91,0.98]	0.69 [0.51,0.88]
Fixed cost in production	Normal	1.25/0.125	1.73 [1.58,1.88]	1.65 [1.48,1.81]
Capital share in production	Normal	0.3/0.05	0.19 [0.15,0.22]	0.24 [0.20,0.28]
Monetary policy parameters				
Interest rate smoother	Beta	0.75/0.1	0.80 [0.75,0.84]	0.80 [0.76,0.84]
Response to inflation	Normal	1.5/0.25	1.11 [1.00,1.24]	1.19 [1.00,1.64]
Response to output	Normal	0.125/0.05	0.08 [0.04,0.14]	0.36 [0.30,0.42]
Response to output growth	Normal	0.125/0.05	0.18 [0.11,0.25]	0.15 [0.08,0.22]
TFP news shocks				
Persistence of TFP	Beta	0.5/0.2	0.95 [0.92 , 0.98]	0.31 [0.18 , 0.44]
Std of TFP news shock - 1 quarter ahead	Gamma	0.1/2	0.06 [0.03 , 0.08]	0.10 [0.02 , 0.19]
Std of TFP news shock - 4 quarter ahead	Gamma	0.1/2	0.07 [0.03 , 0.11]	0.06 [0.02 , 0.10]
Std of TFP news shock - 8 quarter ahead	Gamma	0.1/2	0.08 [0.03 , 0.14]	0.07 [0.02 , 0.11]
Std of TFP news shock - 12 quarter ahead	Gamma	0.1/2	0.12 [0.05 , 0.18]	0.17 [0.08 , 0.27]
QoC news shocks				
Persistence of QoC	Beta	0.5/0.2	-	0.93 [0.87 , 0.98]
Std of QoC news shock - 1 quarter ahead	Gamma	0.1/2	-	0.05 [0.03 , 0.08]
Std of QoC news shock - 4 quarter ahead	Gamma	0.1/2	-	0.05 [0.02 , 0.07]
Std of QoC news shock - 8 quarter ahead	Gamma	0.1/2	-	0.06 [0.03 , 0.10]
Std of QoC news shock - 12 quarter ahead	Gamma	0.1/2	-	0.11 [0.03 , 0.19]

3.5.3 News shocks as a driving force of the business cycle

Figure 3.1 shows the proportion of the variance decomposition explained by the two types of news shock for the set of observable variables considered in the estimation across alternative forecast horizons. Figure 3.1a shows the model where TFP news shocks are estimated alone, while Figure

3.1b shows the proportion of the variance decomposition explained by QoC (black solid line) and TFP (red dashed line) news shocks when both types are included in the DSGE model estimated. The results shown in Figure 3.1a are in line with those reported in the related literature, where TFP news shocks are highlighted as a significant driving force of the business cycle (Beaudry and Portier, 2006; Fujiwara et al., 2011; Görtz and Tsoukalas, 2017).

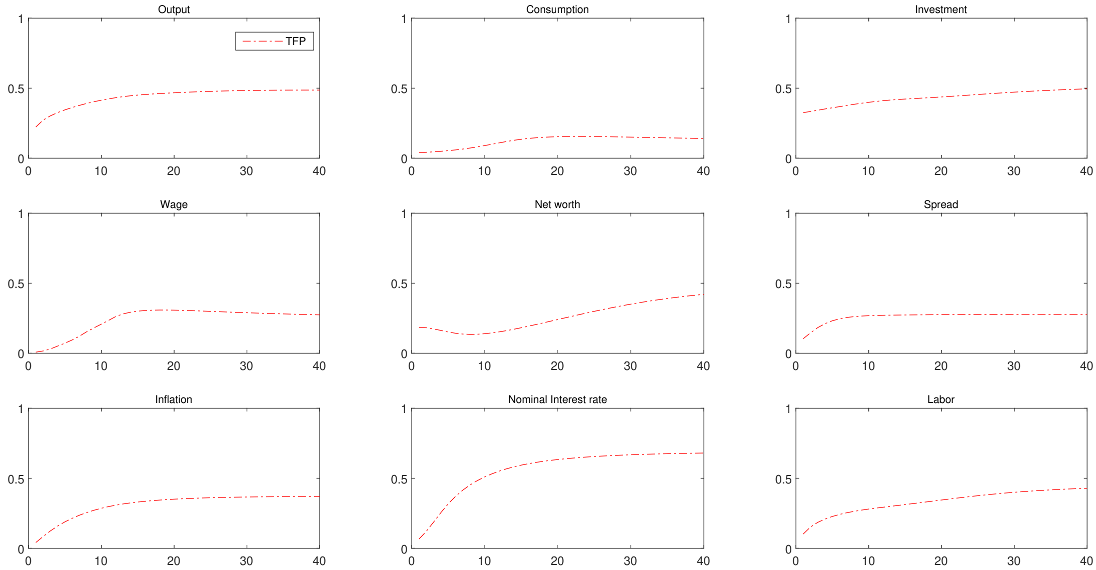
The main finding of this analysis is that the data supports the inclusion of QoC news shocks in the estimated DSGE model in detriment to TFP news shocks, whose importance as a driving force of the business cycle is substantially reduced, as shown in Figure 3.1b. Thus, when TFP news shocks are considered alone they explain a substantial proportion of the variability of all observed variables. More precisely, they explain around 50% of output, investment, and nominal interest rate fluctuations and one third of wage, inflation, and labor fluctuations. They also explain a large proportion of the variability associated with the two financial variables considered (approximately one third for both across medium- and long-term forecast horizons). In sharp contrast, the inclusion of QoC news shocks in addition to TFP news shocks results in a large drop in the relative importance of the latter in explaining the variability of many macroeconomic and financial variables, but they turn out still to be quantitatively very important in explaining inflation, wage, and short-run consumption fluctuations. Nonetheless, QoC news shocks are in general much more significant than TFP news shocks in explaining aggregate fluctuations.

These results are clearly due to the financial impact of QoC news shocks. Consider, for instance, that agents anticipate a positive QoC four quarters in advance. This positive news shock affects the economy through two different channels: The production function and the credit channel. On the one hand, positive QoC and TFP news shocks have an equivalent effect on the production function since both types increase expected future productivity (see Equation 1). On the other hand, in the financial market a positive realization of QoC news shock results in a rise in asset prices since agents anticipate an improvement in the quality of capital, as shown by Equation (2). This rise in asset prices has an immediate impact on the balance sheets of banks since the assets that they hold become more valuable. Moreover, banksâ expected profits increase further due to the expected rise in the value of capital, which increases both credit supply and investment. Some subtle differences aside, this view is largely consistent with the results in Beaudry and Portier (2006), where news shocks are identified with shocks impacting the financial market (stock prices) and anticipating future movements in TFP.[16]

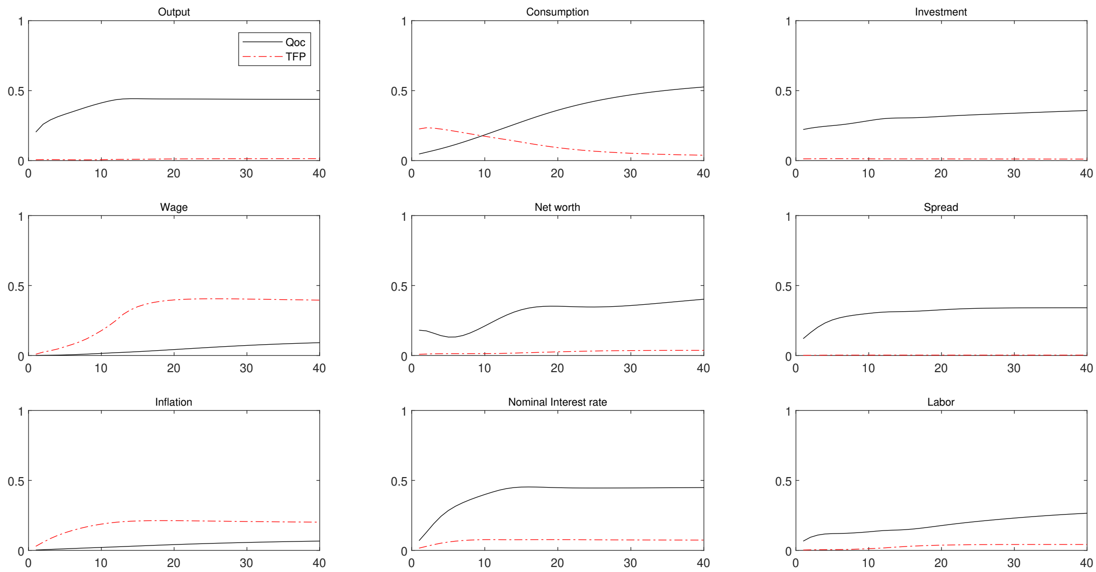
[16] Many studies have stressed the predictability of future economic activity using financial variables. Gilchrist et al. (2009) determine that credit market factors from corporate bond spreads predict future movements in output, employment, and industrial output. Espinoza et al. (2012) show that shocks to financial variables influence real activity. Gilchrist and Zakrajsek (2012) construct a new corporate bond credit spread index that robustly predicts

Figure 3.1: Conditional variance decomposition: Assessing the importance of TFP news vs QoC news

(a) DSGE model including TFP news shocks alone



(b) DSGE model including TFP and QoC news shocks



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future economic activity. Vázquez and Aguilar (2021) and Aguilar and Vázquez (2021) show that the term spread plays an important role in the characterization of adaptive learning dynamics in DSGE models.

In a supplementary appendix to this paper, we also show the conditional variance decomposition for all (surprise) shocks associated with the baseline specification. Given the major importance of QoC news shocks in explaining the fluctuations of real and financial variables, the relative importance of unanticipated shocks decreases substantially when compared to the variance decompositions obtained in the literature abstracting from news shocks (e.g. Smets and Wouters, 2007; Villa, 2016), while price- and wage-markup shocks still explain a large proportion of inflation and wages fluctuations when news shocks are included.[17]

3.5.4 Impulse response functions

The previous sections provide evidence favoring QoC news shocks to the detriment of TFP news shocks. This section provides further insights into this result through an impulse-response function (IRF) analysis. Figure 3.2 shows the responses of output, consumption, investment, asset prices (price of capital), net worth, interest rate spread, inflation, the nominal interest rate, and hours worked to alternative one-percent news shocks. The solid black line represents the IRF of each variable to a four-quarter QoC news shock, while the dashed red line shows the IRF to a four-quarter non-stationary TFP news shock.

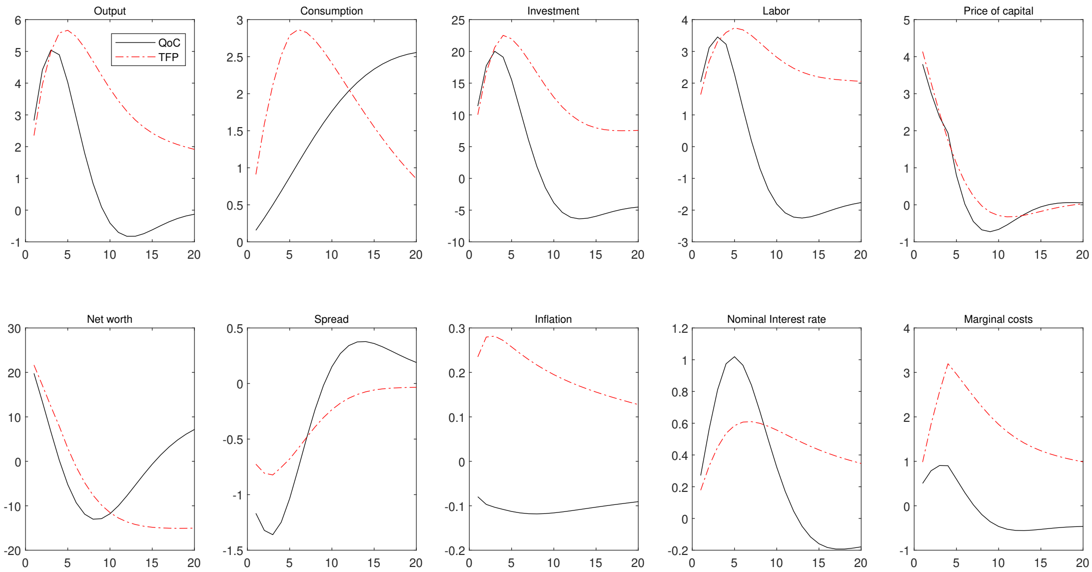
It is noticeable that both QoC and TFP news shocks can generate sound, positive comovements between output, consumption, investment, and labor. However, the transmission mechanisms are substantially different. Thus, a QoC news shock results in greater responses of real variables (output, investment and labor) and the credit spread than those of a TFP news shock at impact. By contrast, TFP news shocks produce a large response of consumption at impact, whereas consumption reacts much more slowly for QoC news shocks. This means that a positive QoC news shock results in a greater boost for investment relative to consumption than TFP news shocks. More precisely, a positive TFP news shock leads agents to anticipate higher output in the future and, consequently, to increase their consumption in advance, while a positive QoC news shock has the same effect as a TFP news shock (recall that both TFP and QoC news shocks are tantamount when only looking at the production function) but also leads to a much lower spread that mainly affects the real side of the economy through an expansion in credit supply. Moreover, notice that a QoC shock means

[17] The supplementary appendix also shows that estimation results are fairly robust when the sample period is restricted to 2006 (i.e. ignoring the Great Recession period): (i) There is a significant improvement of the model fit in terms of the MDD when considering QoC news shocks; (ii) similar results are found for the importance of QoC news in explaning the fluctuations of observables; (iii) when QoC news shocks are considered, the importance of TFP news shocks is greatly reduced in favor of the former. A noteworthy difference when this reduced sample is considered is the drop in the importance of QoC news shocks in explaning output fluctuations, whereas estimation results are fairly robust for the rest of the observables.

a lower peak in the impulse responses of all real variables than a TFP shock. This result is rather intuitive for two reasons. First, the positive response of the nominal interest rate is much stronger in the short/medium term under a QoC shock than under a TFP shock, which partially offsets the expansionary effects of news shocks. Second, the IRF of the spread reverts more rapidly to the steady state under a QoC shock than under a TFP shock.

Another noteworthy difference between QoC and TFP news shocks is the response of inflation. This turns out to be mildly negative for QoC news shocks, while there is an inflationary response to TFP news shocks. This inflationary response to TFP shocks is due to two main effects: (i) The greater reaction of marginal costs to a TFP news shock; and (ii) the milder reaction of the nominal interest rate to such shocks. The reaction of marginal cost is larger for TFP news because real variables need to overreact to produce high fluctuations in financial markets, triggering an inflationary process. The greater reaction of the nominal interest rate in the case of QoC news shocks also enables inflation expectations to be anchored. Both effects together give rise to a change from an inflationary to a deflationary response when the effects of TFP and QoC news shocks are compared. Importantly, this deflationary response of QoC news shocks is in line with the VAR analysis carried out in Görtz et al. (2021). Our findings thus contribute to the literature on the effects of financial shocks where the inflation reaction to these shocks has been part of an ongoing debate. We find evidence of a deflationary response to financial shocks, which is in line with findings in Meh and Moran (2010) and somewhat in contrast with Benes and Kumhof (2015); Ajello (2016); Villa (2016). Clearly, a positive QoC news shock acts as a supply shock by leading to an expansionary response in output and a fall in inflation.

Figure 3.2: IRF to QoC and TFP news shocks



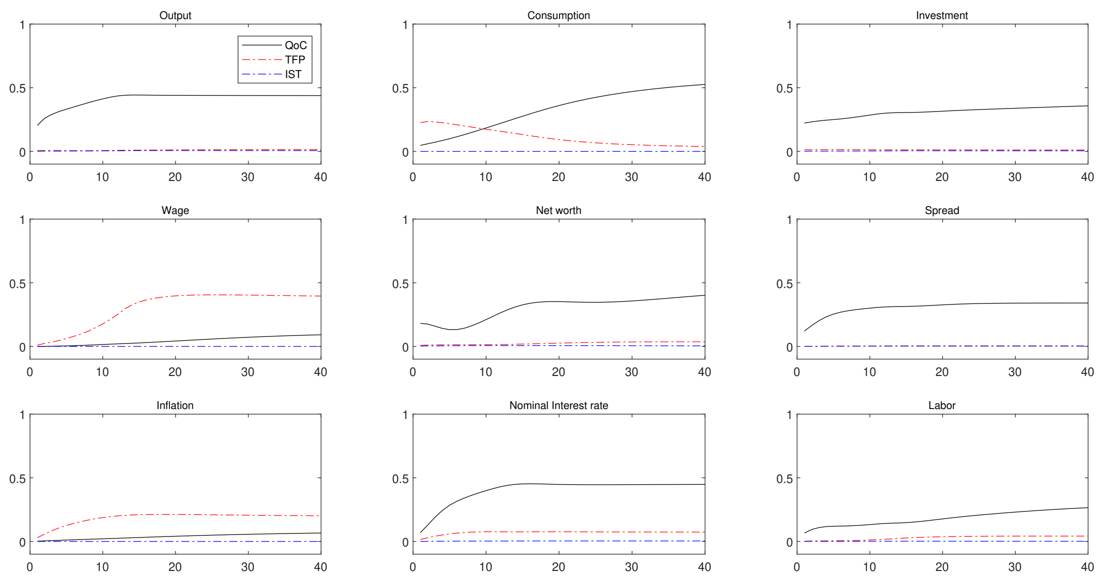
3.5.5 Why do QoC news shocks fit better than IST news shocks?

The previous sections show that by having an amplifying effect on financial markets through the credit channel, QoC news shocks induce a stronger propagation mechanism than TFP news shocks. More precisely, this is due to the more pronounced effect of QoC news shocks on interest rate spreads and thus on the credit supply. IST and QoC news shocks are expected to have similar effects on real macroeconomic variables. Indeed, using a VAR approach, Ben Zeev and Khan (2015) also find that IST news shocks reduce the importance of TFP news shocks, as QoC news shocks do in our analysis based on DSGE modeling. To shed light on this matter, we estimate a model specification that includes QoC and IST news shocks in addition to TFP news shocks.

Figure 3.3 shows the proportions of aggregate variability explained by IST, QoC, and TFP news shocks. It is noteworthy that IST news shocks play no role in explaining aggregate fluctuations while QoC news shocks remain highly important. Moreover, the (log) marginal data density when IST news shocks are included (-997.43) is roughly similar to the baseline case where they are omitted (-996.05). These results indicate that IST news shocks add nothing when QoC news shocks are already considered in the analysis.

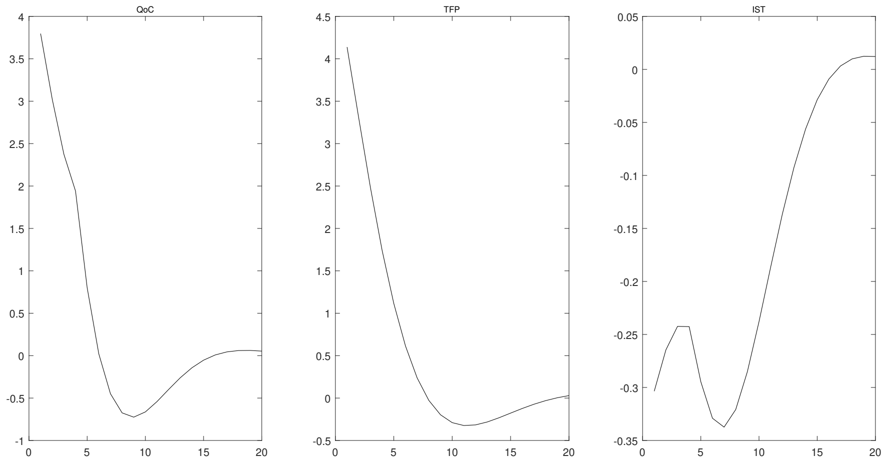
In short, our empirical findings suggest that the results of Ben Zeev and Khan (2015), showing that IST news shocks displace TFP news shocks, can be viewed as a veil cast over the financial effects captured by QoC news shocks. The reason why the data favors QoC news shocks in DSGE modeling lies in the effect of IST news shocks on the price of assets, which is ignored in a VAR analysis. Figure 3.4 shows the IRFs of asset prices for a one-percent positive (i) QoC news shock; (ii) TFP news shock; and (iii) IST news shock, each anticipated 4-quarters in advance. It is noteworthy that QoC and TFP news shocks have positive effects on asset prices, so the supply of credit rises, thus pushing up investment (although the response of investment is larger for QoC, as discussed above). By contrast, IST news shocks negatively affect asset prices. Therefore, the rise in investment triggered by IST news shocks is partially offset by the contraction of the credit supply induced by the drop in asset prices. These results confirm findings in Görtz and Tsoukalas (2017) in a DSGE framework including news and those of Kamber et al. (2015), who only consider unanticipated shocks. Moreover, our findings shed light on the importance of matching the comovements between financial and real variables (investment) in which a specification including QoC news shocks performs better.[18]

Figure 3.3: Variance Decomposition of the DSGE model with QoC, TFP and IST news shocks



[18]Section 7 of the supplementary appendix shows the results of a robustness exercise where we allow all shocks to follow an AR(1) process augmented with a news shock component. We find that, in addition to QoC news shocks, other types of news shock seem to be rather important. The most noteworthy case is that of net worth news shocks, which are able to explain roughly one fourth of both output and interest rate fluctuations, and at least one third of each financial variable. It is also interesting to notice that the two (price and wage) markup news shocks explain 32% and 20% of inflation and wage fluctuations, respectively. In analyzing these results a word of caution is in order since considering such a large number of news shocks without including additional observables may affect their identification. We are further considering the possibility of analyzing the roles of all types of news in future work by including more observables in order to capture expectation changes, such as those reported in the SPF, which may help to discriminate between alternative sources of news.

Figure 3.4: IRF of the price of capital to QoC, TFP and IST news shocks



3.5.6 The role of pure news

A distinctive feature of news shocks is that they affect aggregate variables without changing fundamentals. They do so through agentsâ expectations. However, in the standard specification (also followed in this paper) all innovations ends up realizing, though other news innovations can offset (revise) their effects, characterizing the news revision process and non-realized news. Sims (2016) argues that an analysis of the importance of news shocks through variance decomposition may be biased because it accounts for the pure news effects of each innovation but also for the effect of the shock once it is realized (in which case the effects are not substantially different from those of a standard surprise shock). To assess whether pure news shocks matter and whether news shocks affect aggregate variables without changing fundamentals (i.e. through the expectation channel), Sims (2016) suggests a method for separating these two effects. More precisely, he distinguishes between two impulse response functions: Those associated with pure news and those based on realized news shocks. A pure news IRF is equal to the IRF associated with a news shock at horizons before the realization of that news and zero at horizons thereafter. On the other hand, a realized news IRF takes a value of zero before the realization of the news shock and takes on the values of the IRF for news shocks at horizons thereafter.

We carry out the decomposition proposed by Sims (2016) to assess whether pure QoC news shocks are a major source of macroeconomic fluctuations or whether their importance in the variance decomposition is due to realized news shocks. Figure 3.5 shows the conditional variance decomposition for alternative forecast horizons.

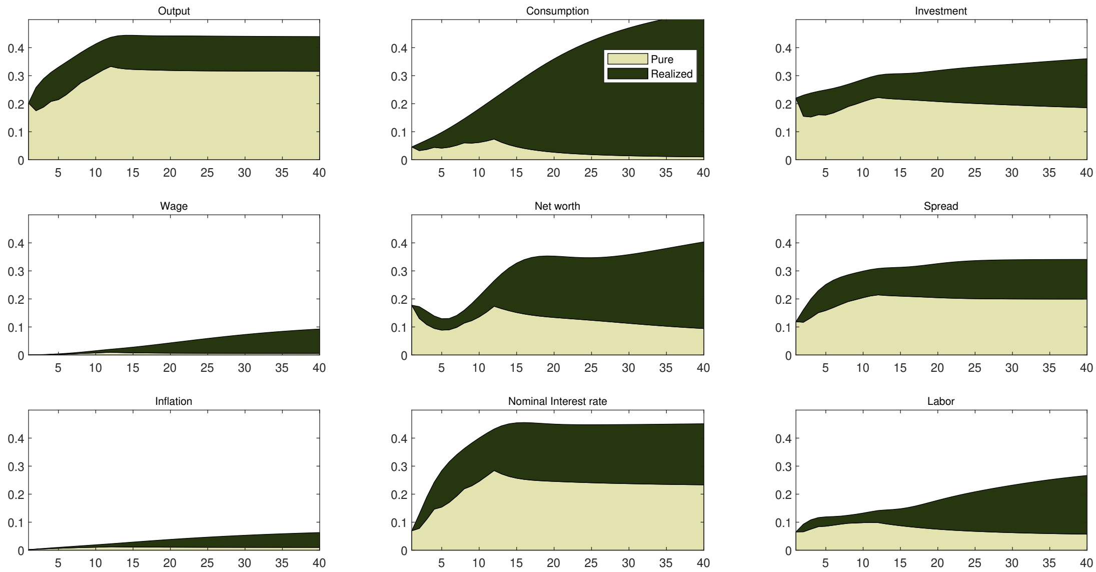
In the long-run pure QoC news shocks account for 31% of output fluctuations, which make up 73% of the total contribution of news shocks. Pure QoC news shocks account for roughly 20% for investment, interest rate spread, and the nominal interest rate fluctuations. By contrast, the proportion of pure QoC news shocks that explain long-run consumption fluctuations is very modest. The news decomposition suggests that pure news has an initial impact on investment through the credit channel and the effect on consumption is mainly due to the reaction of investment to news. This result underscores the importance of the credit channel in producing an expectation-driven business cycle, as suggested by Pigou (1927).[19]

In short, our findings reveal the importance of considering a financial sector and QoC news shocks, which have an amplifying effect on the credit channel in explaining aggregate fluctuations in both the real economy and financial markets. In contrast with the framwork considered in Sims (2016), the direct impact of QoC news shocks in financial markets is transmitted smoothly, through the credit channel, to the rest of the economy.[20]

[19]The importance of pure QoC news is somewhat in contrast to that found by Sims (2016) on analyzing the importance of pure TFP news in a rather different framework (i.e. using the real business cycle model of Schmitt-Grohé and Uribe, 2012). Indeed, he finds that pure TFP news is relatively unimportant, suggesting that such news shocks are not qualitatively different from surprise shocks. These contrasting results do not come as a surprise since, as pointed out by Görtz and Tsoukalas (2017), the lack of transmission channels linking financial markets with real economic activity in a DSGE framework may substantially affect the identification of news shocks and their relative contribution in explaining aggregate fluctuations.

[20]Sims (2016) also argues that under this analysis the role of pure news could be underestimated since the variance decomposition analysis does not account for the effects of unrealized news (surprise shocks that offset news shocks are interpreted as unrealized news but are accounted for in the variance decomposition as surprise shocks).

Figure 3.5: Pure vs. realized QoC news shocks



3.6 Conclusions

The importance of news shocks as a major driver of economic fluctuations has been stressed in recent literature (e.g. Beaudry and Portier, 2006; Fujiwara et al., 2011; Schmitt-Grohé and Uribe, 2012; Görtz and Tsoukalas, 2017). We find that it is crucial to consider the financial impact of such shocks. We provide evidence that actual data supports a version of a standard DSGE model with financial frictions à la Gertler and Karadi (2011) in which quality-of-capital (QoC) news shocks have an impact on financial markets by affecting the price of assets and the balance sheets of banks, and thus triggering an amplifying effect through the credit channel.

More precisely, this paper contributes to two important strands of the literature, namely news shocks and financial frictions. We show that by having an amplifying effect on financial markets QoC news shocks displace standard TFP (and IST) news shocks as a driving force of the business cycle. This result can be understood through the different qualitative and quantitative effects of each type of shock on real variables such as investment and consumption: TFP news shocks affect both variables on impact, but QoC news shocks mainly affect the investment decision. Moreover, the effects of the latter through the credit channel are much larger than those of TFP news. This is also noticeable in the greater effects of QoC news shocks on financial variables. Thus, TFP news shocks need to be much larger than QoC news shocks in order to fit financial data.

The paper also provides empirical evidence on the importance of pure QoC news. We show that the effects of QoC news shocks are mainly driven by pure news rather than realized news through the methodology proposed by Sims (2016). This result stresses the importance of the expectation channel in the transmission of news shocks.

To sum up, this paper provides robust empirical evidence suggesting that QoC news shocks provide a proper way to model expectations-driven business cycles. This empirical evidence is in line with Beaudry and Portier (2006), who find that news shocks are identified with shocks impacting the financial market (stock prices) and anticipating future movements in TFP, and more generally with Pigou (1927) by showing that, by affecting *businessmen's* expectations, news is an important driver of aggregate fluctuations.

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Chapter 4

Learning From News

4.1 Introduction

There is a long tradition in macroeconomics (e.g. Pigou (1927)) of viewing agents' expectations as a central pillar in explaining macroeconomic fluctuations. Changes in expectations, whether due to news shocks in fundamentals (Beaudry and Portier (2004)) or to misperceptions and misinformation (Eusepi and Preston (2011)), are viewed as a major source of aggregate fluctuations.

This paper builds on the growing literature that analyzes the expectation-driven business cycle. More precisely, we contribute to (i) the strand of literature that analyzes the empirical importance of TFP news shocks as a major driver of the business cycle; and (ii) to the AL literature that analyzes the consequences of deviating from RE. In principle, the AL and news shocks strands of literature are closely linked since both emphasize the role of expectations in determining aggregate fluctuations. Therefore, it is important to assess how TFP news shocks and bounded rationality interact and whether the role of TFP news shocks in explaining the business cycle is shaped by the way in which agents form their expectations. Interestingly, the two strands of literature (see, among others, Beaudry and Portier (2004); Eusepi and Preston (2011); Milani (2011)) are strongly motivated on seminal insights put forward in Pigou (1927). This paper can thus be viewed as a more comprehensive approach to assess Pigou's theory of the business cycle by combining expectation shifts induced by anticipated (news) shocks and bounded rationality.

News shocks

In a seminal paper Beaudry and Portier (2004) suggest a modeling approach for Pigou's theory of the business cycle, which suggests that TFP (anticipated) news shocks are a major source of business cycles. Since then, the literature has conducted extensive theoretical and empirical assessments on the importance of so-called news shocks. In particular, Beaudry and Portier (2006) identify two shocks using VAR methods; one shock results in short-run fluctuations in stock prices and is orthogonal to innovations in total factor productivity (TFP). This shock is closely correlated to a second shock that drives long-run movements in TFP. They show that these two shocks anticipate TFP growth by several years. This empirical evidence strongly supports the hypothesis of an expectation-driven business cycle in which the financial sector plays an important role in the transmission mechanism of news shocks to the macroeconomy. In the same vein, Beaudry and Lucke (2010) consider short- and long-run restrictions in their VAR analysis to identify TFP news shocks as an important driver of the business cycle. Barsky and Sims (2011) suggest another strategy for identifying TFP news shocks in a VAR framework. Forni et al. (2014) use a structural factor-augmented VAR approach to assess the importance of news shocks. The last two papers find that TFP news shocks play a smaller role in explaining the business cycle than that found in the previous empirical literature. Moreover, Kurmann and Sims (2021) argue that some of these conflicting results in the VAR literature can be due to TFP measurement errors.

More recently, Görtz and Tsoukalas (2017) highlight the importance of considering a financial sector (such as the one suggested in Gertler and Kiyotaki (2010), and Gertler and Karadi (2011); from now on GK) in a DSGE framework for assessing the role of TFP news shocks. Moran and Queralto (2018) and Queralto (2020) uncover a close link between TFP and financial shocks. These papers emphasize demand driven factors determining medium-term dynamics in TFP and show that financial shocks impact business innovation activities and thus future TFP. Görtz et al. (2022b) use VAR methods to show that TFP news is closely connected with credit spread indicators and that the dynamics of financial variables are decisive for the amplification of TFP news shocks in a two-sector (consumption and investment) DSGE model. In sum, this recent literature suggests that financial markets are crucial in determining the transmission mechanism of expected future events and, therefore, in assessing the empirical importance of TFP news shocks.

Bounded rationality matters in the propagation of news shocks

The effects of (news) shocks on the economy are hard to predict in reality. Policy makers, economic pundits, and economic agents in general have limited knowledge about the economic effects of news shocks regarding the impact of a new technology, a pandemic-fighting vaccine, an armed conflict, a labor strike, a legislation change in the regulation of a specific market (e.g. a specific policy to reform the labor market), etc. In this scenario, agents have to learn the effects of news shocks. This learning process affects agents' decisions through the expectation channel, thereby shaping the transmission mechanism of news shocks.

This paper deviates from the rational expectations (RE) hypothesis in assessing the role of TFP news shocks as a source of business cycles. This is in sharp contrast with the theoretical literature on news shocks highlighted above, which builds on the RE hypothesis, thus overlooking the possibility that agents may have misperceptions regarding the effects of news shocks. Under the RE assumption, agents have full knowledge about the underlying model, the values of the structural parameters, and the minimum set of state variables. Consequently, agents understand perfectly well the equilibrium mapping between all state variables (including news shocks) and the endogenous variables. In particular, they know the reduced-form coefficients linking endogenous variables with news shocks.

RE is a strong assumption, and one that may have deeper implications when news shocks are analyzed in a framework that includes further financial markets for several reasons. First, learning induces higher aggregate persistence in the propagation mechanism of shocks, as emphasized in the AL learning literature (among many others, Milani (2007); Eusepi and Preston (2011); Slobodyan and Wouters (2012); Cole (2021); Vázquez and Aguilar (2021)), because agents may *adaptively learn* from their previous forecasting errors regarding the prospects for the real economy and the financial markets. Second, financial frictions play an important role in both the transmission mechanism of TFP news shocks and the assessment of their relative importance in DSGE frameworks (Görtz and Tsoukalas (2017); Görtz et al. (2022b); Herrera and Vázquez (2023)). Moreover, financial variables are crucial in assessing the role of TFP news shocks in VAR frameworks (Beaudry and Portier (2006), Barsky and Sims (2011) among others). Third, the high flexibility of financial markets in incorporating information about future expected events is in sharp contrast to the sluggish/persistent behavior of real macro variables. This high flexibility also means that financial markets may often overreact to news in reality. This may be viewed by some as a major deviation from the RE assumption (see, for instance, Shiller (2016), Barberis and Thaler (2003), and references therein). In particular, the AL assumption considered in this paper brings forward a potential different mechanism for financial markets overreacting to news by persistently affecting the credit channel which, in turn, has significant implications in the transmission of news shocks to the macroeconomy as discussed below. Finally, previous studies suggested that RE-DSGE models are misspecified in the expectations formation and deviations from RE improve DSGE models in that dimension (e.g. Slobodyan and Wouters (2012); Cole and Milani (2019)). Then, it seems important to assess the role of better specified expectation formations for shocks that are spread through the expectation channel.

Our approach

We introduce bounded rationality by assuming that agents have a somewhat limited knowledge about the underlying model: They observe the minimum set of state variables as under RE, which includes the exogenous shocks that hit the economy, but they *do not* know the structural parameter values and, consequently, they have to learn the reduced-form coefficients—featuring the equilibrium mapping between state and endogenous variables— over time through a constant-gain AL process.[1,2]

We consider a standard (medium-scale) New-Keynesian DSGE model enriched with financial frictions à la GK. We take this financial friction modeling approach because it has been shown that the forward-looking behavior of financial intermediaries in determining credit supply and the interest rate on loans provides a sound identification scheme for TFP news shocks (e.g. Görtz and Tsoukalas (2017); Görtz et al. (2022b)). The rest of the model closely follows the Smets and Wouters (2007) model with the addition of only a news component in the non-stationary TFP shock, to consider a parsimonious model. We focus on this type of news shocks for a few reasons. First, as shown by Görtz and Tsoukalas (2017), nominal price and wage rigidities, along with financial frictions, relative to a real business cycle model studied by Schmitt-Grohé and Uribe (2012), explain a radically different transmission mechanism of TFP news shocks relative the one associated with a real business cycle model. In particular, Görtz and Tsoukalas (2017) show that this mechanism generates a large quantitative role for TFP news shocks in contrast to a very minor role reported in Schmitt-Grohé and Uribe (2012). Second, we focus on *non-stationary* TFP news shocks to clearly distinguished them from other sources of news shocks having only transitory effects, such as those considered in Schmitt-Grohé and Uribe (2012). Third, the appendix reports the log marginal data density statistics for alternative specifications in which news are placed on alternative shocks. These statistics show that the most preferred shock to put news on is the trend TFP shock. Fourth, many papers in the literature on news shocks have focused on TFP news shocks (e.g. Beaudry and Portier (2006); Barsky and Sims (2011); Fujiwara et al. (2011); Forni et al. (2014); Görtz et al. (2022b)).[3]

[1] This approach to AL can be considered as a minor departure from RE. Other approaches, such as the Euler equation approach to AL based on small forecasting models (see, among others, Milani (2007); Slobodyan and Wouters (2012); Vázquez and Aguilar (2021); and references therein) consider larger departures from RE where agents do not know what the state variables are and, in addition, may not observe many of them (for instance, exogenous shocks hitting the aggregate economy). Another influential AL approach suggested by Bruce Preston focuses on long-sighted agents (e.g. Preston (2005); Eusepi and Preston (2011)), as under RE, who take into account the infinite-horizon forecasts associated with their intertemporal decision problem.

[2] We consider here an AL approach because it plays a prominent role in the related literature when analyzing the potential of deviating from the RE assumption in studying macroeconomic dynamics. While there are a number of alternatives coming to mind which might be relevant—such as rational inattention in processing news information or, alternatively, a framework with noisy, rather than perfectly observed news in which agents receive a signal that they use to decompose true information from noise via Bayesian updating— an analysis of these alternative deviations from the RE assumption goes well beyond the scope of this paper.

[3] An important exception is Christiano et al. (2014) who find that news on risk shocks play a prominent role in the

Therefore, considering only news on TFP eases the comparison with previous findings and focuses the discussion on the differences arising from the two alternative expectation hypotheses. Finally, caution is advised in considering a large number of different news shocks without including additional observables because it may affect their identification.[4]

We estimate alternative model specifications under two expectation hypotheses with Bayesian techniques and using recent US macro and financial data. When estimating a model that incorporates news shocks and adaptive learning one should be especially careful about non-fundamentalness problems. The adaptive learning process introduces noise, as agents' expectations are not only shaped by actual news shocks but also by their interpretation and the gradual updating of beliefs. This additional noise complicates the identification of news shocks, as the observed variables might reflect both the actual impact of the news and the noise from the learning process. Therefore, it is key to consider financial variables in the set of observables for the estimation. Financial markets are typically forward-looking and react quickly to new information. This includes news about future economic conditions. Because financial markets incorporate expectations about the future, they can provide immediate signals about how agents are reacting to news shocks. Financial market indicators can help filter out the noise associated with the learning process. Since these indicators are directly influenced by changes in expectations, their inclusion can help isolate the true impact of news shocks from the noise generated by the gradual adjustment of beliefs.

Other possible departures from the rational expectation assumption

In this paper, we explore the implications of relaxing the RE assumption in DSGE models by introducing AL. Two other prominent forms of bounded rationality are cognitive discounting and diagnostic expectations (among others mentioned above), both of which offer alternative perspectives on how agents form expectations and make decisions. Cognitive discounting refers to the idea that agents place less weight on information that is in the distant future, focusing instead on more immediate data. This form of bounded rationality, as explored in the work of Gabaix (2020), suggests that agents may underreact to future-oriented information such as news shocks. In this context, the cognitive discounting framework could imply that the transmission mechanism of news shocks would be dampened compared to the predictions under RE, as agents do not fully incorporate the future implications of news into their current decision-making. Diagnostic expectations, as developed by Bordalo et al. (2018), propose that agents form beliefs by overreacting to signals that confirm their prior views while underreacting to those that contradict them. This form of bounded rationality

estimated DSGE model augmented with a financial accelerator mechanism à la Bernanke et al. (1999).

[4]Nevertheless, the analysis of the implications for demand and monetary policy shock is in our research agenda. The transmission mechanism of such shocks might be affected implying remarkable policy implications.

leads to expectations that are systematically biased in certain directions, depending on the nature of the signals received. Diagnostic expectations can generate overconfidence and excessive volatility in response to news shocks, as agents might overinterpret the importance of positive signals, leading to greater swings in economic outcomes. Comparatively, AL allows for more gradual adjustments in expectations, leading to smoother transitions in response to new information. While these approaches depart from the RE paradigm AL is particularly useful, due to its flexibility, for modeling the dynamics of how news shocks are absorbed into the economy. It allows for the possibility that agents may initially underreact or overreact to news, with their expectations evolving as they gather more information and better understand the implications of the shock.

Main findings

We find that AL improves model performance across two major dimensions: The DSGE model under AL shows a better overall fit in terms of marginal data density and is able to better replicate the size of aggregate fluctuations. This is mainly due to the effects of TFP news shocks on financial variable expectations. Indeed, we find that the transmission mechanism of news shocks persistently affects the credit channel if the RE assumption is relaxed through AL. Thus, the reaction of the credit spread to TFP news is smoother and more persistent under AL, while the responses of consumption are more persistent. Intuitively, the former feature amplifies the effects on consumption through the credit channel. We also find that the effects of news shocks on inflation are reversed. Thus, TFP news shocks are deflationary under AL rather than inflationary as in the RE specification. Importantly, evidence of a deflationary response of TFP news shocks is also found in the VAR analysis carried out in Görtz et al. (2022b) and Forni et al. (2014) in a factor-augmented VAR framework.[5] These differences in model dynamics are quite striking since they are obtained despite rather robust parameter estimates being found across the two expectation hypotheses.

We also find that the importance of *pure* news shocks, as defined in Sims (2016) to distinguish them from realized news shocks, increases under AL. This is an especially important result since by definition a pure news shock isolates the effects of a news shock on the aggregate variables prior to the realization of the shock. Hence, the relative importance of pure news shocks is based exclusively

[5] Notice that this deflationary response of inflation to news shocks is also found in the DSGE literature under RE, where the effects of news shocks are, in one way or another, amplified through the financial sector. Thus, Görtz et al. (2022b) amplifies the effects of TFP news shocks by including an investment sector closely linked to financial intermediaries in their two-sector (consumption and investment) DSGE model. Herrera and Vázquez (2023) includes a quality-of-capital news shock in addition to a standard non-stationary TFP news shock, where the former has a distinctive, amplifying impact on the financial market and an anticipated effect on the aggregate production function as TFP news shocks do.

on their ability to affect the economy through the expectation channel. Finally, we show that the effects of news shocks on both macroeconomic and financial variables featured by an AL-DSGE model are more in line with those estimated through an empirical Bayesian VAR than those implied by the RE version of the model.

The rest of the paper is structured as follows. Section 2 describes the DSGE model augmented with financial frictions. Section 3 outlines the data set and the parameters calibrated. Section 4 discusses the estimation results, highlighting the different transmission mechanisms found under RE and AL assumptions and focusing on the transmission of news shocks. The same section also assesses the relative importance of pure and realized components of news shocks. Section 5 concludes.

4.2 The model

This paper considers a medium-scale DSGE model with several sources of rigidity. The model closely follows the New-Keynesian DSGE model suggested in Smets and Wouters (2007), augmented with the financial frictions à la GK. We also consider that the stochastic balanced growth path is affected by non-stationary TFP shocks. Alternative versions of this model have been widely used in recent macro finance literature (see, among others, Villa (2016); Gelain and Ilbas (2017); Herrera and Vázquez (2023)).

This section outlines the main features of the model, which are needed to address the main objectives of the paper.[6] The demand side of the model economy is formed by households which choose consumption and hours worked and hold riskless assets such as bank deposits and government bonds. A standard Cobb-Douglas production function with labor services and effective capital as inputs characterizes the supply side of the economy. We also consider that both prices and wages are sticky. These nominal rigidities are modeled à la Calvo (1983).

The DSGE model with financial frictions considers that banks lend funds, obtained from household deposits, to non-financial firms (capital-good producers). Hence, banks are the intermediaries that help firms by channeling funds from household deposits to investors. However, banks would like to expand their assets by borrowing additional funds from households indefinitely since the discounted risk premium that they face are always positive by construction. To restrict their ability to do this, a moral hazard problem is introduced. The banks decide whether to divert a fraction of their assets and transfer them to the households to which they belong. The cost for banks of diverting assets is that the depositor can force them into bankruptcy and recover the remaining fraction of assets. Therefore, households only deposit their savings up to the point where the gain of banks

[6] A more comprehensive description of the model is provided in a supplementary appendix.

from diverting assets is equal to the gain of not doing so. This incentive constraint introduces a credit supply rigidity. It is noteworthy that this rigidity depends on the future expected profitability of the banks since their ability to secure deposits directly depends on their incentives to divert their assets. These incentives are determined by the future expected gains of remaining in the financial intermediation business. Thus, the consideration of a forward-looking financial sector is especially important for investigating the implications of alternative expectation hypotheses.

Next, we describe how TFP (news) shocks are included in the DSGE model, the financial channel through which news shocks are amplified, the representation assumed for TFP news shocks, and the expectation formation process under AL.

Production channel

As is standard in the literature, we consider that intermediate good firms produce goods according to a Cobb-Douglas production function, where the endogenous inputs are capital and labor. This production function is affected by a TFP shock with two components. One of them is a stationary component, and it is assumed that news arises from the non-stationary component. Formally, the production function is as follows:

$$Y_t = TFP_t \left(K_{t-1} u_t\right)^{\alpha} \left(L_t\right)^{1-\alpha} - \Psi_t \phi_p, \tag{4.1}$$

where $TFP_t = \epsilon_t^a \Psi_t$, ϵ_t^a is the stationary TFP shock, Ψ_t is the non-stationary TFP shock, and its growth rate is denoted by $\psi_t = ln\left(\frac{\Psi_t}{\Psi_{t-1}}\right)$. K_{t-1} denotes capital stock, u_t is the capital utilization rate, and ϕ_p is the share of fixed costs involved in production.

Financial channel

Capital services firms purchase physical capital at the end of period t at a price Q_t and sell the undepreciated component to capital good producers at the end of period $t+1$ at a price Q_{t+1}. They also decide capital utilization considering the cost of adjustment and the rate at which they rent the installed capital to the intermediate good firms. Capital services firms also finance their purchases of capital at the end of each period with funds from financial intermediaries as described below. Considering that the funding is obtained by issuing claims that are equal to the value of the capital purchased, their price is the same ($Q_t S_t = Q_t K_t$). Thus, the profit-maximizing problem of a representative capital services firm is

$$\begin{aligned} &\max_{K_t} \left\{ r_{t+1}^k u_{t+1} K_t - a\left(u_{t+1}\right) K_t + (1-\delta) Q_{t+1} K_t - R_{t+1}^k Q_t S_t \right\} \\ &s.t. \qquad Q_t S_t = Q_t K_t, \end{aligned}$$

where r^k_t is the rental rate of capital in period t, $a\left(u_t\right)$ is the capital utilization adjustment cost function, and R^k_t is the return of each claim.

The optimal decision obtained from the above problem implies that the optimal demand for capital satisfies

$$R^k_{t+1} = \frac{r^k_{t+1}u_{t+1} - a\left(u_{t+1}\right) + (1-\delta)Q_{t+1}}{Q_t}, \tag{4.2}$$

which shows that the expected real interest rate on external funds is equal to the marginal return on capital. This optimal condition also implies that TFP news shocks affect the price of capital, Q_t, through general equilibrium (i.e. via the rental rate of capital, capital utilization, and the return of each claim) as further discussed below.

Görtz and Tsoukalas (2017) find that the financial sector is crucial for identifying TFP news shocks. We closely follow the characterization of financial intermediaries used in their paper, which was initially suggested by Gertler and Karadi (2011). A fixed fraction of households includes bankers, who do not supply labor but behave as financial intermediaries. These bankers face a survival probability, θ, and in order to keep their proportion constant further households become bankers in each period. As described above, the financial intermediaries finance the acquisition of physical capital by purchasing claims S_t. These purchases are funded through household liabilities. Hence, the balance sheets of financial intermediaries are

$$Q_tS_t = N_t + B_{t+1},$$

where N_t is the net worth of the bankers, and B_{t+1} represents household deposit liabilities in banks. The return on financial claims is R^k_{t+1} and the cost of liabilities is R_t, so the law of motion of the net worth of intermediaries is given by:

$$N_{t+1} = R^k_{t+1}Q_tS_t - R_tB_{t+1} = \left(R^k_{t+1} - R_t\right)Q_tS_t + R_tN_t.$$

Let $\beta\Lambda_{t+1}$ be the stochastic discount factor of financial intermediaries. Bankers' decisions are endogenously determined in the model through the following problem, in which they maximize future expected terminal wealth:

$$V_t = max\ E_t\sum_{i=0}^{\infty}\left(1-\theta\right)\theta^i\beta^i\Lambda_{t+1+i}N_{t+1+i} =$$

$$max\ E_t\sum_{i=0}^{\infty}\left(1-\theta\right)\theta^i\beta^i\Lambda_{t+1+i}\left[\left(R^k_{t+1+i} - R_{t+i}\right)Q_{t+i}S_{t+i} + R_{t+i}N_{t+i}\right].$$

However, a moral hazard issue arises in this maximization problem because $\beta^i\left(R^k_{t+1+i} - R_{t+i}\right) \geq 0$. Otherwise, bankers would not be willing to purchase assets. Therefore, bankers have an incentive to keep borrowing additional funds indefinitely from households. In order to restrict their ability to do this, an enforcement cost is introduced: At the beginning of the period bankers can divert a proportion λ of the funds available. If they do so, the depositors can then only recover a fraction $(1-\lambda)$ of the assets. Hence, for lenders to be willing to supply funds to bankers the following incentive constraint must be satisfied:

$$V_t \geq \lambda Q_t S_t,$$

where V_t, the gain from not diverting assets, can be expressed as

$$V_t = \nu_t Q_t S_t + \eta_t N_t,$$

with

$$\nu_t = E_t \left[(1-\theta) \Lambda_{t+1} \left(R^k_{t+1} - R_t \right) + \beta \theta x_{t,t+1} \nu_{t+1} \right], \tag{4.3}$$

$$\eta_t = E_t \left[(1-\theta) \Lambda_{t+1} R_t + \beta \theta z_{t,t+1} \eta_{t+1} \right], \tag{4.4}$$

where ν_t is the expected marginal gain from expanding assets with net worth held constant, η_t is the expected value of one additional future unit of wealth net worth with assets held constant, $x_{t,t+i} = Q_{t+i} S_{t+i} / Q_t S_t$ is the gross growth rate of assets, and $z_{t,t+i} = N_{t+i}/N_t$ is the gross growth rate of net worth.

The incentive constraint holds with equality at equilibrium:

$$Q_t S_t = \frac{\eta_t}{\lambda - \nu_t} N_t = \phi_t N_t, \tag{4.5}$$

where ϕ_t is the leverage ratio of bankers.

Notice that the leverage ratio and thus the price of capital, Q_t, depend on the forward-looking variables ν_t and η_t determined, subject to a terminal condition, by the expected future stream of the excess return on financial claims, $(1-\theta) \sum_{i=0}^{\infty} E_t \left[(\beta\theta)^i x_{t,t+i} \Lambda_{t+1+i} \left(R^k_{t+1+i} - R_{t+i} \right) \right]$, and the expected future stream of the cost of liabilities, $(1-\theta) \sum_{i=0}^{\infty} E_t \left[(\beta\theta)^i z_{t,t+i} \Lambda_{t+1+i} R_{t+i} \right]$, as can be shown by iterating forward equations (3) and (4). Thus, by affecting the expectations of financial variables through the credit channel, TFP news shocks have a distinctive transmission mechanism in addition to the standard transmission channel via the production function—the real sector of the economy.

Using the incentive constraint, the law of motion of net worth can be rewritten as

$$N_{t+1} = \left[\left(R^k_{t+1} - R_t \right) \phi_t + R_t \right] N_t.$$

Hence, the gross growth rates of assets and net worth can be written as

$$z_{t,t+1} = N_{t+1}/N_t = \left(R^k_{t+1} - R_t \right) \phi_t + R_t, \tag{4.6}$$

and

$$x_{t,t+1} = Q_{t+1}S_{t+1}/Q_tS_t = (\phi_{t+1}/\phi_t)(N_{t+1}/N_t) = (\phi_{t+1}/\phi_t)\, z_{t,t+1}. \tag{4.7}$$

Finally, the law of motion of bankers' net worth is given by the law of motion of the net worth of surviving bankers from the previous period plus the net worth of households that become bankers in this period:

$$\tilde{N}_t = N_t^s + N_t^n, \tag{4.8}$$

with

$$N_t^s = \theta\left[\left(R_{t+1}^k - R_t\right)\phi_t + R_t\right]N_{t-1}, \tag{4.9}$$

$$N_t^n = \omega\epsilon_t^{nw}Q_tS_{t-1}, \tag{4.10}$$

where ω is the fraction of the total assets that households transfer to new bankers, which enable them to start operating in the banking sector, and the disturbance ϵ_t^{nw} captures exogenous variations in the net worth of bankers due.

TFP news shocks

We consider that the growth rate of the non-stationary TFP shock, ψ_t, includes three types of exogenous shock: A standard surprise (unanticipated) shock; a four-quarter ahead news shock; and an eight-quarter ahead news shock. We only consider news in TFP shocks to keep the model as parsimonious as possible and facilitate comparison with previous research, which has mainly focused on this type of news. Moreover, by estimating alternative specifications of the model in which news are placed on alternative shocks, the appendix shows that the best fit is achieved for the one adding news on the trend TFP shock.

The formulation of TFP news shocks follows Schmitt-Grohé and Uribe (2012):[7]

$$\xi_t = \rho\xi_{t-1} + \eta_{t|t}^0 + \eta_{t|t-4}^4 + \eta_{t|t-8}^8, \tag{4.11}$$

where $\eta_{t,t-i}^i$ is a TFP news shock which is expected to realize at time t but is anticipated i periods before (i.e. at period $t-i$). Consequently, agents react in advance to future shocks (i.e. agents react to newly obtained information about future shocks even though nothing fundamental has yet

[7] Like all the lag (and lead) variables of order more than one, auxiliary state variables are considered to keep track of the TFP news in the state-space representation: $ax_t^1 = ax_{t-1}^2$; $ax_t^2 = ax_{t-1}^3$...

changed). More precisely, agents forecast future values of ξ_{t+k} as follows:

$$E_t\xi_{t+k} = \rho E_t\xi_{t+k-1} + \begin{cases} \eta^0_{t+k|t} + \eta^4_{t+k|t-4} + \eta^8_{t+k|t-8}, & for\ k = 0, \\ \eta^4_{t+k|t-4} + \eta^8_{t+k|t-8}, & for\ 0 < k \leq 4, \\ \eta^8_{t+k|t-8}, & for\ 4 < k \leq 8, \\ 0, & for\ k > 8. \end{cases} \tag{4.12}$$

This specification enables us to capture revisions of expectations by agents due to news shocks, which provides additional flexibility by allowing for anticipated future shocks that fail to materialize (i.e. a news shock anticipated by eight periods, $\eta^8_{t+k|t-8}$, can be partially or totally reversed by upcoming news, $\eta^4_{t+k|t-4}$ and $\eta^0_{t+k|t}$). It is important to emphasize that the flow of information represented by equations (11)-(12) is the same under the two expectation hypotheses and is thus not altered by the bounded-rationality assumption. The difference arises solely from the different dynamics of forward looking variables, which results from the different ways of processing information associated with the two alternative expectation hypotheses. In the RE case, agents are perfectly aware what the effects of a news shock on the economy are because they know the unique (RE) equilibrium mapping between the state of the economy (which includes the set of news shocks) and the endogenous variables of the model economy. Therefore, if agents anticipate a TFP shock they will perfectly understand how that shock affects the economy. AL agents still distinguish a news shock in TFP from other type of (unanticipated) shocks but, unlike fully-rational agents, they do not perfectly infer how that TFP news shock affects the economy; instead they have to forecast its effects and learn from their forecast errors.

Expectation formation

The decisions of economic agents depend on their expectations about future (aggregate) macroeconomic variables. News shocks literature typically assumes that such expectations are formed according to the RE hypothesis. Here, we relax the strong informational assumptions imposed by RE and assume that agents form expectations using a perceived law of motion (PLM) of the economy, which is assumed to include the same state variables that appear in the minimum state variable solution of the system under RE. Thus, the departure from RE relies solely on agents' lacking knowledge about the reduced-form model coefficients (Marcet and Sargent (1989); Evans and Honkapohja (1999); Milani (2007)). Consequently, economic agents use historical filtered variables and news to infer unknown coefficients over time. They do so by estimating the following PLM:

$$\Gamma_t = a_t + b_t\Omega_t + c_t\varsigma^{TFP}_t + d_t\varsigma_t + \epsilon_t, \tag{4.13}$$

where $\mathit{\Gamma}_t$ is a vector containing the set of forward-looking variables of the model at time t, $\mathit{\Omega}_t$ is a vector containing the set of endogenous pre-determined state variables, ς_t^{TFP} is a vector including TFP (unanticipated and news) shocks,[8] and ς_t includes all other unanticipated shocks, a_t, b_t, c_t and d_t are conformable matrices of learning coefficients. As mentioned above, agents receive news at time $t-k$ about a shock that materializes at time t. Therefore, the news shock affects the economy from time $t-k$ on. The matrix of coefficients c_t includes the time-varying belief parameters that show how news shocks shape agents' expectations over time. For instance, assume a 1% shock to TFP anticipated 8 quarters in advance. Economic agents know that this shock is going to be realized at time t (unless revisions occur through the standard mechanism described in equation (12)) but can only infer its true effect on the economy through the learning process.

We assume that agents update their beliefs (i.e. the coefficients in matrices a_t, b_t, c_t and d_t) following a constant-gain recursive least square scheme:

$$\Phi_t = \Phi_{t-1} + gR_t^{-1}Z_{t-1}\left(\Gamma_t - \Phi_{t-1}^T Z_{t-1}\right)^T,$$

$$R_t = R_{t-1} + g\left(Z_{t-1}Z_{t-1}^T - R_{t-1}\right),$$

where $\Phi_t = \{a_t, b_t, c_t, d_t\}$ is a matrix containing all belief coefficients and Z_t is a matrix of regressors that includes the minimum set of state variables (i.e. an intercept, all the endogenous state variables, $\mathit{\Omega}_t$, and both unanticipated and news shocks).[9]

4.3 Data and estimation

We estimate the model using Bayesian techniques by considering a data set with US data for nine macroeconomic variables: Output growth, consumption growth, investment growth, wage growth, hours worked, inflation, the nominal interest rate, the GZ spread suggested in Gilchrist and Zakrajšek (2012), and the growth rate of the net worth of banks. The set of observables is the same as that in Smets and Wouters (2007) with the addition of the GZ spread and the net worth of banks, which seek to provide information about financial market dynamics.[10] The GZ spread is considered in the

[8] As in RE state-space representation, variables lagged by more than one period are included in the state-space form by using auxiliary variables (i.e. x_{t-2} is represented by ax_t^2, being $ax_t^0 = ax_{t-1}^1$; $ax_t^1 = ax_{t-1}^2$ and $ax_t^2 = x_{t-2}$). In our case, we consider 8 auxiliary variables since we assume that they are anticipated by up to 8 periods. All those auxiliary variables are contained in the vector ς_t^{TFP} as in Cole (2021).

[9] Notice that the RE equilibrium mapping does not contain an intercept, but it captures the uncertainty about the balanced-growth path under AL.

[10] The net worth observable is the total equity capital for US commercial banks considered in Görtz and Tsoukalas (2017). The GZ spread is also included in the set of observables considered in Gelain and Ilbas (2017) and Görtz

related literature as a reasonable proxy for the corporate bond premium since Gilchrist and Zakrajšek (2012) show that this spread is closely related to measures of financial distress and has predictive power for future GDP, which might help to identify news shocks. Moreover, given that the sample period considered in the estimation includes the Great Recession, which started around 2008, we have replaced those values of the federal funds rate that reach the zero lower bound by the shadow rate constructed by Wu and Xia (2016).[11] The sample considered covers the period 1987q1-2018q4, where the starting quarter is determined by data availability for all the time series considered in the empirical analysis. All the time series used in the estimation procedure are transformed into (growth rate or log) deviations from their respective means, so the measurement equations are straightforward.[12] We also consider a presample of 16 quarters in order to avoid the effects of estimated news that is assumed to be observed before the sample period begins.

We estimate a subset of parameters using Bayesian techniques and calibrate the remaining parameters. Thus, the discount factor β is set at 0.99, which implies a quarterly real interest rate of one percent. Both wage and price markup are assumed to be 0.2. The quarterly depreciation rate is 0.025 and the share of government spending is assumed to be 0.2. The parameters associated with the financial sector (i.e. the time survival rate of bankers, the steady-state fraction of funds given to new bankers, and the fraction of funds that bankers may divert) are set to hit the following two targets that correspond to the data mean over the sample period: a steady-state (annualized) interest rate spread of 200 basis points, and a steady-state leverage ratio of 5.47. The survival rate parameter, θ, is fixed at 0.96 as in Görtz and Tsoukalas (2017), which analyzes a rather similar sample period including the Great Recession.

4.4 Estimation results

This section discusses the estimation results from the Bayesian estimation of the medium-scale DSGE model under the two alternative expectation hypotheses considered.

et al. (2022b), among others.

[11] Recent papers (e.g. Wu and Zhang (2019); Aguirre and Vázquez (2020)) use the shadow rate instead of the federal funds rate in the estimation of DSGE models.

[12] As advocated by many papers in the related literature (among others, Del Negro et al. (2007), Christiano et al. (2014), Görtz and Tsoukalas (2017), Görtz et al. (2022b)), we remove sample means from the data in order to prevent the possibility that counterfactual implications of the model for the low frequencies may distort inference on business cycle dynamics. For example, consumption grew faster, on average, than GDP in our sample, while our model features a balanced growth path implying that consumption and GDP share a common long-run growth rate. As emphasized by Görtz et al. (2022b), if we impose a counterfactual common long-run growth rate in the two series, we may distort inference on business cycle implications that is important in our analysis.

4.4.1 Model fit

In this section we analyze the differences that arise in model fit when AL is used instead of RE. Table 1 shows a few alternative measures of model fit. The upper panel of Table 1 shows the (log) marginal data density (MDD) associated with each expectation hypothesis. The AL specification clearly outperforms the RE specification by roughly 21 points. This large improvement in model fit not only points to the existence of substantial differences between the two specifications but also suggests that AL provides an improved framework for assessing the role of news shocks in DSGE models.

Table 4.1: Model fit

	RE	AL				
MDD	-856.37	-837.35				
	RMSE			Standard deviation		
	RE	AL		Actual	RE	AL
Output growth	0.46	0.43		0.59	0.80	0.69
Consumption growth	0.36	0.27		0.55	0.72	0.64
Investment growth	0.85	0.84		1.86	3.20	2.94
Hours	0.34	0.28		4.44	2.53	2.29
Wage growth	0.90	0.88		0.90	0.98	0.93
Inflation	0.15	0.15		0.21	0.24	0.24
Spread	0.13	0.12		0.26	0.41	0.38
Interest rate	0.07	0.06		0.68	0.33	0.28
Net worth growth	1.96	2.52		1.57	7.73	6.57
	Autocorrelation			Correl. with output growth		
	Actual	RE	AL	Actual	RE	AL
Output growth	0.27	0.49	0.46	1	1	1
Consumption growth	0.36	0.54	0.57	0.68	0.65	0.62
Investment growth	0.70	0.71	0.71	0.66	0.60	0.56
Hours	0.99	0.95	0.97	0.24	0.35	0.31
Wage growth	-0.19	0.08	0.06	-0.04	0.18	0.19
Inflation	0.46	0.39	0.57	0.07	-0.06	-0.12
Spread	0.87	0.83	0.84	-0.64	-0.32	-0.33
Interest rate	0.99	0.93	0.95	0.18	0.12	0.06
Net worth growth	0.20	-0.01	0.02	0.03	0.26	0.23

Notes: The marginal data density is computed using Geweke (1999) modified harmonic mean method. The computations are based on a Monte Carlo Markov chain of length 2,4 millions draws for each model and discard the first 20% of the draws.

The middle-left panel of Table 1 shows the RMSE statistics with respect to actual data for each expectation hypothesis (i.e. these statistics are computed across the differences between the one-step-ahead forecasts and the corresponding actual data). While the MDD statistic provides an overall measure of model fit under the two expectations hypotheses, the RMSE statistics allow us to assess for which specific observable variables model fit improves under AL. These RMSE statistics show that the AL model performs better for most of the observable variables, especially for consumption growth and hours worked. In order to assess business cycle dynamics under the two expectation hypotheses, the middle-right and bottom panels of Table 1 show actual and model-implied second moment statistics: The standard deviation, the first-order autocorrelation, and the correlation with output growth for each observable variable. In line with actual data the AL specification results in a less volatile business cycle than the model under RE. Regarding the correlations (bottom panels), the two models perform similarly.

In sum, our empirical results clearly indicate that introducing bounded rationality through AL improves model fit along a few important dimensions.

Table 4.2: Structural and policy parameter estimates

Parameter	Prior distribution		Posterior Mean	
	Type	Mean/Std	RE	AL
Structural parameters				
Investment adjustment cost	Normal	4/1.5	1.87 [0.92,2.81]	1.71 [1.13, 2.42]
Habit formation	Normal	0.7/0.1	0.62 [0.50,0.75]	0.59 [0.52,0.66]
Calvo probability for wages	Beta	0.5/0.1	0.81 [0.76,0.89]	0.82 [0.78,0.87]
Calvo probability for prices	Beta	0.5/0.1	0.94 [0.93,0.95]	0.949 [0.94,0.95]
Indexation of past inflation in wages	Beta	0.5/0.15	0.39 [0.16,0.61]	0.26 [0.09,0.44]
Indexation of past inflation in inflation	Beta	0.5/0.15	0.19 [0.07,0.31]	0.18 [0.07,0.30]
Utilization adjustment cost	Gamma	0.5/0.15	0.86 [0.77,0.95]	0.89 [0.83,0.96]
Fixed cost in production	Normal	1.25/0.125	1.59 [1.44,1.74]	1.57 [1.42,1.71]
Capital share in production	Normal	0.3/0.05	0.16 [0.12,0.19]	0.14 [0.11,0.16]
Constant gain learning	Gamma	0.05/0.03	-	0.016 [0.01,0.02]
Monetary policy parameters				
Interest rate smoothing	Beta	0.75/0.1	0.77 [0.73,0.82]	0.78 [0.73,0.82]
Response to inflation	Normal	1.5/0.25	1.21 [0.99,1.44]	1.002 [1,1.01]
Response to output	Normal	0.125/0.05	0.09 [0.07,0.11]	0.08 [0.06,0.09]
Response to output growth	Normal	0.125/0.05	0.23 [0.16,0.30]	0.19 [0.12,0.27]

4.4.2 Parameter estimates

This section discusses the estimates of structural parameters and shock process parameters, including those that characterize TFP news shock processes. Interestingly, Tables 2-3 show that the estimation results are rather robust across the two alternative expectation hypotheses. Indeed, the highest posterior density intervals associated with the estimated parameters under the two expectation assumptions largely overlap. The only striking difference appears for the two parameters associated with the (unanticipated) net-worth shock shown in Table 3. Thus, the persistence parameter of this shock is high under AL and close to zero under RE, while the opposite occurs for the estimated standard deviation of this shock. The constant gain learning parameter points to the importance of the updating of beliefs in the AL process. The posterior mean estimate of this parameter is 0.016, which lies a bit below from the middle range of estimates (0.01 0.05) found in the related literature surveyed by Evans and McGough (2020).

Table 4.3: Shock parameter estimates

Parameter	Prior distribution		Posterior Mean	
	Type	Mean/Std	RE	AL
Non-stationary TFP shocks				
Persistence of TFP shock	Beta	0.5/0.2	0.92 [0.89, 0.96]	0.94 [0.92 , 0.97]
Std of unanticipated TFP shock	Inv-gamma	0.1/2	0.06 [0.05, 0.08]	0.05 [0.04 , 0.06]
Std of TFP news shock - 4 quarter ahead	Inv-gamma	0.1/2	0.05 [0.03, 0.06]	0.04 [0.03 , 0.05]
Std of TFP news shock - 8 quarter ahead	Inv-gamma	0.1/2	0.08 [0.06 , 0.09]	0.06 [0.04 , 0.08]
Stationary unanticipated shocks				
Persistence of TFP shock	Beta	0.5/0.2	0.93 [0.90, 0.95]	0.92 [0.90, 0.94]
Persistence of risk shock	Beta	0.5/0.2	0.83 [0.75, 0.91]	0.94 [0.92, 0.96]
Persist. of government spend. shock	Beta	0.5/0.2	0.90 [0.86, 0.94]	0.91 [0.88, 0.95]
Persist. of investment-specific shock	Beta	0.5/0.2	0.84 [0.76, 0.92]	0.93 [0.90, 0.95]
Persist. of monetary shock	Beta	0.5/0.2	0.42 [0.33, 0.52]	0.38 [0.27, 0.48]
Persist. of net-worth shock	Beta	0.5/0.2	0.03 [0.00, 0.07]	0.93 [0.89, 0.96]
Persist. of price-markup shock	Beta	0.5/0.2	0.14 [0.02, 0.25]	0.21 [0.07, 0.35]
Persist. of wage-markup shock	Beta	0.5/0.2	0.13 [0.02, 0.23]	0.05 [0.01, 0.10]
Std of TFP shock	Inv-gamma	0.1/2	0.42 [0.37, 0.47]	0.43 [0.38, 0.48]
Std of risk shock	Inv-gamma	0.1/2	2.24 [1.11, 3.38]	2.03 [1.64, 2.44]
Std of government spend. shock	Inv-gamma	0.1/2	0.39 [0.35, 0.44]	0.39 [0.35, 0.43]
Std of investment-specific shock	Inv-gamma	0.1/2	1.05 [0.50, 1.61]	0.92 [0.67, 1.17]
Std of monetary shock	Inv-gamma	0.1/2	0.10 [0.09, 0.12]	0.09 [0.08, 0.11]
Std of net-worth shock	Inv-gamma	0.1/2	1.70 [1.39, 2.02]	0.09 [0.06, 0.12]
Std of price-markup shock	Inv-gamma	0.1/2	0.15 [0.12, 0.17]	0.14 [0.11, 0.16]
Std of wage-markup shock	Inv-gamma	0.1/2	0.50 [0.42, 0.57]	0.46 [0.41, 0.51]

These robust estimates, together with the different transmission mechanisms of TFP news shocks resulting from the two expectation hypotheses as discussed below in Section 4.3, underline the importance of belief formation in the transmission of news shocks.

4.4.3 News shock transmission mechanism

This section shows the major differences in the transmission mechanisms of TFP news shocks implied by RE and AL. Figure 1 shows the impulse-response functions (IRFs) of the observable variables for a one-percent 4-quarter ahead news shock.[13] The blue line shows the median pseudo-IRFs of the AL model over the sample.[14] The black line shows the median IRFs of the RE model. Dashed lines show the associated 16%-84% posterior bands.

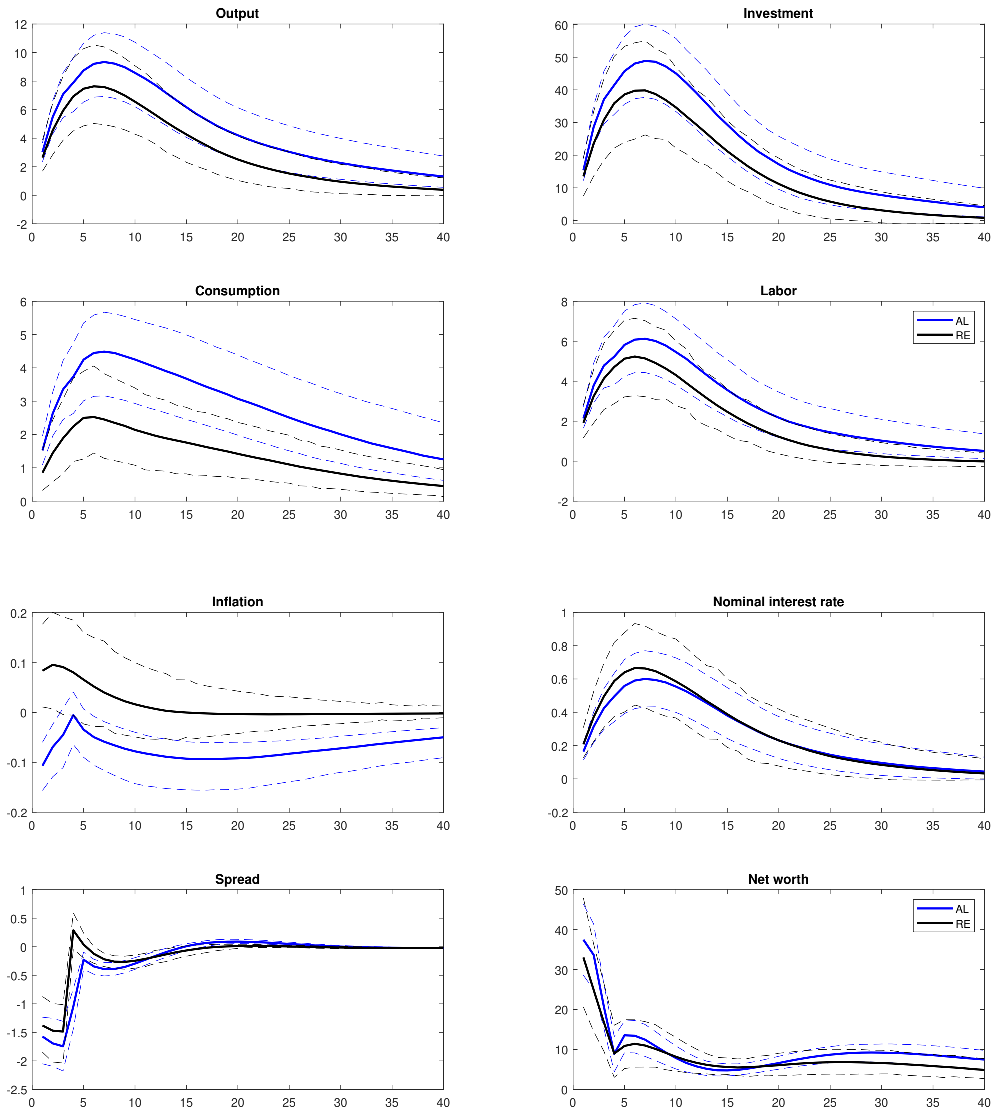
The first two rows of graphs in Figure 1 show the IRFs for output, investment, consumption, and labor (hours worked). They clearly show the high persistence of macroeconomic variables to news shocks under the two expectation hypotheses. The median IRFs show that the effect of TFP news shocks on these real macroeconomic variables is larger under AL over most IRF horizons, but the posterior bands associated with each expectation hypothesis largely overlap. The exception to this pattern shows up for consumption, where its median IRF under RE lies well below the lower bound of the AL posterior band across all horizons. This feature highlights that the effects of TFP news shocks on consumption are larger and much more persistent under AL. This distinctive feature suggests that AL mainly amplifies the transmission mechanism of TFP news shocks in consumption through beliefs that feature bounded rationality. Notice also that the news shock is able to produce a positive comovement between output and hours worked under the two expectations hypotheses in line with the findings in Görtz and Tsoukalas (2017) and Görtz et al. (2022a), but in contrast to the negative comovement found by Barsky and Sims (2011) and Forni et al. (2014) using alternative approaches in identifying news shocks.[15]

[13] The IRFs associated with an 8-quarter ahead TFP news shocks are more similar for the two expectation assumptions. Hence, for the sake of brevity, we have decided to only show the IRFs for 4-quarter ahead TFP news shocks.

[14] To plot the IRFs of the AL model, we consider that the PLM are fixed at the values in which the shock is realized. As in Slobodyan and Wouters (2012) and Aguilar and Vázquez (2021), we have also computed the time-varying AL pseudo-IRF, which are computed using the fixed belief coefficients obtained using the information available at each point in time, but then ignoring the updating of those beliefs driven by the shock. Since these time-varing IRFs look very similar across sample periods we do not report them here, but they are available in a supplementary appendix.

[15] Kurmann and Sims (2021) shed some light on this debate. They argue that TFP measurement errors are likely to be confounded by business cycle fluctuations, which might be problematic with the zero-impact restriction imposed in many VAR approaches to identify TFP news shocks. Kurmann and Sims (2021) suggest to identify news shocks by maximizing the forecast error variance of TFP at a long finite horizon, as we do in the empirical VAR analysis carried out below, but without imposing a zero-impact restriction on TFP.

Figure 4.1: Impulse-response functions following a TFP news shock



Notes: The blue (black) solid line shows the median of the responses obtained from the posterior distribution of the model under AL (RE), while dashed lines show the corresponding 16%-84% posterior bands. The units of the vertical axes are percentage deviations from the steady state.

The third row of IRFs in Figure 1 shows the responses of inflation and the nominal interest rate to a TFP news shock. The nominal interest rate reacts similarly to news shocks under RE and AL, but inflation dynamics are dramatically different because news shocks are inflationary under RE but have a negative effect on inflation under AL. A positive TFP news shock acts as an aggregate supply shock under AL, because it leads to an expansionary response in output and a fall in inflation. This implication of the AL model challenges conventional wisdom of interpreting TFP news shocks as demand shocks. The deflationary response of TFP news shocks under AL is in line with Barsky and Sims (2011), Forni et al. (2014) and Görtz et al. (2022b), among others, who use VAR frameworks. Moreover, some recent findings in DSGE models are also aligned with this deflationary response (Görtz et al. (2022b); Herrera and Vázquez (2023)), where the effects of news shocks are somewhat amplified through the financial sector as discussed below.

The last row of graphs in Figure 1 shows the IRFs of the two observable financial variables used in the estimation procedure for a TFP news shock. At first sight, these IRFs show rather similar dynamics under RE and AL. There are, however, substantial differences in the medium-term credit spread dynamics: The credit spread response is clearly more persistent in the AL model than in the RE model. Thus, the response of the credit spread under RE returns quickly to the steady state in less than a year, while the negative credit response under AL remains significant for more than three years. This different response of the credit spread to news shocks under the two expectation hypotheses has important implications for the role played by the credit spread in the transmission mechanism of news shocks. Thus, the short-lived responses of the credit spread to news under RE downplay the transmission mechanism of TFP news via the financial market (i.e the credit channel) to the real economy. In contrast, the more persistent responses of the credit spread to news under AL largely amplifies the effects of news shocks on consumption through the credit channel. Moreover, the financial amplification of news driven by AL triggers larger expected changes in credit conditions. Therefore, the effect of news on inflation expectations in the AL model is driven by future expected financial conditions.[16] The tight connection between low inflation and credit expansion (expectations) is aligned with the empirical evidence reported in Christiano et al. (2010) showing that inflation is low during stock market booms, and also with the theoretical modelling suggesting that financial frictions reduce the procyclicality of inflation (Christiano et al. (2015), and Gilchrist et al. (2017)). These more persistent credit spread responses of the AL model to TFP news shocks are also in line with the VAR findings reported in Görtz et al. (2022b), where news shocks are also associated with persistent fluctuations in credit spreads.

Notice also that in addition to the high persistence of macroeconomic variables to news shocks across the two expectations hypotheses discussed above, the relative lower persistence effects of new shocks on financial variables means that financial variables portend the future economic outlook, which is consistent with the findings in the literature.[17]

[16] Here, it is useful to emphasize the importance of the interaction between the credit and expectation channels under AL. In contrast, these two channels are rather weak under RE because the credit channel shows a weak persistence which reduces the capacity of TFP news shocks in affecting inflation expectations.

[17] Many studies have provided evidence on the predictability of future economic activity using financial variables. Among many others, Gilchrist et al. (2009) finds that corporate bond spreads help to predict the evolution of output,

4.4.4 Beliefs

Previous sections document both the robustness of the structural parameter estimates and the differences in the transmission mechanisms of TFP news shocks across the two specifications concerning expectations. Clearly suggesting that these differences are due mainly to alternative assumptions on expectation formation and, in particular, how expectation formation affects the transmission mechanism of TFP news shocks through the credit channel.

This section shows how TFP news shocks shape the PLM of several forward-looking variables under the two expectation specifications studied. More precisely, Figure 2 shows changes in the coefficients of auxiliary variables that keep track of TFP news shocks until they are realized.[18] The blue (black) lines represent belief coefficients under AL (RE), while the solid (dashed) lines show belief coefficients associated with 8-quarter (4-quarter) TFP news shocks. RE beliefs are constant by construction while AL are time-varying due to the belief updating process. The belief coefficients for news shocks associated with the PLM of consumption are relatively similar across the two alternative hypotheses on expectations. The belief coefficients for news shocks associated with investment are much smaller, and more similar across news shocks, under AL.

The belief coefficients for news shocks on financial variables (i.e. the growth rates of the value of assets, net worth, and the interest rate on loans) are positive under AL, which is in contrast to the negative RE belief coefficients. Moreover, these belief coefficients are much larger, in absolute terms, under AL showing a sort of overreaction of financial markets to news much in line with the irrational exhuberance hypothesis (Shiller (2016)). These larger belief coefficients for news shocks on financial variables further explain the amplified power of the credit channel under AL discussed above. These results also shed light on the ability of financial variables (and the credit spread in particular) to anticipate the evolution of real macroeconomic aggregates under AL. When agents are assumed to be bounded rational the transmission mechanism of the TFP news shocks is mainly triggered through the credit channel as shown by the larger effects on financial variable expectations, and a reduced impact on real variable (consumption and investment) expectations.

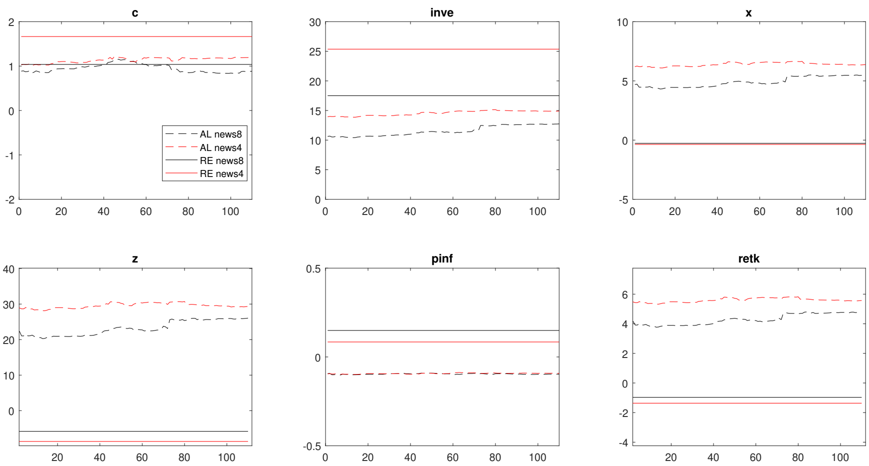
Finally, note also the negative (positive) response of inflation expectations to TFP news shocks

employment, and industrial output. Espinoza et al. (2012) shows that shocks to financial variables influence real activity. Gilchrist and Zakrajšek (2012) suggests a corporate bond credit spread index that predicts future economic activity. More recently, Aguilar and Vázquez (2021) and Vázquez and Aguilar (2021) show that the term spread provides helpful information in characterizing aggregate dynamics in DSGE models under AL.

[18] Here, for the sake of clarity, we show only parameters associated with the auxiliary variables at time $t-4$ and $t-8$ (i.e. the parameters associated with the anticipation horizon of each news shock). The learning coefficients associated with the rest of the auxiliary variables are consistent with those shown in Figure 2 and are available upon request.

under AL (RE), which is consistent with the IRF analysis discussed above showing a distinctive deflationary response to TFP news shocks under AL.

Figure 4.2: Belief coefficients associated with TFP news



Notes: The blue (black) lines represent belief coefficients under AL (RE), while the solid (dashed) lines show belief coefficients associated with 8-quarter (4-quarter) TFP news shocks.

4.4.5 Variance decomposition and pure news

Previous sections discuss at length the substantial differences in the transmission mechanisms of news shocks when one departs from the RE assumption. This section analyzes the implications of considering AL rather than RE in assessing the relative contribution of TFP news shocks in explaining the business cycle.

Table 4.4: Unconditional variance decomposition

Rational Expectations									
	Output	Invest.	Cons.	Inflation	Wage	Interest rate	Labor	Net worth	Spread
Stat. TFP	0	0	1	9	2	4	24	1	1
Risk premium	10	2	69	0	4	4	11	3	2
Public spending	3	1	2	0	1	1	3	1	0
IST	2	4	1	0	1	1	2	13	4
Monetary policy	12	11	6	0	4	25	9	24	8
Price markup	2	1	1	84	4	6	1	3	2
Wage markup	0	0	0	4	73	2	0	1	1
Net worth	1	3	0	0	0	1	1	19	25
Non-stat. TFP	22	29	4	0	0	14	17	22	20
News 4	14	15	4	0	2	11	10	4	9
News 8	34	33	13	2	10	31	21	8	28

Adaptive Learning									
	Output	Invest.	Cons.	Inflation	Wage	Interest rate	Labor	Net worth	Spread
Stat. TFP	0	1	0	6	1	3	21	2	1
Risk Premium	23(↑13)	5	74	2	0	23(↑19)	26(↑15)	4	3
Public spending	3	0	2	0	0	3	3	0	2
IST	8	9	3	0	0	26(↑25)	6	19	12
Monetary policy	1(↓11)	2	0	0	3	1(↓24)	1	12(↓12)	29(↑21)
Price markup	1	2	0	70(↓14)	4	5	1	2	2
Wage markup	1	4	0	2	0	1	1	29(↑28)	5
Net worth	18(↑17)	25(↑22)	5	1	0	8	13(↑12)	13	16
Non-stat. TFP	1(↓21)	4(↓25)	0	17(↑17)	87(↑87)	10	1(↓16)	7(↓15)	4(↓16)
News 4	18	21	6	1	1	9	11	5	12
News 8	26	26	10	1	2	12(↓19)	16	6	14(↓14)

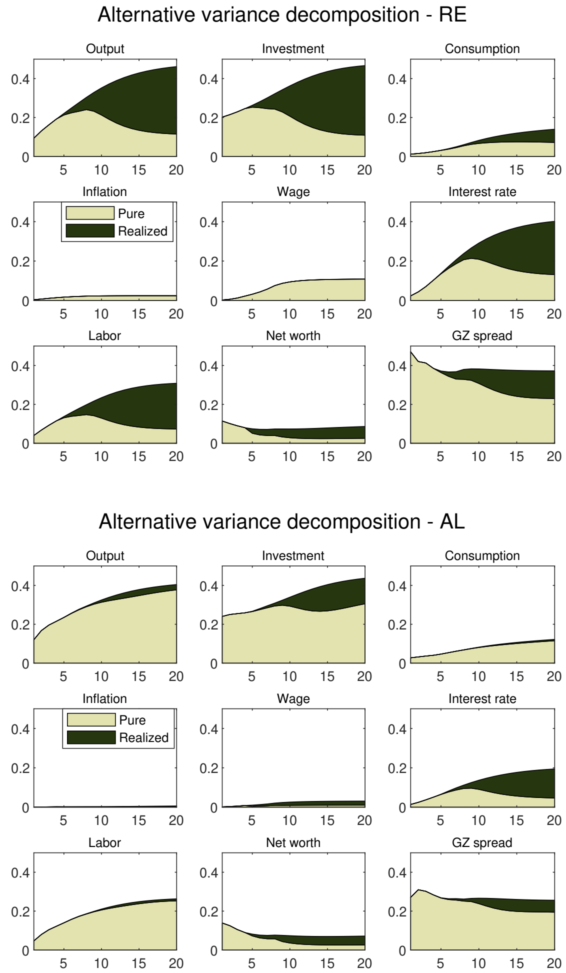
Table 4 shows the unconditional variance decomposition for each model specification. The top panel shows the variance decomposition for the RE model while the bottom panel shows the one associated with AL. The arrows and the numbers in some entries in the bottom panel highlight the direction and the quantity of the change in the variance decomposition, respectively, when one shifts from RE to AL. Two major differences are noteworthy. First, we find an increase in the relative empirical importance of both the risk premium shock and the net worth shock. This clearly suggests that the AL specification amplifies the transmission mechanism of the (forward-looking) financial sector and, consequently, these shocks become more significant in explaining aggregate fluctuations. Second, we find that *unanticipated* monetary and non-stationary TFP shocks become less significant in explaining fluctuations in real macroeconomic variables under AL.

Regarding the importance of TFP news shocks as a source of aggregate fluctuations, the unconditional variance decomposition shows that the sum of the two TFP news shocks considered explains a large proportion, roughly 46%, of the output and investment fluctuations under the two expectation specifications, whereas the contributions of TFP news in explaining labor and consumption fluctuations are more modest (at around 30% and 17%, respectively). Interestingly, the contribution of 8-quarter ahead news shocks is larger than that of 4-quarter ahead shocks under the two specifications, mainly due to the larger size of the former, but bounded rationality seems somewhat to reduce the importance of the anticipation period due to the larger belief coefficients in the PLM of financial variables associated with the latter.

The decomposition of news shocks into pure and realized shocks might also be important, as emphasized by Sims (2016). A pure news shock captures the effects of a news shock on the aggregate variables prior to the realization of the shock, but its effect once realized is not conceptually different from that of an unanticipated shock. Indeed, in analyzing the importance of news shocks we are interested in their ability to shape agents' expectations as drivers of aggregate fluctuations. Since we are analyzing the consequences of a deviation from the RE hypothesis, it is important to assess the extent to which the contribution of pure news shocks in explaining the business cycle is affected by considering some form of bounded rationality. Figure 3 shows the sum of the proportions in the variance decomposition explained by the 4- and 8-quarter ahead news shocks considering RE (upper-panel) and AL (bottom-panel) for alternative (from 1- to 20-quarter) forecasting horizons. Following Barsky et al. (2015) and Sims (2016), the variance decomposition is further decomposed into two areas that represent pure news (yellow) and realized news shocks (dark). The effect of a pure news shock is computed by subtracting the effect of an unanticipated shock at a particular anticipation horizon from the total effect of a news shock so as to leave the relevant exogenous variable unchanged.[19]

[19] As explained in Sims (2016), this decomposition does not deliver separate percentages of pure and realized news that add up to the total proportion explained by the total news shock. Therefore, for illustrative purposes we add up both (pure and realized news) proportions and compute their pseudo-proportion in the actual total news proportion shown in Figure 3 as follows: $\frac{\epsilon^{pure}}{\epsilon^{pure}+\epsilon^{realized}}\epsilon^{total}$, and $\frac{\epsilon^{realized}}{\epsilon^{pure}+\epsilon^{realized}}\epsilon^{total}$.

Figure 4.3: Decomposition of news in pure and realized



There is a noteworthy difference between the RE and AL models: The proportion in the variance decomposition attributed to pure news shocks in the AL model is much larger than in RE. These findings are clearly in contrast with Sims (2016), who finds that in the DSGE model considered in Schmitt-Grohé and Uribe (2012) (i.e. a non-financial RE-DSGE model) the proportion of pure news shocks is rather small.[20]

[20]The high significance of pure news shocks found is also in line with Herrera and Vázquez (2023), who consider a similar DSGE model with financial frictions à la GK but under RE. These two papers introduce two alternative specifications that boost the importance of pure news shocks by amplifying the transmission mechanism of (TFP) news shocks through the financial sector. Thus, in this paper, the departure from RE amplifies the responses of the macroeconomy to TFP news shocks, while the quality-of-capital news shocks considered in Herrera and Vázquez (2023) have a similar amplifying impact through the financial market. Altogether, these papers emphasize the importance of including an explicit financial sector in DSGE modeling to properly identify the transmission mechanisms of news shocks.

4.4.6 VAR evidence

In previous sections, we show the differences in model fit, empirical importance and transmission mechanism of news shocks under RE and AL and provided evidence on the better performance of the latter assumption. This section focuses on the ability of the DSGE model to match empirical responses that we estimate through a VAR model. Following closely Barsky et al. (2015) and Görtz et al. (2022b), we compare the empirical IRF from the VAR model with those estimated with identical VAR specification on artificial data samples generated by each (RE and AL) version of the DSGE model. All estimations consider a seven-variable empirical VAR model using five lags with a Minnesota prior. In contrast to the observables used in the estimation of the alternative versions of the DSGE model, all time series considered in the VAR enter in (log) levels as is standard practice in the empirical VAR literature. Moreover, as an observable measure of TFP we use the utilization-adjusted aggregate TFP, described in Fernald (2014) in all VARs estimated (either with actual or simulated data). We follow the identification scheme suggested in Francis et al. (2014) to identify the TFP news shock from the VAR model.[21] This identification method estimates the TFP news shock by (i) maximizing the variance of TFP at a specific long but finite horizon (we set the long horizon to 40 quarters), and (ii) imposing a zero impact restriction on TFP conditional on the news shock.

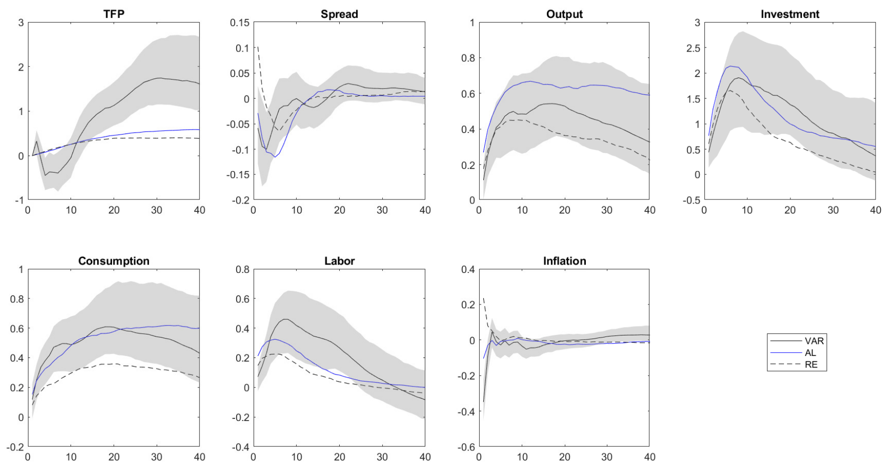
Figure 4 shows the empirical responses of the seven variables to a TFP news shock (black line), their 16%-84% posterior bands (shaded-gray areas), and the median of the responses obtained from the estimation of the VAR across 500 simulated time series resulting from the AL (blue line) and the RE (dashed line) versions of the DSGE model. The empirical IRFs from the VAR are largely similar to those reported in Görtz et al. (2022b):[22] Namely, (i) the TFP confidence band only excludes the zero value after roughly three years; (ii) the TFP news shock rise output, consumption, investment, and hours significantly on impact, and they exhibit hump-shaped dynamics; (iii) the spread decreases, which is in line with an economic boom favored by credit expansion; and (iv) a short-lived fall in inflation. Many of these features are well captured, at least qualitatively, by the two versions of the DSGE model, but there are a few remarkable differences. First, the median IRFs from the DSGE model under AL lie inside the confidence bands of the empirical VAR for all variables and across most forecast horizons. Meanwhile, the IRFs corresponding to the RE version of the DSGE model have trouble in capturing the short-run responses of many variables featured by

[21] The results are robust to other identification strategies that are also commonly used in news literature (e.g. long- and short-run restrictions and Barsky and Sims (2011) identification method).

[22] In spite of considering a different sample period—we use the same sample period considered in the estimation of the DSGE model— and including investment (instead of S&P 500).

the empirical VAR, such as output, investment, spread, and inflation. In particular, as pointed out above, TFP news shocks are inflationary under RE but have a negative effect on inflation both in the empirical VAR and in the DSGE under AL. Second, the ability of the AL model to reproduce the countercyclical response of the spread at impact suggests that the bounded rationality assumption underscores the importance of the credit channel in the transmission mechanism of TFP news shocks. Finally, the medium- and long-term responses of model-based TFP are significantly smaller, but consistent with those estimated by Forni et al. (2014) using a factor-augmented VAR approach to identify TFP news shocks.

Figure 4.4: Comparison of empirical and DSGE-simulated VAR responses to a TFP news shock



Notes: The black line shows the empirical responses to a TFP news shock, while shaded-gray areas show their corresponding 16%-84% posterior bands. The blue line (dashed line) shows the median of the responses obtained from the estimation of the VAR across 500 simulated time series resulting from the AL (RE) DSGE model. The units of the vertical axes are percentage deviations from the steady state.

4.5 Conclusions

This paper builds on the growing literature that analyzes the expectation-driven business cycle by (i) analyzing the empirical importance of TFP news shocks as one of the main driving forces of the business cycle; and (ii) assessing the consequences of deviating from the rational expectations (RE) assumption through adaptive learning (AL). In principle, the AL and news shocks strands of literature are closely related since both try to assess how expectations may affect the aggregate economy. Therefore, it seems crucial to investigate how the role of news shocks in explaining the business cycle is affected by the way in which agents form their expectations. All empirical analyses in news shock literature to date have been carried out through the prism of the RE assumption, but here we consider AL instead. This introduces distinctive dynamics into the model through the effects of news shocks on the expectation channel, which substantially change their transition mechanism and their relative empirical significance.

We find that a departure from the RE assumption via AL improves model performance. The AL specification provides a better overall fit in terms of marginal data density and also better replicates the size of aggregate fluctuations. We show that these findings are mainly due to the impact of TFP news shocks on financial expectations under AL, while the estimates of structural parameters remain fairly robust under the two specifications concerning expectations. We also find that introducing a source of bounded rationality has a significant impact on the transmission mechanism of news shocks. In particular, the responses of consumption are more persistent under AL. Moreover, the credit spread shows different effects, with TFP news shocks triggering a more persistent effect under the AL hypothesis. Altogether, these features imply that financial variables anticipate the future economic outlook, which is in line with the empirical literature. Furthermore, the effects of news shocks on inflation are reversed, so that news shocks are deflationary under AL. This finding is in line with recent literature (Forni et al. (2014); Görtz et al. (2022b)), but in sharp contrast with the inflationary response to news shocks obtained in the RE specification.

Interestingly, we find that the importance of pure news shocks increases under AL. This is a particularly important finding because the importance of (anticipated) news shocks is usually assessed on their ability to affect the economy via the expectation channel as pure news shocks do by construction—i.e. pure news shocks are computed as in Sims (2016) to be distinguished from *realized* news shocks, which can be viewed just as unanticipated shocks. Finally, we also show that the AL-DSGE, rather than the RE-DSGE, model generates dynamics implied by news shocks that are more in line with those estimated through an empirical Bayesian VAR.

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Chapter 5

Building-up Financial Resilience: The Role of Borrower-Based Macroprudential Policies

5.1 Introduction

Excessively leveraged agents are a central explanation of deep and long-lasting financial recessions like the Great Recession. Fisher (1933) and Minsky (1986) already suggested that the credit cycle is a major driver of the business cycle, and more recently, Jordà et al. (2013) found that stronger credit growth in the expansionary phase of an economic cycle tends to be followed by a deeper recession. Therefore, policies that target agents' indebtedness are potentially useful to enhance financial resilience. For instance, Borrower-Based Macroprudential (BBM) policies constrain credit by imposing limits on how much debt households can acquire, typically relative to the value of the underlying collateral or income. Thus, these policies prevent excessive credit growth and enhance household financial resilience. Policy-makers can view these policies as an important tool to reduce financial fluctuations and prevent the materialization of potential financial risks.

The implications of BBM policies are frequently analyzed in DSGE model featuring collateral constraints.[1] These types of constraints can capture the amplification effects triggered by household indebtedness. In this framework, borrowers are typically constrained by the value of the underlying

[1] See for example Lambertini et al. (2013), Rubio and Carrasco-Gallego (2014), Alpanda and Zubairy (2017), Rubio and Yao (2020) and Chen et al. (2023), among others.

collateral when taking on loans. Therefore, when recessionary shocks hit the economy they need to react more abruptly by changing their consumption and investment decision since they cannot increase their leverage to accommodate the shock. BBM policies reduce the initial level of debt and consequently alleviate this amplification effect driven by the collateral channel. Nevertheless, this might not be the only channel in which BBM policies operate.[2] Indeed, the first contribution of this paper is to analyze empirically the interaction between the amplification effects of borrowers' indebtedness and lenders' vulnerabilities to financial shocks. For this aim, I estimate a state-dependent pannel local projection model. The model considers 4 alternative states: (i) both banks and households are vulnerable, (ii) only households are vulnerable, (iii) only banks are vulnerable, and (iv) tranquil times. Household debt over GDP is considered the state variable that defines household vulnerability. Similarly, banks' expected default frequencies determine banks' states. Then, following Furlanetto et al. (2019) I identify a credit shock under each state through sign restrictions. Regarding household vulnerabilities (indebtedness), the results are in line with those found in the literature, suggesting that households carrying elevated levels of debt may serve as amplifiers, exacerbating the impact of credit shocks on overall financial stability. For instance, Barnichon and Brownlees (2019) analyze how positive and negative credit supply shocks are amplified depending on the state of the business cycle. Alpanda et al. (2021) estimate a state-dependent LP model finding that monetary policy effects depend on the level of household indebtedness. In this vein, Couaillier and Scalone (2020) find that households' financial vulnerability affects the propagation of housing and credit shocks. High banks' expected default frequency state implies a similar effect, suggesting that banks' vulnerability works as an amplifier for credit shocks. More importantly, the estimates show that when both households and banks are vulnerable the credit shock is largely amplified, suggesting an important interaction between the two states.

The main contribution of this paper is to analyze the potential benefits and challenges that BBM policies imply under the prism of a DSGE model that considers not only collateral constraints but also credit supply frictions. Therefore, BBM policies are analyzed in a DSGE model that captures the empirical evidence mentioned above. More precisely this paper analyzes potential benefits on both households' and banks' financial resilience, activation costs, interplay with unconventional monetary policy, and short- vs. long-run implications of the BBM policies through the lens of a non-linear DSGE model.

The credit supply frictions considered in the model add an important channel as also suggested by Justiniano et al. (2019) who show in an analytical model how credit supply and demand rigidities

[2] Giannoulakis et al. (2023) using a micro-macro model shows the important effect of BBM in banks' balance sheets.

can drive a recession like the Great Recession. In this vein, Gertler and Karadi (2011), Gertler and Karadi (2013) and Karadi and Nakov (2021) show the importance of considering constrained banks to resemble scenarios like the 2008 financial crisis and its aftermath. The credit supply within this model is intermediated by banks, modeled based on Gertler and Karadi (2011). More precisely, banks receive deposits from savers and extend loans to both households and firms. Savers deposit an amount of savings that prevents banks from diverting their assets, reflecting the inherent moral hazard issue. During periods of financial distress, when banks exhibit heightened leverage, deposits become scarce. Consequently, banks are compelled to increase lending rates above the risk-free rate, creating a lending spread. Importantly, the two described frictions, namely the collateral constraint on borrowers and the moral hazard issue faced by banks interact together amplifying each other. The heightened deleverage of households, particularly when indebtedness is high, negatively impacts the balance sheets of banks. Simultaneously, the increase in lending rates triggers financial distress in borrower households. This interplay of frictions enables a comprehensive assessment of the implications of BBM policies for financial resilience on both sides of the credit market. By incorporating these dynamics into the model, this paper aims at offering a deeper understanding of the benefits and challenges associated with BBM policies.

After the global financial crisis, macroprudential policies were introduced as policies that improve the financial resilience ex-ante by reducing agents vulnerabilities. Other instruments like the unconventional monetary policy are deployed when the risks are already materialized alleviating the economic downturn. Both types of policies aim to address similar distress scenarios. The consideration of credit supply frictions in this model calls for an analysis of the interaction between BBM policies and unconventional monetary policies, like Quantitative Easing. The analysis of this interplay is an area that requires further research as suggested by de Bandt et al. (forthcoming).

The findings of the paper are fourfold. First, empirical evidence is found that household indebtedness and bank vulnerability amplify financial shocks individually and show an interaction increasing the amplification effect. Hence, BBM policies may serve as an important tool for increasing financial resilience. This makes this type of policy interesting for policymakers, considering that their goal is to reduce the materialization of financial risks and smooth out the business cycle. Second, a non-linear DSGE model with a collateral constraint and constrained banks is developed, resembling the empirical findings and serving as a laboratory to assess the costs and benefits of activating BBM policies. This model shows that tighter BBM policies increase financial resilience by reducing household indebtedness. Less leveraged households reduce the amplification driven by the collateral channel and the feedback effect of constrained banks, whose assets are less depreciated. These two features together result in that credit supply shocks are better accommodated by both households and banks when facing BBM policies. Moreover, shocks originating in the housing markets are restrained with BBM policies, reducing their impact on the balance sheets of the banks and consequently reducing systemic risk since the transmission of these shocks to the rest of the economy is highly mitigated. The third result relies on the interaction of unconventional monetary policies and BBM policies. It is found that the effects of asset purchase programs are downplayed when BBM policies are activated. This is because BBM policies reduce the amplification driven by financial frictions, and since QE aims to cut back the effects driven by financial distress, milder financial frictions imply a smoother transmission of QE. Therefore, BBM policies imply an enhancement of ex-ante financial conditions but reduce the efficacy of ex-post instruments to alleviate financial distress scenarios. Moreover, it is found that the activation cost of BBM policies is remarkably higher when activated under financial distress. However, this higher cost of activation can be reduced by smoother activation that allows a smoother reduction in credit and consequently allows banks to accommodate the activation through retained earnings. Finally, the paper shows that BBM policies are beneficial by decreasing the risk of financial distress that arises from the non-linear interaction between collateral and banks' leverage constraints. The marginal gain of reducing the LTV is larger when households' indebtedness is high. However, for already lower levels of LTV the marginal gains of further tightening are largely reduced, while the long-term welfare reductions are still remarkable for both borrowers and savers. Therefore, reducing LTV should be seen as a policy aimed at decreasing the likelihood of entering a distress scenario rather than directly reducing high levels of household debt.

The structure of the paper is as follows. In section 2, I estimate a state-dependent panel local projection model conditioned on households' indebtedness and banks' vulnerabilities. Section 3 builds a simple model to focus on the two financial frictions that drive the results of the analysis. Then, section 4 incorporates these two frictions in a medium-scale non-linear DSGE model to provide a thorough analysis of the issues addressed in this paper. Section 5 describes the solution and the calibration of the model. Section 6 shows the main results of the paper regarding: (i) the transmission mechanism of financial shocks under BBM policies, (ii) the interaction of BBM policies with central bank asset purchases, (iii) the state-dependent activation cost of BBM policies, (iv) and the short- vs long-run implications of BBM policies. Finally, section 7 concludes.

5.2 The amplification effect of household indebtedness and banks' vulnerability: Empirical evidence

This section shows the estimation through the local projection technique proposed by Jordà (2005) of a state-dependent model and identifies the impulse responses of a credit shock using sign restrictions. The state-dependent model is the following panel local projection:

$$
\begin{aligned}
z_{i,t+h} = I^h_{i,t-1} I^b_{i,t-1} \left[\alpha^a_{i,h} + \beta^{a\prime}_h y_{i,t} + \sum_{l=1}^{L} \delta^a_{h,l}{}' y_{i,t-l}\right] + \left(1 - I^h_{i,t-1}\right)\left(1 - I^b_{i,t-1}\right)\left[\alpha^b_{i,h} + \beta^{b\prime}_h y_{i,t} + \sum_{l=1}^{L} \delta^b_{h,l}{}' y_{i,t-l}\right] + \\
(1 - I^h_{i,t-1}) I^b_{i,t-1} \left[\alpha^c_{i,h} + \beta^{c\prime}_h y_{i,t} + \sum_{l=1}^{L} \delta^c_{h,l}{}' y_{i,t-l}\right] + I^h_{i,t-1}(1 - I^b_{i,t-1})\left[\alpha^d_{i,h} + \beta^{d\prime}_h y_{i,t} + \sum_{l=1}^{L} \delta^d_{h,l}{}' y_{i,t-l}\right] + \epsilon_{i,t+h}
\end{aligned}
$$

where $I^h_{i,t-1} \in \{0,1\}$ and $I^b_{i,t-1} \in \{0,1\}$ are indicator variables representing the state of the economy in country i just before the shock realization. $I^h_{i,t-1}$ captures the state defined by household indebtedness and $I^b_{i,t-1}$ represents the state defined by banks' vulnerability. $z_{i,t}$ is the variable of interest, and $y_{i,t,1} = [z_{i,t,1}, ..., z_{i,t,j}]$ collects all the variables of interest. Two lags are considered for the y_i matrix. Note that α_i captures fixed effects.

The local projection approach has been shown to estimate the same IRF as vector autoregression models plagborg2021local. However, in a state-dependent context, LP models have some advantages. They allow, by running a simple regression, the estimation of a response of each variable z at a particular horizon h. Therefore, the impulse responses are directly recovered from the coefficients estimated for that particular horizon in each state with no need of modelling transitions between states. More precisely, the estimation for each variable and horizon would just include as regressors a constant α_i that captures country fixed effects and variables y at time t, time $t-1$, and time $t-2$. Then, the estimated coefficients for each horizon together with a specific identification strategy allow the construction of the responses of z at each horizon h for a structural shock materialized at time t. In sum, the coefficients β^a_h, β^b_h, β^c_h and β^d_h represent the average effects of the shock conditional on the initial state. Moreover, considering a *panel* LP model allows exploiting the cross-country dimension of the data to refine the identification of the state-dependency of the IRF.

The set of variables of interest considered in the estimation are the log-difference of real output, CPI, real housing prices, household loans, investment-GDP ratio, and short term rates. The sample considers the period 1980q1-2018q4 and seventeen different countries.[3] The state variables that give rise to the four states of the economy are household indebtedness and banks' expected default

[3] The countries considered in the sample are Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States.

frequencies. The definition of high and low periods of indebtedness closely follows Alpanda et al. (2021). More precisely, the debt gap measure is defined as the deviation of the household debt over GDP ratio from its smooth trend, obtained using the HP filter with a large smoothing parameter (λ = 400.000). The high-debt states are defined as periods in which the gap is above the 75th percentile of the distribution.[4] The two banks' vulnerability states are constructed in the same way. Hence, the two state variables combined give rise to the four states of the economy.

5.2.1 Identification strategy

In order to obtain the impulse responses to credit shocks from the LP model above we need to impose restrictions to identify these structural shocks. The identification strategy considers sign restrictions that are directly applied to the local projection model as suggested by Plagborg-Møller and Wolf (2021) and first used in an empirical analysis by Alpanda et al. (2021).

The IRF estimation can be described as follows. First, the state-dependent local projection model is estimated. Then, the impulse response of variable z for horizon h and state $I = \{a, b, c, d\}$ is constructed as a linear combination of the coefficients $\beta_h^I = \{\beta_h^a, \beta_h^b, \beta_h^c, \beta_h^d\}$. Hence, the impulse response is $IRF_h^I = \beta_h^I \epsilon$, where ϵ is a unit length vector such that the IRF satisfies the imposed sign restrictions. The procedure is analogous to the standard sign restriction applied in the VAR literature. The only difference is that the reduced form coefficients are estimated through the local projection model. Second, the specific sign restrictions considered to identify the credit shock are in line with the standard dynamics found in most theoretical and empirical DSGE models, and closely follow the signed restrictions suggested by Furlanetto et al. (2019). This identification strategy assumes that after a credit shock, output growth, inflation, housing prices growth, investment-GDP ratio, and short-term rates all comove with credit growth.

5.2.2 Results

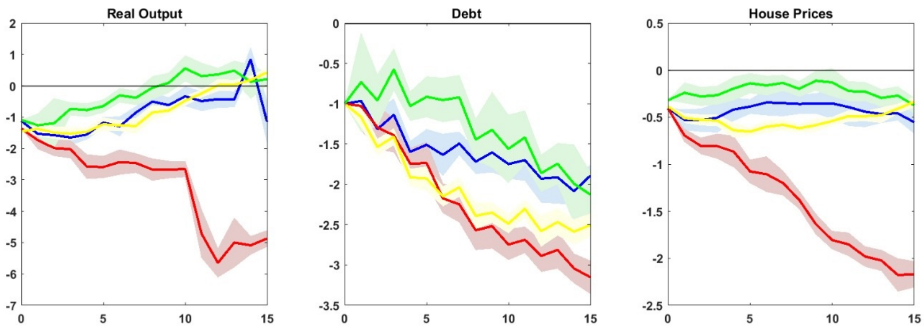
Figure 1 shows the state-dependent IRF of output growth, credit growth, and housing price growth estimated in the local projection model and identified through the sign restrictions strategy. The IRFs have been normalized to trigger a 1% drop in household debt. The green lines represent the responses of each of the variables to a negative credit shock in tranquil times. The blue lines show those same responses but when the economy is in a high-household indebtedness state. The differences in the responses across the two different states suggest that households carrying high levels

[4] For a more detailed explanation the reader can refer to Alpanda et al. (2021)

of debt serve as amplifiers, exacerbating the harmful impact of negative credit shocks on overall financial stability. The yellow lines show the response to a negative credit shock in a high banks' vulnerability state. Similarly to household indebtedness, banks' vulnerability implies an amplification of credit shock effects. Finally, the red lines represent the responses to credit shocks when both households and banks are vulnerable. Interestingly, the estimates suggest a non-linear interaction between these two states showing that the amplification effect is largely increased when both borrowers and lenders are vulnerable.

This empirical evidence motivates the implementation of BBM policies to contain financial distress and its detrimental implications for the macroeconomy. The reduction of household indebtedness would have a direct effect by reducing household vulnerabilities but also a second-order effect triggered by the interaction with banks' vulnerability. In the following sections, I develop a non-linear DSGE model that captures the empirical evidence found here and, consequently, is well-suited to assess the role of BBM policies, from a quantitative perspective, in building financial resilience in the broader economy.

Figure 5.1: State-dependent Local Projection



Notes: This figure shows the impulse response function to a credit shock estimated through the LP model. The green line shows the IRF corresponding to the high household indebtedness and high bank vulnerability state. The blue dashed line shows the IRF of the high household indebtedness state. The yellow line shows the IRF of the high banks' vulnerability state. Finally, the green line shows the IRF in tranquil times. The IRF has been normalized to have a 1% reduction in household loans.

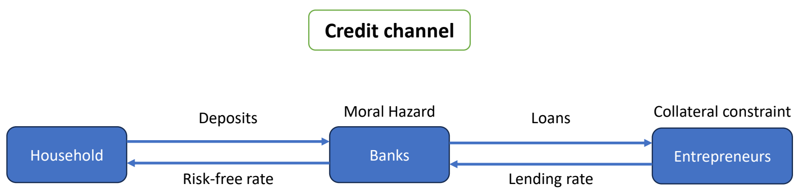
5.3 A simple model

This section builds a simple model that considers the two occasionally binding constraints that are central to the analysis of BBM policies in this paper. These financial frictions allow us to capture the empirical evidence found in the previous sections, where household indebtedness and banks' vulnerability work as shock amplifiers but also amplify each other. The two financial frictions are

(i) the households' collateral constraint, and (ii) the banks' balance sheet constraint. This model just aims to illustrate the mechanism of each of the constraints and their interaction. Four variants of the model are simulated with this precise goal: (i) the model with both constraint in place, (ii) the model with only the collateral constraint, (iii) the model including only the banks' constraint, and (iv) the model with no constraints in place. The strategy followed here of relaxing these constraints is not a policy itself but only a theoretical exercise to assess the effects of these frictions and their interplay. In the following section, these two constraints are included in a more comprehensive medium-scale DSGE model where BBM policies are implemented. The BBM policies are modeled as policy limits (in addition to the private limits) on how much debt households can acquire relative to the value of the underlying collateral aiming at reducing borrowers indebtedness.

Figure 2 shows a diagram that summarizes the credit flow in this simple model. Households keep their savings in banks' deposits which pay a risk-free interest rate. Then, banks use deposits and their own net worth to issue loans to entrepreneurs. When banks are too leveraged their incentive compatibility constraint becomes binding making credit supply scarce and creating a spread between the risk-free interest rate and the lending rate. On the credit demand side, entrepreneurs face a collateral constraint. The fact that they need to adjust their borrowing to the value of their collateral implies an amplification effect, especially when they are highly indebted since they cannot adjust their leverage to accommodate shocks. These dynamic features will become clearer in the following section.

Figure 5.2: Diagram



Patient households

The patient household decides consumption C_t^c, labor supply L_t, and savings in banks' deposits D_t to maximize the following utility function

$$E_t \sum_{k=0}^{\infty} \beta^k \left[log(C_t^C) - \frac{\sigma_l}{1+\varphi_l} L_t^{1+\varphi_l} \right] \tag{5.1}$$

where β is the household discount factor. Banks' deposits pay the risk-free real interest rate, R_t. Savers also obtain dividends from capital goods producers, and financial intermediaries Π_t. Hence, the budget constraint is given by

$$C_t^c + D_t = R_t D_{t-1} + w_t L_t + \Pi_t \tag{5.2}$$

Entrepreneurs

The entrepreneurs decide on consumption C_t^b, capital acquisition K_t, and loans S_t^k to maximize the following utility function

$$E_t \sum_{t=0}^{\infty} (\beta^e)^k log(C_t^e), \tag{5.3}$$

where the discount factor β^e is assumed to be lower than the patient households, so they have incentives to borrow. The budget constraint is given by

$$C_t^e + R_t^k S_{t-1}^k + Q_t \left(K_t - (1-\delta)\epsilon_t K_{t-1} \right) = S_t^k + Y_t - w_t L_t, \tag{5.4}$$

where Y_t is total goods production, Q_t is the price of capital (Tobin's q), ϵ_t is a quality of capital shock and S_t^k represents loans taken from banks at a rate R_t^k. Moreover, entrepreneurs can only borrow a fraction, LTV, of the future expected value of their collateral,

$$S_t^k \leq LTV E_t \, Q_{t+1} \, K_t \tag{5.5}$$

The rationale of this collateral constraint follows the limited contract enforceability suggested by Kiyotaki and Moore (1997): if borrowers repudiate their debt obligations, the bank can repossess the borrowers' assets by paying a proportional transaction cost $(1 - LTV_t)Q_{t+1}K_t^b$.

The functional form of production is assumed to be a standard Cobb-Douglas function

$$Y_t = (\epsilon_t K_{t-1})^{\alpha} \, L_t^{1-\alpha}, \tag{5.6}$$

Financial intermediaries

A fixed share of patient household agents is assumed to be bankers who do not supply labor but behave as financial intermediaries. At the beginning of each period a share, $1 - \theta_t$, returns to the family they belong. To keep the proportion constant, that share of bankers is replaced by the same number of new bankers. The net worth of retired bankers is transferred to households as dividends and the new bankers enter with some fixed startup funds to operate in the intermediation business

These financial intermediaries fund the acquisitions of physical capital using their own equity capital and deposits from patient households. Therefore, the balance sheets of the bankers are

$$S_t^k = N_t + D_t, \tag{5.7}$$

where N_t is the net worth of the bankers. Since the return on financial assets is represented by R_t^k and the cost of liabilities is R_t the net worth of the intermediaries evolves as follows:

$$N_{t+1} = R_{t+1}^k S_t^k - R_{t+1} D_t = (R_{t+1}^k - R_{t+1}) S_t^k + R_{t+1} N_t. \tag{5.8}$$

Let $\beta\Lambda_{t+1}$ be the stochastic discount factor of the financial intermediaries. The bankers' decisions are endogenously determined in the model through a problem in which they maximize the discounted stream of dividends paid to households, which is equivalent to their expected terminal net worth,

$$\begin{aligned} V_t &= \max \ E_t \sum_{k=0}^{\infty} (1-\theta)\theta^k \beta^k \Lambda_{t+1} N_{t+1+k} \\ &= \max \ \ E_t \sum_{k=0}^{\infty} (1-\theta)\theta^k \beta^k \Lambda_{t+1+k} \left[(R_{t+k+1}^k - R_{t+k+1}) S_{t+k}^k + R_{t+k+1} N_{t+k} \right]. \end{aligned}$$

This paper follows Gertler and Karadi (2011, 2013) and Karadi and Nakov (2021) to introduce an agency problem between bankers and depositors. Banks face a moral hazard problem that motivates a limit on their ability to obtain deposits: At the beginning of the period, the bankers can choose to divert a fraction λ of the assets they hold and transfer them to the household of which they are members. The cost to the banker is that the depositors can force the intermediary into bankruptcy and recover the remaining fraction of assets. Hence, for savers to be willing to supply deposits to the bankers, the following incentive constraint must be satisfied:

$$V_t(S_t^k, N_t) \geq \lambda S_t^k, \tag{5.9}$$

where V_t, the gain from remaining in the intermediation business, should be at least as large as the gain of diverting assets. The bankers then choose S_t^k to maximize V_t subject to the incentive constraint. This constraint implies a limit to the credit supply: if banks become too leveraged depositors would worry since bank incentives to divert would increase. If their incentives to divert become equal to their gain of remaining in the business, savers would restrain the supply of deposits to prevent a bank run. This implies that under tranquil times, when the incentive constraint is not binding, excess returns are zero, and banks can be seen as a veil, since credit is directly priced by saver households. However, when bank net worth declines enough for the constraint to bind, they have to reduce the credit supply, triggering an increase in the lending spread that works as a shock amplifier. Hence, the dynamics of the spread are represented by:

$$\Lambda_{t+1}\Omega_{t+1}(R^k_{t+1} - R_{t+1}) = \begin{cases} \lambda\mu_t^{bank} & \text{if lev} > 1/\lambda \\ 0 & \text{if lev} \leq 1/\lambda \end{cases}$$

where μ_t^{bank} is the Lagrange multiplier associated with the banks' balance sheet constraint. Moreover, $\Omega_t = (1 - \theta_t + \theta_t\nu_t)$ is the banks' discount factor, where ν_t is the shadow value of a unit of net worth at the beginning of the period ($\nu_t = \partial V_t/\partial N_t$). This term expresses the modified utility value of an extra unit of future income for banks relative to households. With probability $(1 - \theta_t)$, the bank exits, so the extra income delivers the same utility as an extra income would for the household. With probability θ_t, however, the bank survives and the extra income raises its net worth, which is valued at the marginal utility $\partial V_t/\partial N_t$. The banks' discount factor is different from the household discount factor whenever the value of bank net worth exceeds unity as a result of the balance sheet constraint that binds or has the potential to bind in the future. Finally, the evolution of bankers' net worth is given by

$$N_{t+1} = \theta_t\left[(R^k_{t+1} - R_{t+1})S^k_t + R_{t+1}N_t\right] + \Theta \tag{5.10}$$

where Θ represents a fixed transfer to new bankers, and $\theta_t = \rho^\theta\theta_{t-1} + \epsilon^\theta_t$ is the survival rate of banks that follows a AR(1) process .

Capital goods producers

Capital goods producers turn out and repair depreciated physical capital and sell it to entrepreneurs at price Q_t. Investment goods are purchased from final goods producers. Capital goods producers are assumed to face quadratic adjustment costs, $\varphi(I_t/I_{t-1})$. The adjustment costs function $\varphi(I_t/I_{t-1})$ is assumed to be a strictly increasing twice differentiable function. Thus, the optimization problem of the capital goods producers is

$$Max\ E_t\left\{\sum_{k=0}^{\infty}\beta^k\Lambda_{t+k}\left[Q_{t+k}I_{t+k} - I_{t+k} - I_{t+k}\varphi(\frac{I_{t+k}}{I_{t+k-1}})\right]\right\}, \tag{5.11}$$

where $\varphi(\cdot)$ is assumed to have the properties $\varphi(1) = \varphi'(1) = 0$, $\varphi''(1) = \hat{\varphi} > 0$. Therefore, the parameter $\hat{\varphi}$ captures the degree of investment adjustment cost, in absence of adjustment cost the price of capital is 1. Capital accumulation follows the standard equation

$$K_t = (1 - \delta)\epsilon_t K_{t-1} + \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right)\right] I_t. \tag{5.12}$$

5.3.1 The amplification feedback of both financial frictions

This section sheds light on the implications of each of the two financial frictions that will be used to resemble the empirical evidence found before. To do so, I simulate a quality of capital shock that affects the real side of the economy through the production function but also directly affects the prices of the assets. This shock has been used in the literature that analyzes financial frictions [e.g.][]gertler2011model, villa2016financial, herrera2023significance. A negative realization of this shock captures a worsening in the quality of intermediary assets that produces a sharp decline in the net worth of these institutions but also a worsening of the financial conditions of borrowers, since their collateral is devalued. Figure 2 shows the IRFs of (i) a model without financial frictions (green dotted line), (ii) a model with only banks' leverage constraints (blue dashed line), (iii) a model with only LTV constraint (red dashed-dotted line), and (iv) the baseline model (black solid line), which includes the two constraints.[5]

First, let us focus on the baseline model (black line) to describe the model dynamics. A negative capital quality shock triggers a devaluation of banks' net worth making banks become more leveraged and their incentive constraint then starts binding. Consequently, credit supply becomes scarce reducing the access to credit to finance capital acquisition. Moreover, on the credit demand side, borrowers suffer a negative wealth effect since the value of their assets is reduced, which reduces their consumption and investment. The collateral constraint amplifies these effects because borrowers cannot accommodate the shock by increasing leverage but they have to reduce borrowing to comply with the LTV constraint in a scenario featuring a fall in the value of the collateral.

The collateral constraint behaves as a shock amplifier. The differences between the green dotted line (model with no constraints) and the red dashed-dotted line (model with the collateral constraint) show the amplification effect of this specific constraint. When this constraint is not in place, entrepreneurs increase their leverage to accommodate the shock as shown in the bottom-right chart. However, when the constraint is active they are forced to reduce their loans more abruptly

[5] Model (ii) is obtained by allowing the LTV to vary in order to keep the Lagrange multiplier associated with the LTV constraint at the steady-state level. This implies that households can freely adjust their leverage in response to the shock. Model (iii) gets rid of banks' frictions by increasing λ up to a point that is never reached, and consequently, the balance sheets of the banks play no role in the model dynamics having a constant spread. Model (i) considers both conditions implemented in models (ii) and (iii).

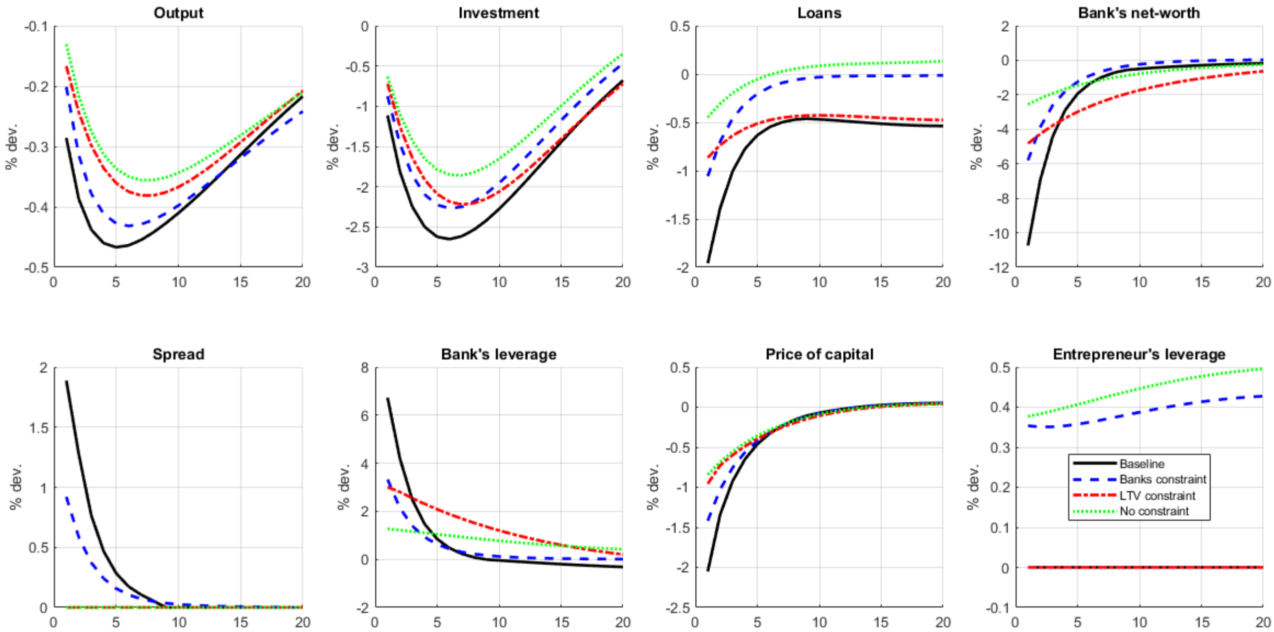
since they cannot increase their leverage more than the LTV limit. This case features two amplification channels: (i) they have to respond with a larger decrease in consumption and investment, and (ii) the decrease in credit demand harms banks' balance sheets increasing the response of the lending spread, which further harms consumption and investment.

The banks' credit constraint also implies a shock amplification. The effect of the bank incentive constraint is captured by the difference between the dashed blue line and the dotted green line. The recessionary shock affects negatively the value of the collateral (the price of capital) triggering a devaluation of banks' balance sheets and increasing their leverage. Since savers are concerned about the moral hazard of banks' intermediating too many assets relative to their own net worth, deposits become scarce, forcing banks to reduce the credit supply and increase the lending spread. This case involves two amplification effects: (i) the reduction in credit supply implies a reduction in the capability of funding capital acquisition, and (ii) the increase in the spread harms households' financial conditions.

The amplification channels of these two frictions interact with each other. The effects of both constraints operating simultaneously is captured by the difference between the dotted green line and the black solid line. As already pointed out above, the response of entrepreneurs cutting aggregate demand has a second-order effect on asset prices harming banks' balance sheets. Simultaneously, the increase in the lending spread and the reduction of the credit supply triggered by the devaluation of banks' net worth, reinforce the negative effect on households' financial conditions since the repayment of the debt becomes more expensive.

In summary, this analysis shows the crucial importance of considering credit supply frictions due to their interaction with collateral constraints. Since BBM policies operate on collateral constraints, it is essential to account for the significant interplay between these two frictions. Analyzing BBM policies solely in the presence of collateral constraints overlooks a critical aspect of their effects. By incorporating both credit supply frictions and collateral constraints, we gain a comprehensive understanding of the broader implications and effectiveness of BBM policies. In the following section, BBM policies will be modeled as a reduction in the limits on how much debt households can acquire relative to the value of their collateral. Therefore, the implications of less indebted borrowers will be studied.

Figure 5.3: The role of the financial frictions



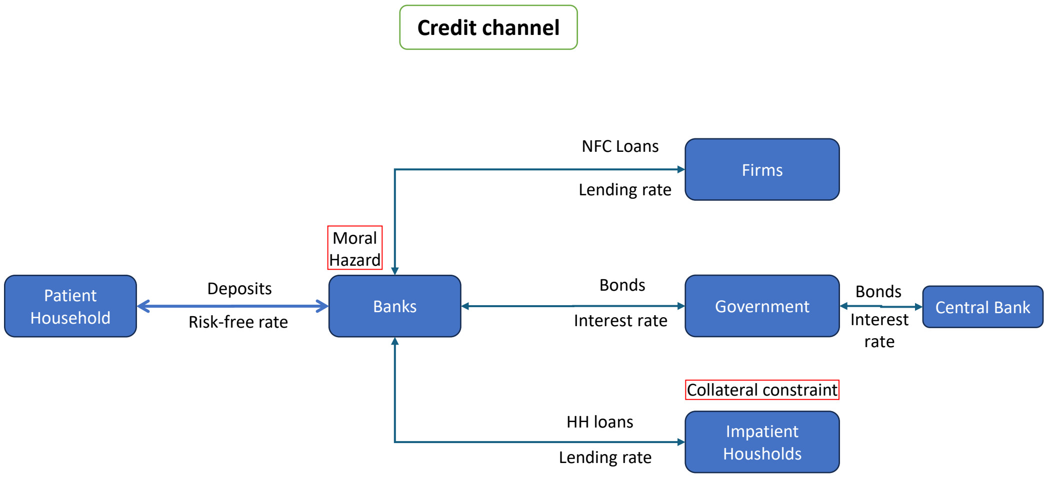
Notes: This figure shows the impulse response function to a capital quality shock. The solid black line shows the IRF of the baseline model with 2 constraints, the blue dashed line represents the IRF of the model with only banks constraint, the red dashed-dotted line shows the IRF of the model with only collateral constraint, and the gren dotted line shows the IRF of the model with none of the 2 constraints in place. All variables are plotted in percentage deviation from the steady state, except for the lending spread, policy rate and inflation which are plotted in annualized deviations.

5.4 A full-fledged DSGE model

The previous section introduced two financial frictions that can capture the interaction between households' and banks' vulnerabilities, replicating the empirical evidence. These frictions were initially presented in a simple two-agent RBC model to understand their individual effects and interplay. This section extends the simple model into a medium-scale DSGE model, featuring a range of nominal and real rigidities, to analyze the role of BBM policies in a more comprehensive framework.

Figure 4 illustrates the credit channel of the full-fledged DSGE model studied here. The model considers a saver-type of household that deposits their savings in banks similar to the savers in the previous model. Then, those banks' face the same financial friction described above where the value of their net worth constrains their level of lending. However, in this model, banks also make a portfolio choice across three types of loans: (i) loans to firms, (ii) loans to borrower-type households, and (iii) long-term government bonds acquisition. The collateral constraint described in the previous section is implemented as a financial friction only in the borrower-type households' demand for loans. This is because these kinds of constraints, as well as BBM policies, are typically in place in the mortgage credit market. However, considering firm loans provides a comprehensive framework for analyzing the implications of how BBM policies address housing-specific risks or their activation costs for the entire credit market. Finally, the model also assumes that the central banks can purchase long-term government bonds from banks. This additional modeling feature allows me to capture the financial implications of unconventional monetary policies.

Figure 5.4: The role of the financial frictions



Saver households

The saver household decides on consumption C_t^s, housing goods H^s, labor L_t^s, and savings in riskless assets to maximize a utility function whose functional form closely follows Iacoviello and Neri (2010),

$$E_t \sum_{k=0}^{\infty} \beta^k \left[log(C_t^s - hC_{t-1}^s) - \frac{\sigma_l}{1+\varphi_l}(L_t^s)^{1+\varphi_l} + \sigma_h \epsilon_t^h \, log(H_t^s) \right] \tag{5.13}$$

where β is the household discount factor, h represents the degree of habit persistence, and ϵ_t^h captures exogenous changes in housing preferences.

Household savings are represented by deposit liabilities in (private and central) banks and government bonds. These riskless assets, $D_t^T = D_t + D_t^{cb}$, are perfect substitutes and pay the same nominal interest rate, R^n. Savers also obtain dividends from intermediate goods firms, financial intermediaries, capital goods producers, and housing producers Π_t. Hence, the budget constraint is given by

$$C_t^s + Q_t^h(H_t^s - \delta_h H_{t-1}^s) + D_t^T = \frac{R_{t-1}^n D_{t-1}^T}{\pi_t} + w_t L_t^s + \Pi_t + T_t \tag{5.14}$$

where π_t represents the inflation rate, w_t is the real wage, T_t denotes lump-sum taxes, Q_t^h is the price of housing goods, and $R_t = R_{t-1}^n/\pi_t$ is the real interest rate. I additionally assume, as it is common in the literature, that savers do not adjust their housing over the business cycle but instead keep a fixed level of housing $\bar{H}^s$. This captures that wealthy agents use housing purchases as long-term investments.

Borrower Households

The borrower household are an extension of entrepreneurs. They are equally financially constrained by a borrowing limit conditioned in the value of their collateral, in this case housing goods. In what follows, only the differences with the simple model are described. The borrower household decides consumption C_t^b, hours worked L_t^b, housing goods H_t^b, and borrowing to maximize a utility function similar to that of savers. Formally,

$$E_t \sum_{k=0}^{\infty} (\beta^b)^k \left[log(C_t^b - hC_{t-1}^b) - \frac{\sigma_l}{1+\varphi_l}(L_t^b)^{1+\varphi_l} + \sigma_h \epsilon_t^h \; log(H_t^b) \right] \tag{5.15}$$

where β^b is the borrower household discount factor. The budget constraint is given by

$$C_t^b + Q_t^h(H_t^b - \delta_h H_{t-1}^b) + R_t^h S_{t-1}^h = S_t^h + w_t L_t^b + T_t, \tag{5.16}$$

where S_t^h represents loans to borrower households, and R_t^h is the real lending rate paid to the financial intermediaries. Their borrowing is limited through the following collateral constraint,

$$R_{t+1}^h S_t^h \leq LTV_t \; Q_{t+1}^h H_t^b \tag{5.17}$$

Then, the housing demand is affected by the financial constraint as follows,

$$\lambda_t^s \left(Q_t^h - \lambda_t^{ltv} \mathrm{LTV}_t Q_{t+1}^h / R_{t+1}^h \right) = \frac{\sigma_h \epsilon_t^h}{H_t^b} + \beta^b \left(Q_{t+1}^h \lambda_{t+1}^s \right) \tag{5.18}$$

where λ_t^s is the multiplier associated with the budget constraint and λ_t^{ltv} is the multiplier associated with the collateral constraint. The BBM policy analyzed in the following sections implies a reduction of the LTV limit to levels below that baseline LTV.

Capital services firms

Capital services firms purchase capital from capital good producers at price Q_t and rent it to the intermediate good producers at a rate r_t^k. At the end of the period t, they resell the depreciated capital to capital good producers at price Q_{t+1}.

They do not have their own net worth so they need to finance their capital acquisition through bank loans. They issue claims on each unit of acquired capital $Q_t S_t^k = Q_t K_{t-1}$. They operate in perfect competition giving rise to the following zero-profit condition:

$$R_{t+1}^k = \frac{r_{t+1}^k + (1-\delta_k)Q_{t+1}}{Q_t} \tag{5.19}$$

where R_t^k is the real lending rate paid to financial intermediaries and δ_k is the capital depretiation rate.

Financial intermediaries

Financial intermediaries behave in the same manner as those in the simple model described above. The main difference is that in this extended model, they have a portfolio choice. They finance the acquisition of capital for firms, extend credit to borrower households, and purchase long-term government bonds. Therefore, the balance sheets of the bankers are

$$Q_t S_t^k + S_t^h + Q_t^b B_t^b = N_t + D_t, \tag{5.20}$$

where N_t is the net worth of the bankers. The return on household loans, firms loans, and long-term government bonds are represented by R_t^h, R_t^k, and R_t^g, respectively.

Similarly to the simple model, banks face a moral hazard problem that motivates a limit on their ability to obtain deposits. The incentive constraint in the extended model looks as follows:

$$V_t(S_t^k, S_t^h, B_t^b, N_t) \geq \lambda Q_t S_t^k + \lambda \Gamma_1 S_t^h + \lambda \Gamma_2 Q_t^b B_t^b, \tag{5.21}$$

where parameters $\Gamma_1, \Gamma_2 \leq 1$ capture the idea that it is more difficult to divert funds from household loans and government bonds. When bank net worth declines enough for the constraint to bind, they have to reduce the credit supply, triggering an increase in the lending spread that works as a shock amplifier.

Final good firms

Competitive final good producers buy intermediate goods and assemble them to finally sell homogeneous goods to households. The intermediate good aggregation follows

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{1}{1+\epsilon^p}} di \right]^{1+\epsilon^p}, \tag{5.22}$$

where Y_t is the homogeneous good, $Y_t(i)$ is the heterogeneous good supplied by firm i, and $1+\epsilon^p$ is the desired markup of prices over the marginal costs of firms. Final good firms maximize profits in a perfectly competitive market

$$\max_{Y_t(i)} \quad P_t Y_t - \int_0^1 P_t(i) Y_t(i), \tag{5.23}$$

where Y_t is subject to the goods aggregation function, $P_t(i)$ is the price for differenciated goods, and P_t is the aggregate price index. The optimality condition of this maximization problem results in the following goods demand function for goods

$$Y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\frac{1+\epsilon^p}{\epsilon^p}} Y_t. \tag{5.24}$$

Hence, the good demand function and the intermediate goods aggregator imply the following price aggregator

$$P_t = \left[\int_0^1 P_t(i)^{\frac{1}{\epsilon^p}} di \right]^{\frac{1}{1-\epsilon^p}}. \tag{5.25}$$

Intermediate good firms

Intermediate goods firms are assumed to only be able to adjust prices with probability ξ_p. Those firms that cannot adjust prices in period t simply reset their prices according to the indexation rule:

$$P_{t+1}(i) = P_t(i)\bar{\pi}, \tag{5.26}$$

where $\bar{\pi}$ is the steady state inflation. Firms able to decide their optimal prices P_t^* at time t choose them by maximizing current and future expected profits. Denoting the real marginal costs and the inflation rate by MC_t and π_t, respectively, the price setting optimization problem faced by intermediate goods firms is

$$E_t \sum \beta^k \Lambda_{t+k} \xi_p^k \left[\frac{P_{t+k}(i)\bar{\pi}^k}{P_{t+k}} Y_{t+k}(i) - MC_{t+k} Y_{t+k}(i) \right], \tag{5.27}$$

subject to the price indexation rule and the demand function for goods.

In addition to setting prices, intermediate goods firms decide on the output of goods. They choose the amount of production inputs by maximizing the flow of discounted profits given by

$$\{Y_t(i) - r_t^k K_t(i) - w_t L_t(i)\}, \tag{5.28}$$

where r_t^k is the rental rate of capital. The production function is assumed to follow a Cobb-Douglas technology:

$$Y_t(i) = K_t(i)^{\alpha} L_t(i)^{1-\alpha} \tag{5.29}$$

The optimal input decision results in the following optimality conditions:

$$r_t^k = MC_t \; \alpha \; K_t(i)^{\alpha-1} L_t(i)^{1-\alpha}, \tag{5.30}$$

$$w_t = MC_t \, (1-\alpha) \, K_t(i)^{\alpha} L_t(i)^{-\alpha}. \tag{5.31}$$

Capital goods producers and housing goods producers

The problem of the capital goods producers is the same as that in the simple model described in the previous section. Moreover, the optimization problem of housing goods producers is analogous to that of capital goods producers.

Market clearing

The aggregate resource constraint is

$$Y_t = C_t + I_t + I_t^H + G_t, \tag{5.32}$$

where G_t represents government spending. The stock of houses in the economy is the aggregation of the two housing goods,

$$H_t = H_t^s + H_t^b \tag{5.33}$$

The aggregate labor supply in the economy is the sum of the two labor supplies,

$$L_t = L_t^s + L_t^b \tag{5.34}$$

The long-term government bonds are perpetuities with geometrically decaying coupons: they pay a real coupon of $\varrho^i \Xi$ at each period $i = 1, 2, ...$ The gross real rate of return on the bond R_{t+1}^g is given by

$$R_{t+1}^g = \frac{\Xi + \varrho Q_{t+1}^b}{Q_t^b} \tag{5.35}$$

The market clearing condition of government bonds is

$$B_t = B_t^b + B_t^{cb} \tag{5.36}$$

where government bonds are assumed to be in fixed supply $B_t = \bar{B}$ and B_t^{cb} captures central bank purchases of government bonds.

The central bank

The central bank decides both asset purchases and nominal interest rates. The central bank is assumed to hold zero long-term bonds in steady state since the QE is innocuous when banks do not hit the constraint. The central bank asset purchase is determined exogenously and follows an AR(1) process $B_t^{cb} = \rho^{qe} B_{t-1}^{cb} + \eta_t^{qe}$. To finance asset purchases, the central bank issues riskless short-term debt that pays a risk-free interest rate. The transmission mechanism of QE is driven by the upward pressure on government bond prices triggering an appreciation of banks' balance sheets. This effect would reduce banks' leverage reducing the increase in lending rates.[6]

The central bank follows a standard Taylor rule that reacts to inflation in setting nominal interest rates. Moreover, it also includes a smoother component seeking to minimize the volatility of the nominal interest rate,

$$\frac{R_t^n}{R^n} = \left[\frac{R_{t-1}^n}{R^n}\right]^{\rho} \left[\left(\frac{\pi_t}{\pi}\right)^{r_\pi}\right]^{1-\rho}. \tag{5.37}$$

5.5 Model solution and calibration

The two financial frictions considered in both the simple and the fully-fledged model imply that the model cannot be solved considering a linear approximation around the steady state. To address the non-linearities, such as the two occasionally binding constraints, I consider global solution methods. More precisely, a perfect foresight solver that implements a Levenberg-Marquardt mixed complementarity problem solver is used kanzow2004semismooth.

The choice of the calibrated parameters is based on related literature that estimates or calibrates DSGE models for the Euro Area. Table 1 shows the parameter values considered. The weight of labor in utility, the habit formation parameter, the Taylor rule coefficients, and the price rigidity parameter are set to roughly match those from the estimates of the New Euro Area Wide Model II - NEAWM - coenen2018new. The Frisch labor supply elasticity is set to 1, in line with the range

[6] Following Gertler and Karadi (2011) the model focuses on the financial effects of QE, ignoring the fiscal implications of this policy, which are out of the scope of this paper.

of available estimates in the literature, somewhat in between that considered in the NEWM and Gertler and Karadi (2011); Karadi and Nakov (2021). The baseline LTV parameter is calibrated using the Households Finance and Consumption Survey (HFCS). The median of the distribution of the EA households is around 0.85.[7] Housing preference parameters have been set to match the housing stock value over GDP of the EA (2.4). The saver discount factor implies a real rate of 100 basis points. The choice for the borrowers' discount factor follows Iacoviello (2005).

Following Coenen et al. (2018), the share of divertable assets is calibrated to match the average asset-over-equity ratio of monetary and other financial institutions as well as non-financial corporations, with weights equal to their share of assets in total assets between 1999Q1 and 2018Q4. The survival probability of the banks is set to match the annual dividend payout ratio of EA banks (40%), similar to Meeks et al. (2017). The relative divertability of household loans and long-term government bonds are chosen to capture the smaller riskiness of each of these two assets, also similar to Meeks et al. (2017).[8] The rest of the parameters are set to standard values.

Table 5.1: Model calibration

Households parameters			Production parameters		
Savers discount factor	β^s	0.99	Capital share	α	0.33
Borrowers discount factor	β^b	0.975	Price markup	ϵ_p	0.2
Housing preference param.	σ^h	0.55	Calvo parameter	ξ_p	0.85
Labor preference param.	σ_l	1	Capital depreciation	δ^k	0.025
Frisch labor supply elasticity	φ_l	1	Housing depreciation	δ^h	0.01
Habit formation	h	0.7	Capital investment adj. cost	φ_k	5
Loan to value	LTV	0.85	Residential investment adj. cost	φ_h	5
Financial intermediries parameters			**Government parameters**		
Divertable assets	λ	1/6	Government spendings - GDP ratio	g	0.2
Bankers survival probability	θ	0.9	Interest rate smoother	ρ	0.85
Relative deliverability of HH loans	Γ_1	0.5	Response to inflation	r_π	2.5
Relative deliverability of govern. bonds	Γ_2	0.2			
Geometric decay of government bond	ϱ	0.97			

[7] This parameter is consistent with those chosen in the literature. For example, it is close to the 0.91 chosen by Alpanda and Zubairy (2017) for the US and the 0.85 chosen by Chen et al. (2023) for Sweden.

[8] The choice for each of these risk weights is consistent with those in Basel III for mortgage loans and domestic sovereign bonds rated from A+ to A-.

5.6 Results

This section evaluates the effects of BBM policies and their interactions with other policy tools. As already mentioned above, the collateral constraint faced by borrower households is derived from the limited contract enforceability suggested by Kiyotaki and Moore (1997) where if borrowers repudiate their debt obligations, the bank can repossess the borrowers' assets by paying a proportional transaction cost $(1 - LTV)$ of the value of the collateral. Then, borrowers are not allowed to borrow more than a fraction LTV of the value of their housing (collateral). The BBM policies simulated in the following exercises imply a reduction of the loan limit to levels below the baseline level ($LTV^{BBM} < LTV$). Therefore, BBM policies trigger a reduction of borrower households' indebtedness. This decrease triggers a further reduction in the shock amplification driven by both credit demand and supply frictions by increasing households' and banks' resilience. These results are in line with those observed empirically through the state-dependent LP model. Moreover, the interplay between unconventional monetary policy and the state dependency on the activation cost is further analyzed.

Regarding the activation of the BBM, the illustrative LTV tightening used in the subsequent analyses is chosen to match the long-term effect on household loans that is implied by the activation of different types of BBM policies malovana2022borrower. Even though the illustrative reduction is chosen to be 2% of the LTV, the qualitative results are robust to larger and smaller BBM tightenings.

5.6.1 Recession Scenarios

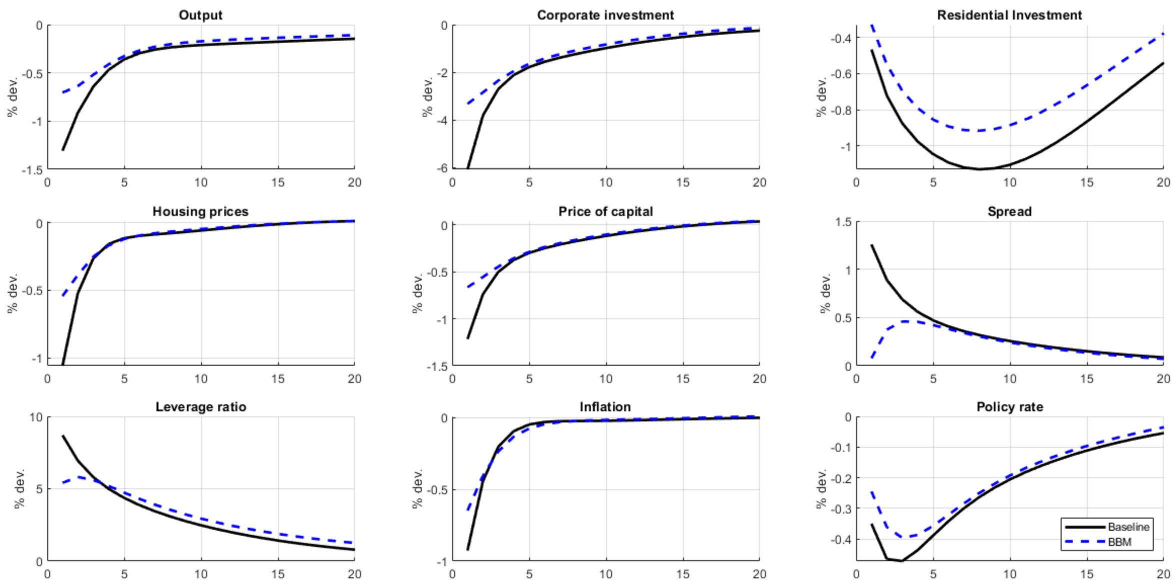
This section aims to show the transmission mechanism of alternative financial shocks in which banks' balance sheet constraints and households' collateral constraints become binding in a scenario featuring financial distress. First, a shock to the survival probability of bankers is simulated to resemble a credit supply shock that directly affects banks' balance sheets. Then, I focus on a credit demand shock captured by a housing preference shock to mimic a housing market-driven recession. The role of BBM policies is analyzed in both scenarios.

Credit supply shock

This experiment mimics the financial distress scenario that occurred during the Great Recession (GR). I simulate a shock to the survival probability of banks that has a direct impact on their net worth resembling the bank equity drop accounted for during the GR. This shock hit banks' equity triggering an increase in their leverage. Under this financial distress scenario, banks hit the incentive constraint that makes deposits scarce triggering an increase in the spreads. The tighter financial conditions reduce credit and aggregate demand triggering a deep recession.

Figure 5 shows the IRF of the financial shock. The black solid line represents the baseline model where BBM policies have not been activated whereas the blue dashed line represents the IRF for the same shock but in an economy where BBM policies are in place. The baseline economy has a large impact effect on all real variables and asset prices. The economy with activated BBM policies shows a similar persistence of the recession but entails remarkable benefits on impact. This is attributed to the influence of household indebtedness on the economy through two main channels: (i) better-collateralized household loans undergo a smaller adjustment under financial distress leading to not only a smaller reduction of aggregate demand but also a milder response in housing prices what directly affect banks' balance sheets, and (ii) the credit demand drop of less indebted households, that is amplified through the collateral channel, has a smaller impact on banks' net worth since it represents a smaller share of their assets. In sum, tighter BBM policies increase households' and banks' resilience resulting in a less harmful adjustment to the unfavorable financial shock.

Figure 5.5: Credit supply shock



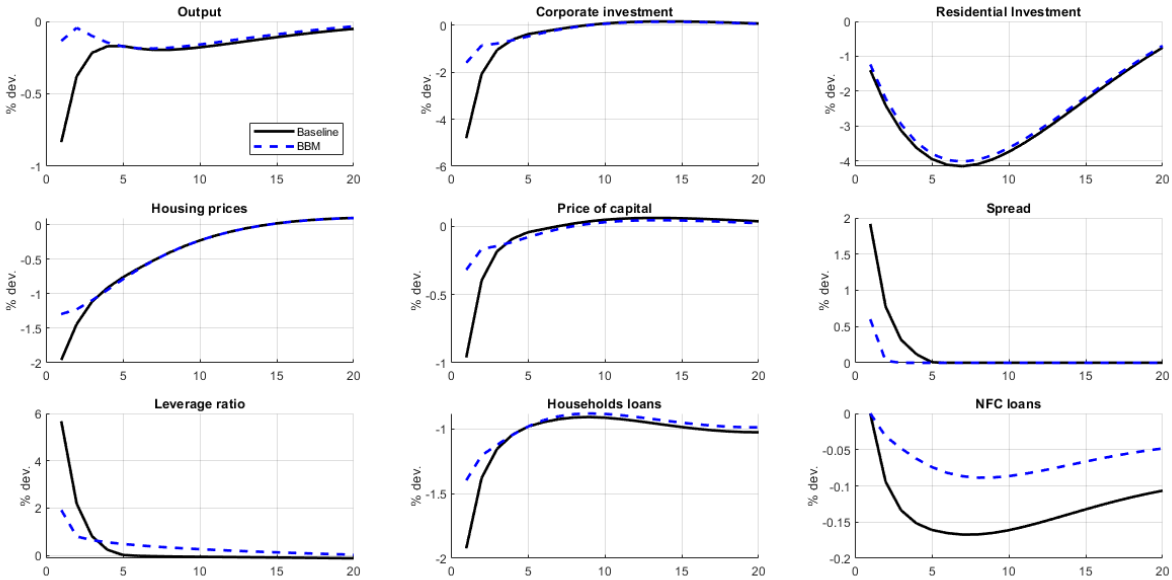
Notes: This figure shows the impulse response function to a negative credit supply shock. The solid black line shows the IRF of the model under the baseline calibration and the blue dashed line represents the IRF of the model in which BBM policies have been activated. All variables are plotted in percentage deviation from the steady state, except for the lending spread, policy rate and inflation which are plotted in annualized deviations.

Housing market-specific shock

This scenario replicates a housing market-driven recession. A drop in housing prices driven by an exogenous change in housing preferences is simulated. The negative preference shock triggers a reduction in housing demand which has two main implications for the financial system. First, a drop in the credit demand to finance housing purchases. Second, a reduction in housing prices which serves as collateral for the banks, and therefore decreases the value of this asset. Both effects harm the balance sheets of the banks increasing their leverage and making them hit the incentive constraint. This scenario results in an increase in the spread that worsens household financial conditions amplifying the initial negative impact of the shock. Moreover, the shock that initially originated in the housing sector passes through the credit channel to firms since worse capitalized banks also imply higher lending rates for them.

Figure 6 shows the effects of the housing preference shock in the baseline economy (black solid line) and the economy with BBM policies in place (blue dashed line). BBM policies enhance the financial resilience of households and banks as already mentioned in the previous recession scenario. The most remarkable finding in this scenario is that financial resilience minimizes the systemic effect of the housing sector-specific shock. The smaller effect on aggregate demand and housing prices reduces the impact of the shock on the banks' balance sheets triggering a smaller increase in the lending rates, and consequently reducing the negative impact of worse financial conditions on firms. Therefore, BBM policies contain housing market-specific risk reducing the prospects of contagious risk.

Figure 5.6: Housing preference shock



Notes: This figure shows the impulse response function to a negative housing preference shock. The solid black line shows the IRF of the model under the baseline calibration and the blue dashed line represents the IRF of the model in which BBM policies have been activated. All variables are plotted in percentage deviation from the steady state, except for the lending spread, policy rate and inflation which are plotted in annualized deviations.

5.6.2 Interaction of BBM policies with central bank large asset purchase

Exploring the interplay between BBM policies and central bank asset purchases (i.e. a quantitative easing policy) gains significance in the post-Great Recession era, when both policies emerged as crucial tools for macro and financial stability. As a response to the lessons learned from the global financial crisis, understanding the interaction between BBM policies and quantitative easing (QE) becomes crucial. Both BBM policies and QE influence financial and macroeconomic stability. Studying their interaction allows us to gauge how the effects of BBM policies may affect QE, providing insights into the combined impact on financial stability and economic resilience. This is a question in which further research is required as noted by de Bandt et al. (forthcoming).

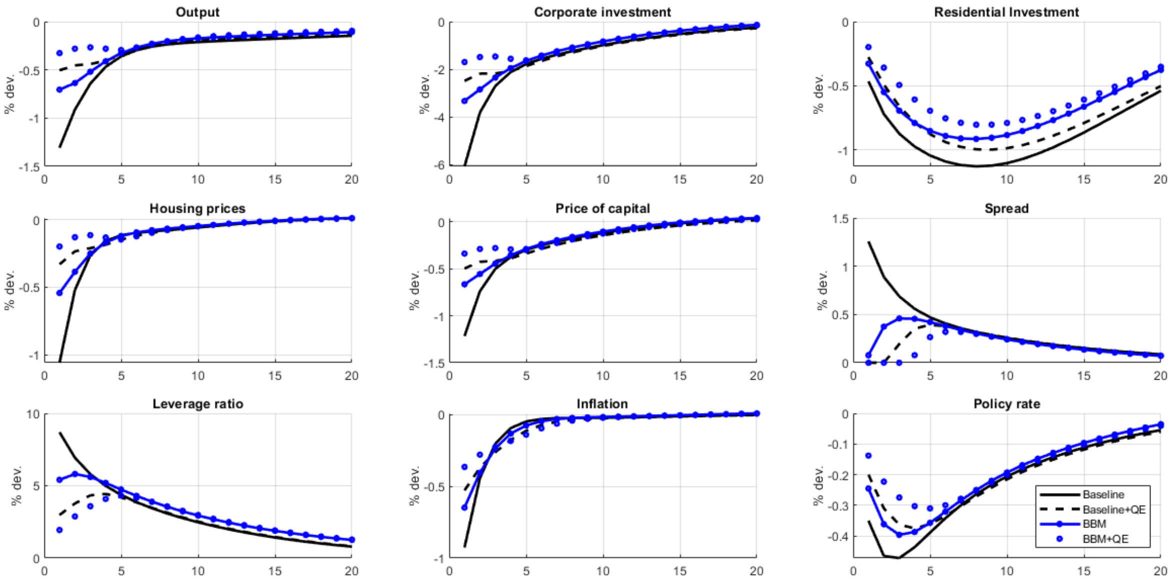
Figure 7 shows the same scenario as in Figure 5 where an unfavorable credit supply shock resembles the banks' equity drop experienced during the Great Recession in the (i) baseline economy (black solid line) and in the (ii) economy with activated BBM policies (blue dotted solid line). The two additional lines represent a QE intervention in case (i) and case (ii), black dashed line and dotted blue line, respectively. The QE policy is equivalent in both cases and follows an AR(1) process capturing an increase of 10% of the Central Bank balance sheet over GDP with a persistence of 0.9.[9]

The IRF analysis suggests that the effect of QE is reduced when BBM policies are in place. This is due to two main channels. First, the non-linearity of the model implies that QE is more efficient under more severe recessions, and consequently in the already attenuated recession by BBM policies, the same QE has smaller effects. Second, in the baseline economy, QE has a larger effect in alleviating the amplification driven by the collateral constraint. This channel plays a less important role when BBM policies are in place.

To try to disentangle the latter channel one credit supply shock is simulated in each economy to produce the same GDP drop in both. The generalized IRF to the QE policy is shown in Figure 8. The blue solid line represents the difference between the cases with and without QE when BBM policies are in place. The dashed black line represents the same but in the baseline calibration. In the former case, the benefits of QE are remarkably larger since larger financial frictions amplify the transmission of QE. In sum, the improvement of households' and banks' financial resilience driven by tighter BBM policies comes at the cost of decreasing the efficiency of QE. Therefore, the policymakers should keep in mind that BBM policies can prevent very severe recessions but once they take place a larger asset purchase would be needed to keep macro stability.

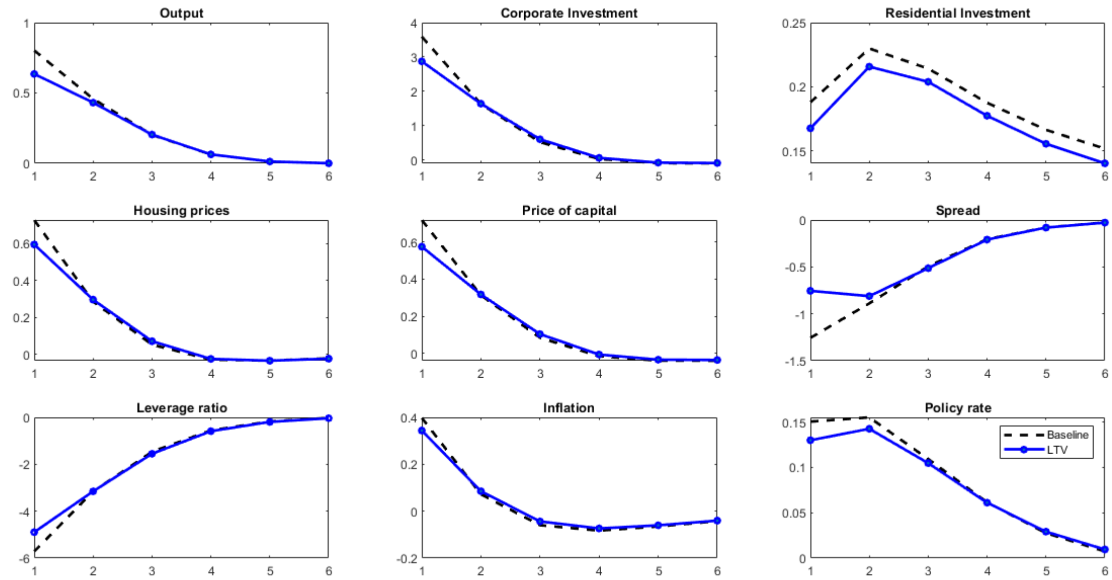
[9] This increase is similar to the one observed in the Fed and the ECB during the Global Financial Crisis and its aftermath.

Figure 5.7: Credit supply shock - QE policy



Notes: This figure shows the impulse response function to a negative credit supply shock. The black lines show the IRF of the model under the baseline calibration and the blue lines represent the IRF of the model in which BBM policies have been activated. The solid lines capture the scenario where QE has taken place whereas solid lines shows the credit shock with no QE intervention. All variables are plotted in percentage deviation from the steady state, except for the lending spread, policy rate and inflation which are plotted in annualized deviations.

Figure 5.8: Generalized impulse response function to a QE intervention



Notes: This figure shows a generalized impulse response function to a QE intervention. Each GIRF is obtained by subtracting the IRF of a credit supply shock (normalized to have the same effect on GDP) and no QE intervention to the IRF of the same scenario but with QE intervention. The black line shows the IRF of the model under the baseline calibration and the blue line represents the IRF of the model in which BBM policies have been activated. The solid lines capture the scenario where QE has taken place whereas solid lines show the credit shock with no QE intervention. All variables are plotted in percentage deviation from the steady state, except for the lending spread, policy rate, and inflation which are plotted in annualized deviations.

5.6.3 State dependent cost of activation

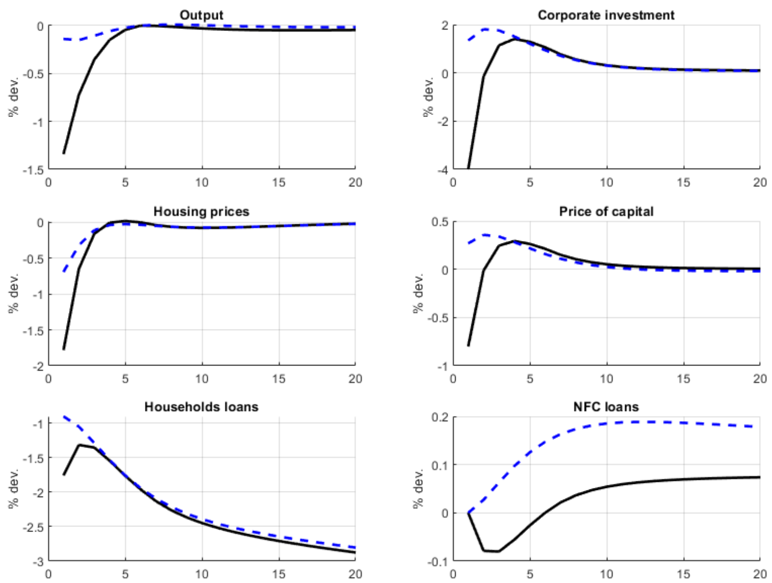
Previous sections have analyzed the benefits of financial resilience achieved through BBM policies. This section focuses on the transition cost of activating such policies. Tightening the LTV implies a reduction in credit demand and housing purchases that triggers a drop in housing prices and potentially affects the balance sheets of the banks. Hence, the activation cost depends on the stage of the credit cycle. Figure 9 shows the transition cost of a smooth 1% tightening in the LTV under two different scenarios:[10] (i) under financial distress when the LTV activation makes the banks hit the

[10]This model only considers short-term debt, which means that any changes in LTV ratio are immediately applied to all outstanding loans. As a result, the effects of transitioning between different LTV levels appear oversized. In reality, changes in the LTV ratio only affect new loans rather than the entire stock of existing loans. To better reflect this, the model gradually implements LTV changes over 16 quarters, more accurately representing how these

incentive constraint triggering an increase in the spreads (black solid line), and (ii) under tranquil times, the LTV is activated when banks are well capitalized, and consequently, does not imply an increase in the spread (blue dashed line).[11] In the first scenario the LTV activation creates financial distress that passes through financial intermediaries to firms giving rise to a downturn in the whole economy. However, when banks are well capitalized in the second scenario the spread does not increase and the cut in household credit is redirected by financial intermediaries to firms, this way being able to accommodate the activation costs.

In addition to the timely activation, the graduality of the activation also plays a central role in minimizing the transition costs. Figure 10 shows the activation under financial distress for two different degrees of activation smoothness, as shown by the bottom-right chart. A more gradual activation implies a smoother adjustment of credit and housing demand triggering remarkably smaller responses of lending rates and housing prices. This allows the policymaker to reproduce similar dynamics to those observed under tranquil times even though the banks' constraints can become binding.

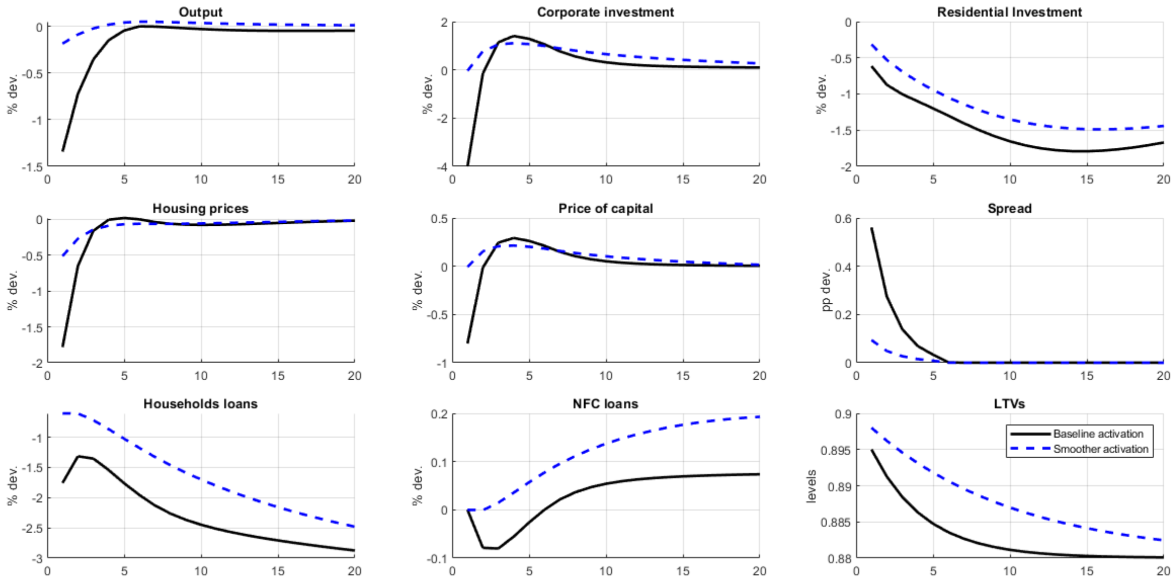
Figure 5.9: Activation of BBM



adjustments occur in practice.

[11] I remain agnostic about the sequence of shocks that leads the economy to the second scenario.

Figure 5.10: Activation of BBM



5.6.4 The short- vs the long-run implications

This section analyzes the welfare implications of tightened BBM policies in the short and long run. First, let's define borrowers' welfare, savers' welfare, and central bank losses function. Saver and borrowers households welfare are the discounted sum of their corresponding utility:

$$W^i = E_t \sum_{k=0}^{\infty} \beta^k \left[log(C^i_{t+k} - hC^i_{t-1+k}) - \frac{\sigma_l}{1+\varphi_l}(L^i_{t+k})^{1+\varphi_l} + \sigma_h \epsilon^h_t \; log(H^i_{t+k}) \right] \tag{5.38}$$

where $i = \{s, b\}$ represents an index defining savers and borrowers, respectively. The central bank loss function captures the dual mandate of a central bank that stabilizes inflation and output growth:

$$\mathcal{L}_t = E_t \sum_{k=0}^{\infty} \beta^k \left[Y^2_{gr,t+k} + \pi^2_{a,t+k} \right] \tag{5.39}$$

where $Y_{gr,t}$ represents quarterly output growth and $\pi_{a,t}$ represents annualized inflation rate. Therefore, larger fluctuations of these variables translate into larger losses for the central bank.

To account for the short-run benefits of BBM policies, I simulate a financial recession driven by the credit supply shock considered in section 6.1. Figure 11 shows the effects of the financial recession on households' welfare, the central bank's losses, and the implications of alternative LTV levels. The main short-run benefits are driven by the decrease in the likelihood of entering a distress scenario where lending spreads rise rapidly, activating the feedback effect between the collateral constraint and the banks' leverage constraint. Hence, the marginal gain of tighter LTV values when indebtedness is already low is significantly reduced. This is particularly notable in the context of central bank losses, where the gains from LTV values below 80

Figure 12 shows the steady-state levels of several variables conditional on LTV levels. The results are consistent with those found in the literature [e.g.,][]campbell2009welfare. Looser LTV values raise borrowers' labor, which endogenously shifts factor prices in favor of savers. Moreover, greater levels of lending imply larger profits for savers. Hence, savers' steady-state income equals $RD^T + wL^s + \Pi$, which increases as LTV rises. Therefore, tightening LTV levels reduces savers' steady-state welfare. Looser LTV values also raise borrowers' welfare, as they can take on larger debt levels and finance housing acquisitions. Consequently, increasing the LTV shifts borrowers' steady-state allocation away from leisure and consumption and towards housing goods. However, the relationship between borrowers' welfare and the LTV level is not linear. LTV levels greater than roughly 79% reduce borrowers' welfare. Borrowers need to acquire certain levels of housing goods to comply with the collateral constraint, which no longer compensates for the reduction in consumption and leisure. Sufficiently high levels of LTV imply that banks become too leveraged, and the bank incentive constraint starts binding. Then, lending spreads rise, triggering a more pronounced decrease in borrowers' welfare and an increase in savers' welfare.

Reducing LTV is primarily a policy aimed at decreasing the likelihood of entering a distress scenario rather than directly reducing high levels of household debt. This is because while lower LTV values can mitigate the rapid rise in lending spreads and the activation of feedback effects between collateral constraints and bank leverage during financial downturns, the long-term costs of such policies are significant. The short-run benefits of lowering LTV are substantial only up to certain levels; beyond this, the marginal gains diminish, particularly when household indebtedness is already low. Thus, the focus on LTV reduction should be on preventing financial distress rather than substantially lowering household debt levels, as the latter can be costly in the long run.

Figure 5.11: The short-run implications

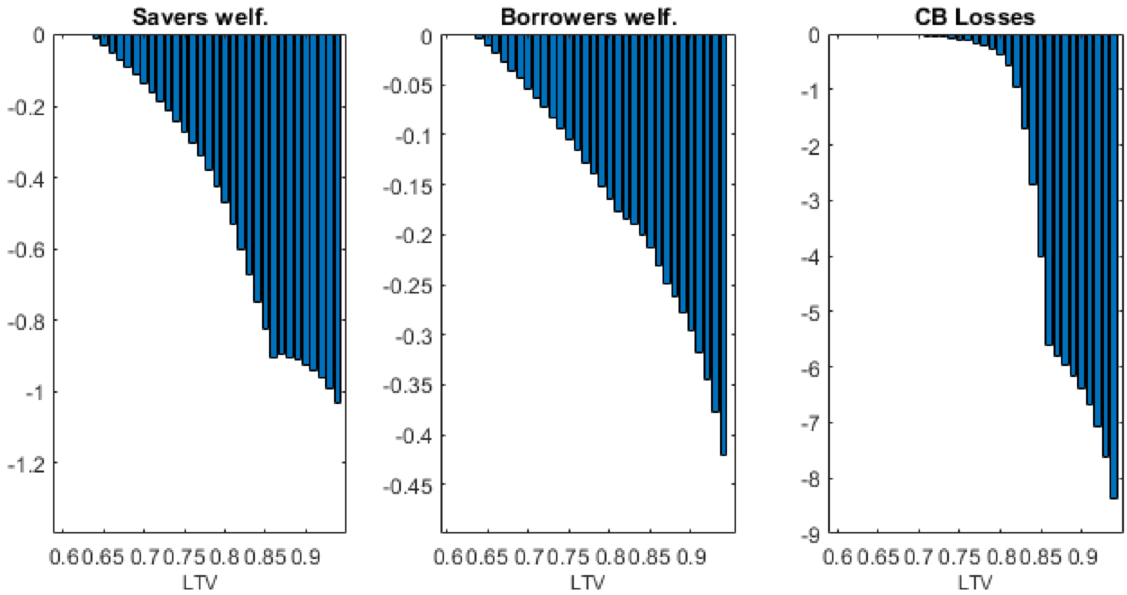
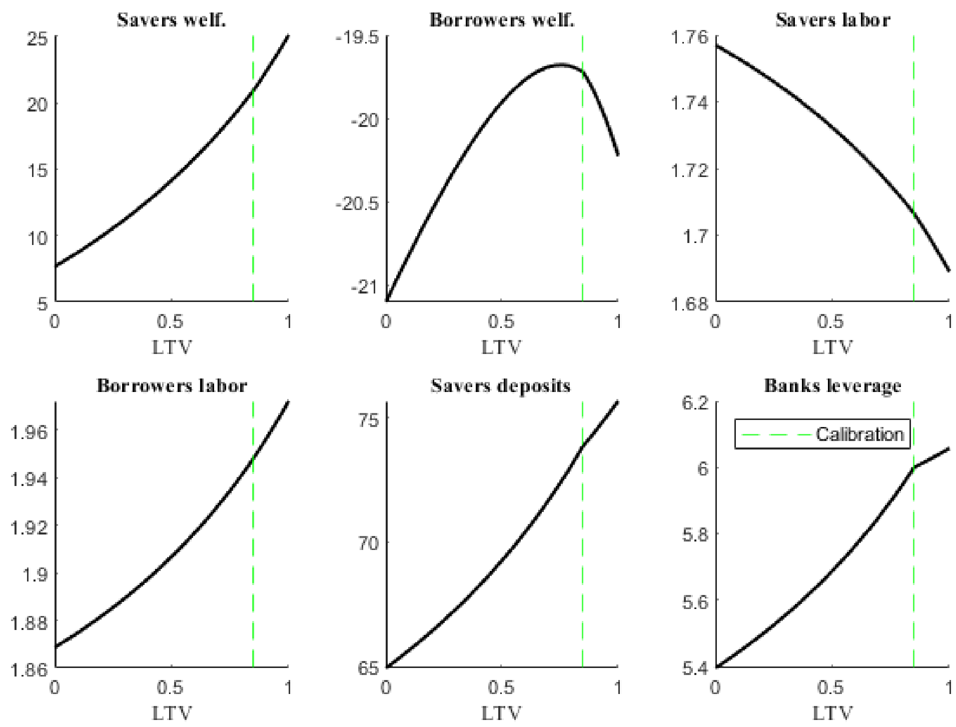


Figure 5.12: The long-run implications



5.7 Conclusion

This paper highlights the crucial role of the interaction between credit supply frictions and collateral constraints in determining the effectiveness of BBM policies. Empirical analysis shows that both household indebtedness and bank vulnerabilities independently amplify financial shocks, and their interaction further intensifies this amplification. Therefore, BBM policies can significantly enhance financial resilience, making them a valuable tool for policymakers aiming to reduce financial risks and stabilize business cycles.

To analyze the benefits and challenges of BBM policies, this paper develops a non-linear DSGE model that incorporates both collateral constraints and credit supply frictions. The model suggests that tighter BBM policies reduce household leverage, thereby diminishing the amplification effects driven by the collateral channel and mitigating the feedback effect triggered by its interaction with credit supply frictions. Consequently, BBM policies improve the financial stability of both households and banks.

Moreover, this paper studies the interplay between BBM policies and unconventional monetary policies, such as Quantitative Easing (QE). The findings suggest that while BBM policies enhance financial conditions ex-ante, they also reduce the efficacy of QE in mitigating financial distress ex-post.

Regarding the cost of implementing these types of policies, the DSGE model suggests that smoothing their activation can prevent banks' balance sheets from being adversely affected, thus avoiding a financial distress scenario where activation costs would be especially high.

The findings also indicate that the marginal benefits of reducing LTV ratios are most pronounced when household indebtedness is high. However, for lower LTV levels, the marginal gains diminish, while long-term welfare costs remain significant. Thus, BBM policies should be viewed primarily as measures to prevent financial distress rather than tools for directly reducing household debt levels.

In summary, this paper provides a comprehensive analysis of BBM policies, emphasizing the critical role of the interaction between households' and banks' financial conditions.

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Chapter 6

Appendix

6.1 Appendix: chapter 1

6.1.1 The model

We consider a DSGE model that resembles the Smets and Wouters (2007) model, extended with the financial accelerator of Bernanke, Gertler and Gilchrist (1999). This appendix briefly describes the model and the log-linearized equations that characterize the general equilibrium. All variables in the log-linearized equations are expressed in log-deviations from their steady states except those measured in percentage terms, which are expressed in simple deviations from their respective steady-state values.

Households

The representative household i decides consumption, hours worked, and holds riskless assets, aiming at maximizing a non-separable utility function in consumption and labor which also includes external habit formation.

$$E_t \sum_{k=0}^{\infty} \beta^k \left[ln(C_{t+k}(i) - hC_{t+k-1}) - \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l} \right],$$

where C_t and L_t are consumption and hours worked, β is the discount factor, h denotes the habit persistence parameter, and σ_l is the labor elasticity.

Household savings are allocated to deposit liabilities in banks and holdings of government bonds. These riskless assets, B, are perfect substitutes and pay the same interest rate, R^n. Households also obtain dividends, D, from intermediate firms, capital goods producers, and labor unions. Hence, the budget constraint is as follows:

$$C_{t+k}(i) + \frac{B_{t+k}(i)}{e^{\epsilon_t^b} R_{t+k}^n P_{t+k}} - T_{t+k} = \frac{W_{t+k}(i) L_{t+k}(i)}{P_{t+k}} + \frac{B_{t-1+k}(i)}{P_{t+k}} + \frac{D_{t+k}}{P_{t+k}},$$

where R_t^n is the nominal interest rate, P_t is the aggregate price level, and the risk premium shock, ϵ_t^b, is an exogenous premium on the bond yields, which is assumed to follow an AR(1) process.[1] T are lump-sum taxes and W is the nominal wage.

From the optimality conditions of the household maximization problem the following Euler equation is obtained:

$$c_t = \frac{h}{1+h}\, c_{t-1} + (1 - \frac{h}{1+h})\, E_t c_{t+1} - \frac{1-h}{(1+h)} \left[R_t^n - E_t \pi_{t+1} + \epsilon_t^b \right]. \tag{6.1}$$

Labor union

As in Smets and Wouters (2007), households supply homogeneous labor to intermediate labor unions that differentiate labor services. These intermediate labor unions then set wages to sell labor services to a labor packer who aggregates the differentiated labor and resells it to intermediate goods firms. Aggregation of labor services follows

$$L_t = \left[\int_0^1 L_t(i)^{\frac{1}{1+\epsilon_t^w}}\, di \right]^{1+\epsilon_t^w},$$

where $1+\epsilon_t^w$ is the desired markup of wages over the household's marginal rate of substitution, which is assumed to follow a stochastic process around its steady-state value. Labor packers maximize profits in a perfectly competitive market

$$\max_{L_t(i)} \quad W_t L_t - \int_0^1 W_t(i) L_t(i),$$

where L_t is subject to the labor aggregation function, W_t is the aggregate wage that intermediate firms pay for labor services, and $W_t(i)$ is the wage that labor packers pay for the differentiated labor. This optimization problem gives rise to the following labor demand function

$$L_t(i) = \left(\frac{W_t(i)}{W_t} \right)^{-\frac{1+\epsilon_t^w}{\epsilon_t^w}} L_t.$$

Both labor demand function and labor services aggregation function imply the wage aggregation function

[1]As shown below, this risk premium shock can be also understood as a credit supply shock.

$$W_t = \left[\int_0^1 W_t(i)^{\frac{1}{\epsilon_t^w}} di \right]^{\epsilon_t^w} . \tag{6.2}$$

Following Calvo's lottery scheme, it is assumed that labor unions can only adjust nominal wages with probability: $1 - \xi_w$. The fraction of labor unions ξ_w that cannot adjust wages are assumed to follow the indexation rule, $W_{t+1}(i) = W_t(i) \left[\frac{P_t}{P_{t-1}} \right]^{\gamma_w}$, where γ_w is the wage indexation parameter to past inflation. Hence, the labor unions choose an optimal W to maximize,

$$E_t[k=0]\infty \sum \beta^k \xi_w^k \left[\Lambda_{t+k} W_t(i) L_{t+k}(i) - \epsilon_{t+k}^b \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l} \right], \tag{6.3}$$

subject to the labor demand and the indexation rule. $\beta^k \Lambda_{t+k} = \frac{\beta \lambda_{t+k}}{\lambda_t}$ denotes the stochastic discount factor between t and $t+k$, and λ_t is the marginal utility of consumption for households at time t.

Hence, this setup gives rise to the following log-linearized equation for real wages, w_t :

$$\begin{aligned} w_t = {} & \frac{\beta}{1+\beta} \left(E_t w_{t+1} + E_t \pi_{t+1} \right) + \left(1 - \frac{\beta}{1+\beta}\right) w_{t-1} - \frac{1+\beta\gamma_w}{1+\beta} E_t \pi_t + \\ & + \frac{\gamma_w}{1+\beta} \pi_{t-1} - \frac{1}{1+\beta} \frac{(1-\beta\xi_w)(1-\xi_w)}{(1+(1+\lambda_w)\sigma_l/\lambda_w)\xi_w} \left[w_t - \sigma_l l_t - \frac{1}{1-h}(c_t - hc_{t-1}) \right] + \epsilon_t^w, \end{aligned} \tag{6.4}$$

where the term in brackets on the right-hand side of the equation defines the wedge between the real wage and the marginal rate of substitution between labor and consumption.

Final good firm

Competitive final good producers buy intermediate goods and assemble them to finally sell homogeneous goods to households. The intermediate goods aggregation follows

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{1}{1+\epsilon_t^p}} di \right]^{1+\epsilon_t^p},$$

where Y_t is the homogeneous good, $Y_t(i)$ is the heterogeneous good supplied by firm i, and $1 + \epsilon_t^p$ is the desired markup of prices over the marginal costs of firms, which is assumed to follow a stochastic process around its steady-state value. Final good firms maximize profits in a perfectly competitive market

$$\max_{Y_t(i)} \quad P_t Y_t - \int_0^1 P_t(i) Y_t(i),$$

where Y_t is subject to the goods aggregation function, $P_t(i)$ is the price for differentiated goods, and P_t is the aggregate price index. The optimality condition of this maximization problem results in the following demand function for goods

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\frac{1+\epsilon_t^p}{\epsilon_t^p}} Y_t. \tag{6.5}$$

Hence, the goods demand function and the intermediate goods aggregator imply the following price aggregator

$$P_t = \left[\int_0^1 P_t(i)^{\frac{1}{\epsilon_t^p}} di\right]^{\frac{1}{1-\epsilon_t^p}}. \tag{6.6}$$

Intermediate goods firms

As in the labor market, it is assumed that intermediate goods firms can only adjust prices with probability: $1-\xi_p$. Those firms which cannot adjust prices in period t simply reset their prices according to the indexation rule: $P_{t+1}(i) = P_t(i)\left[\frac{P_t}{P_{t-1}}\right]^{\gamma_p}$, where γ_p represents the degree of price indexation to past inflation. Firms able to decide their optimal prices P_t^* at time t choose them by maximizing current and future expected profits. Denoting the marginal costs and the inflation rate by MC_t and π_t, respectively, the price setting optimization problem faced by intermediate goods firms is

$$E_t[k=0]\infty \sum \beta^k \xi_p^k \Lambda_{t+k} \frac{P_t}{P_{t+k}} \left[P_t^*(i) \prod_{l=1}^k \pi_{t+l-1}^{\gamma_p} - MC_{t+k}\right] \quad Y_{t+k}(i), \tag{6.7}$$

subject to the price indexation rule and the demand function for goods.

Hence, this setup gives rise to the following so-called New-Keynesian Phillips curve:

$$\pi_t = \frac{\beta}{1+\beta\gamma_p} E_t\pi_{t+1} + \frac{\gamma_p}{1+\beta\gamma_p}\pi_{t-1} + \frac{1}{1+\beta\gamma_p}\frac{(1-\beta\xi_p)(1-\xi_p)}{\xi_p}\left[\alpha r_t^k + (1-\alpha)w_t - \epsilon_t^a\right] + \epsilon_t^p, \tag{6.8}$$

where the term in brackets on the right-hand side of the equation is the firms' marginal cost.

In addition to setting prices, intermediate goods firms decide on the output of goods. They choose the amount of production inputs by maximizing the flow of discounted profits

$$E_t\left\{\beta\Lambda_{t+1}\left[Y_{t+1}(i) - r_{t+1}^k K_{t+1}^s(i) - \frac{W_{t+1}}{P_{t+1}} L_{t+1}(i)\right]\right\}, \tag{6.9}$$

where r_{t+1}^k is the rental rate of capital, and $K_{t+1}^s(i)$ denote capital services. The production function is assumed to follow a Cobb-Douglas technology:

$$Y_t = \epsilon_t^a \left(K_t^s(i)\right)^{\alpha} L_t(i)^{1-\alpha} - \phi_p, \tag{6.10}$$

where ϕ_p is the share of fixed costs implied in production, and ϵ_t^a is a disturbance capturing TFP shocks. The log-linearized equilibrium conditions of this maximization problem are:

$$y_t = \phi_p \alpha k_{t-1}^s + \phi_p(1-\alpha)l_t + \phi_p\epsilon_t^a$$

$$l_t = k^s_{t-1} + r^k_t - w_t$$

Capital-good producers

Capital-good producers build capital goods and sell them to entrepreneurs at price Q_t. They turn out capital goods by combining investment goods purchased from final good producers and installed capital rented from entrepreneurs.[2] We also consider that capital-good producers face quadratic adjustment costs, $S(I_t/I_{t-1})$. We assume that $S(I_t/I_{t-1})$ is a strictly increasing, twice differentiable function. Then, the optimization problem of the capital-good producers is:

$$[I_t] Max\ E_t \left\{ \sum_{k=0}^{\infty} \beta^k \Lambda_{t+k} \left[Q_{t+k} I_{t+k} \epsilon^i_{t+k} - I_{t+k} - Q_{t+k} I_{t+k} \epsilon^i_{t+k} S(\frac{I_{t+k}}{I_{t+k-1}}) \right] \right\},$$

where the disturbance ϵ^i_t follows an AR(1) process that represents the investment-specific technology shock. The log-linearization of the first order condition of this optimization problem gives rise to the following investment equation:

$$i_t = \frac{1}{1+\beta} i_{t-1} + \frac{\beta}{1+\beta} E_t i_{t+1} + \frac{1}{\varphi(1+\beta)} (q_t + \epsilon^i_t), \tag{6.11}$$

where φ captures the steady-state elasticity of investment adjustment cost function, $S(I_t/I_{t-1})$. Notice that a higher elasticity reduces the sensitivity of investment to the value of the existing capital stock, q_t.

The capital stock evolves according to:

$$K_t = (1-\tau) K_{t-1} \epsilon^k_t + \left[1 - S\left(\frac{I_t}{I_{t-1}} \right) \right] I_t.$$

In log-linearized form:

$$k_{t+1} = (1-\tau) k_t + \tau i_t + \tau \epsilon^i_t, \tag{6.12}$$

where τ is the depreciation rate of capital.

Entrepreneurs and banks

[2] This rental rate is assumed to be zero, as in Bernanke et al. (1999).

As mentioned above, some households are assumed to be entrepreneurs. Since entrepreneurs face a constant survival probability the proportion of such households is also constant. Entrepreneurs use their own and external funds to finance the acquisition of capital, which is rented to goods producers. Once capital is acquired they observe the realization of an idiosyncratic shock (ω) and decide the degree of capital utilization (U_t) facing an adjustment cost.[3] Hence, the amount of capital that the entrepreneurs rent to firms is $K^s_{t+1} = U_{t+1}K_t$. At the end of the period, they sell back the undepreciated capital to the capital-good producers at a price Q_{t+1}. Formally, entrepreneurs solve the following optimization problem:

$$[U_t]max \qquad \left[r^k_{t+1}U_{t+1} - a(U_{t+1})\right]\omega K_t.$$

The (aggregate) log-linearized optimality conditions derived from this optimization problem are as follows:

$$k^s_{t+1} = u_{t+1} + k_{t+1}, \tag{6.13}$$

$$u_t = ((1-\psi)/\psi)r^k_t, \tag{6.14}$$

where equation (13) describes the capital used in production, and equation (14) determines the degree of capital utilization as a function of the rental rate of capital. The parameter ψ is a positive function of the elasticity of the capital utilization adjustment cost, which is normalized to take a value between zero and one. Thus, the higher the value of ψ, the higher the cost of adjustment faced by that entrepreneurs.

Moreover, the average (across entrepreneurs) rate of return of capital utilized in production should be consistent with the following (non-arbitrage) equilibrium equation:

$$E_tR^k_{t+1} = E_t\left[\frac{r^k_{t+1}U_{t+1} - a(U_{t+1}) + Q_{t+1}(1-\tau)}{Q_t}\right],$$

where the real expected interest rate on external funds is equal to the expected marginal return of capital— otherwise, entrepreneurs would not be behaving rationally in their decision on capital utilization. Log-linearizing the previous equation gives the corresponding arbitrage-free condition for the value of capital:

$$q_t = \frac{\bar{r}^k}{\bar{R}^k}E_tr^k_{t+1} - E_tR^k_{t+1} + \frac{1-\tau}{\bar{R}^k}E_tq_{t+1}, \tag{6.15}$$

where $\bar{R}^k$ and $\bar{r}^k$ are the steady-state values of capital return and the rental rate, respectively.

[3]This idiosyncratic shock does not show up in the log-linearized equations due to the linearity assumption, which makes the model more tractable.

The equilibrium condition that describes the cost of external funding is obtained from the optimal-debt contract problem, which implies the maximization of entrepreneurs' utility and the zero-profit condition associated with the assumption of perfectly competitive banks: [4]

$$E_t\ R^k_{t+1} = E_t\ \left[s\Big(\frac{N_{t+1}}{Q_t K_{t+1}}\Big) e^{\epsilon^b_t} R_t \right],$$

where $s\Big(\frac{N_{t+1}}{Q_t K_{t+1}}\Big)$ is a function that represents the elasticity of external funding rates to the leverage ratio. The log-linearization of this expression results in:

$$E_t R^k_{t+1} = -\epsilon E_t[n_{t+1} - q_t - k_{t+1}] + R^n_t - E_t \pi_{t+1} + \epsilon^b_t, \tag{6.16}$$

where the term in brackets is the wedge between the (log of the) net worth of the entrepreneurs (n_{t+1}) and the (log of the) gross value of capital ($q_t + k_{t+1}$). This difference represents the proportion of projects that the entrepreneur is not able to self-finance and, by the same token, the external funding required. The parameter ϵ is the elasticity of the external finance premium to this entrepreneurial financial wealth. Therefore, a higher value of this parameter would make the interest rate spread more sensitive to the leverage ratio. Moreover, this spread is also characterized by an exogenous process, ϵ^b_t, that captures the fluctuations of this risk premium beyond those generated by the financial frictions considered in the model. Notice that this shock also shows up in the consumption-Euler equation (1). Therefore, it can also be viewed as a shock to the supply of credit that exogenously changes the interest rate spread.

Entrepreneurial net worth accumulation is given by the profits of the surviving entrepreneurs:

$$n_{t+1} = \gamma \left[\big(R^k_t Q_{t-1} K_t - E_{t-1} R^k_t \left(Q_{t-1} K_t - N_t \right) \big) + W^e_t \right] \epsilon^{nw}_t. \tag{6.17}$$

where γ is the survival rate of entrepreneurs, and W^e_t is the transfer to all the entrepreneurs who are in business in period t. This profit is determined by the difference between the revenue from holding capital and the cost of external finance. The log-linearized equation is given by

$$n_{t+1} = \gamma \bar{R}^k \left[\frac{\bar{K}}{\bar{N}} (R^k_t - E_{t-1} R^k_t) + E_{t-1} R^k_t + n_t \right] + \epsilon^{nw}_t, \tag{6.18}$$

where $\frac{\bar{K}}{\bar{N}}$ is the steady-state capital net worth ratio, and ϵ^{nw}_t is an AR(1) shock capturing exogenous fluctuations in entrepreneurs' net worth.[5] This equation shows that the variations in entrepreneurs'

[4] For a detailed explanation see Bernanke et al. (1999)

[5] The assumption of exogenous fluctuations of net worth is rather common in the financial frictions literature (e.g. Gertler and Karadi, 2011; and Rychalowska, 2016).

net worth are mostly explained by unexpected changes in the real return. Therefore, one of the main sources of volatility in this framework is *unexpected* changes in asset prices.

Market clearing condition

The standard market clearing condition is augmented by considering the cost of capital utilization and bankruptcy:

$$y_t = c_t + i_t + c_t^{kutil} + c_t^{bankrupt}. \tag{6.19}$$

Nevertheless, these additional terms are negligible under a reasonable parameterization (De Graeve, 2008) . Moreover, we consider a measurement error on y_t.[6]

Central Bank

Finally, we close the model with a Taylor rule where the short-term nominal interest rate set by the central banker reacts to inflation, changes in inflation, output gap, and output gap growth. The output gap is defined as the ratio between output determined in the economy featuring price-wage rigidity and the one determined in a fully-flexible economy:

$$\frac{R_t^n}{R^n} = \left[\frac{R_{t-1}^n}{R^n}\right]^{\rho} \left[\left(\frac{\pi_t}{\pi}\right)^{r_\pi} \left(\frac{Y_t}{Y_t^f}\right)^{r_y}\right]^{1-\rho} \left[\frac{Y_t/Y_t^f}{Y_{t-1}/Y_{t-1}^f}\right]^{r_{\triangle y}}. \tag{6.20}$$

In log-linearized form:

$$R_t^n = \rho R_{t-1}^n + (1-\rho)\left[r_\pi \pi_t + r_y(y_t - y_t^f)\right] + r_{\triangle\pi}(\pi_t - \pi_{t-1}) + r_{\triangle y}((y_t - y_t^f) - (y_{t-1} - y_{t-1}^f)) + \eta_t^R, \tag{6.21}$$

where η_t^R is an i.i.d. process.

6.1.2 Robustness checks

This section is structured in three parts. The first part focuses on the responses of the observable variables to a selected group of structural shocks. The second shows identification test statistics

[6] The difference between output data and its model counterpart is defined as a measurement error in order to overcome stochastic singularity in the estimation procedure. The estimated measurement error explains less than 3% of output fluctuations in each of the sample periods studied.

following the methodology suggested by Iskrev (2010). Finally, the third part shows the historical variance decomposition of output for the Great Depression and the Stagflation periods obtained from the DSGE model with BGG financial frictions and extended with a fiscal building block.

Figures 8-12 show the impulse-response functions (IRF) associated with a price markup shock, a wage markup shock, a monetary policy shock, a net worth shock, and a risk premium shock, respectively. In all the figures the solid line represents the IRF corresponding to the Great Depression, the dotted line represents the IRF of the Stagflation, and the dashed line represents the IRF of the Great Recession. Four main conclusions can be reached from these IRF analysis. First, price markup shocks are more important in the Stagflation than in the other recessions. Second, wage markup shocks are more persistent in the Great Depression than in the other two recessions, which capture the legislation changes affecting the labor market (Wagner Act). Third, the transmission of monetary shocks is much weaker during the Stagflation due to a lax monetary policy and low price stickiness. Finally, the effects of net worth and risk premium shocks on real variables are more important in the Great Depression than in the other two recession periods.

Figure 6.1: IRF price markup shock

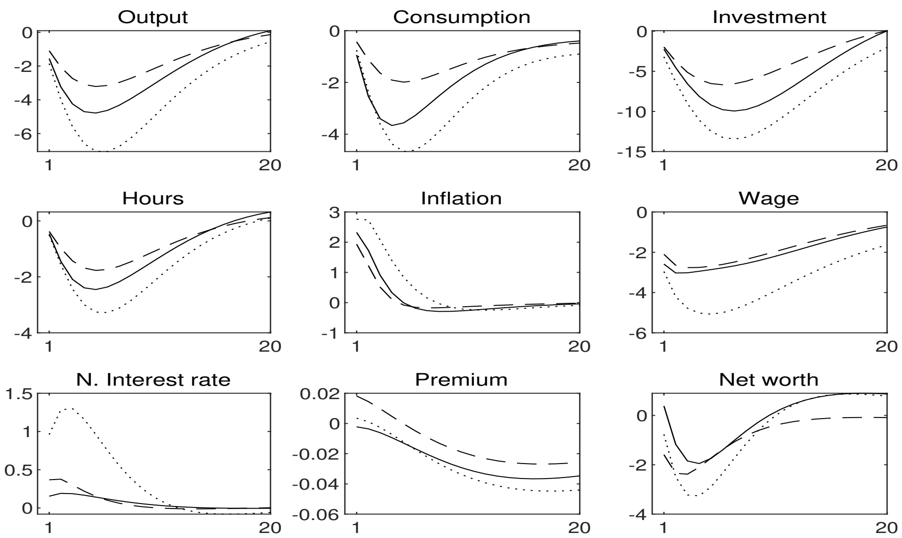


Figure 6.2: IRF wage markup shock

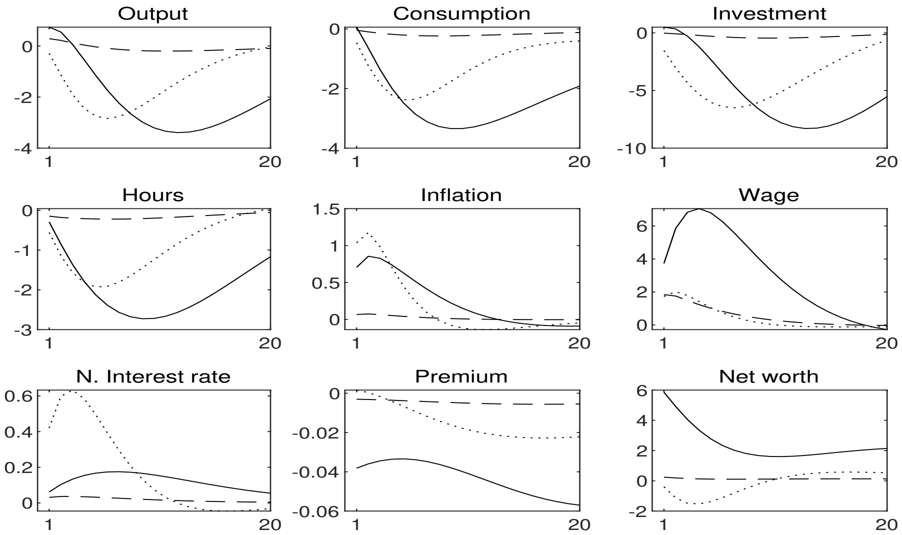


Figure 6.3: IRF monetary policy shock

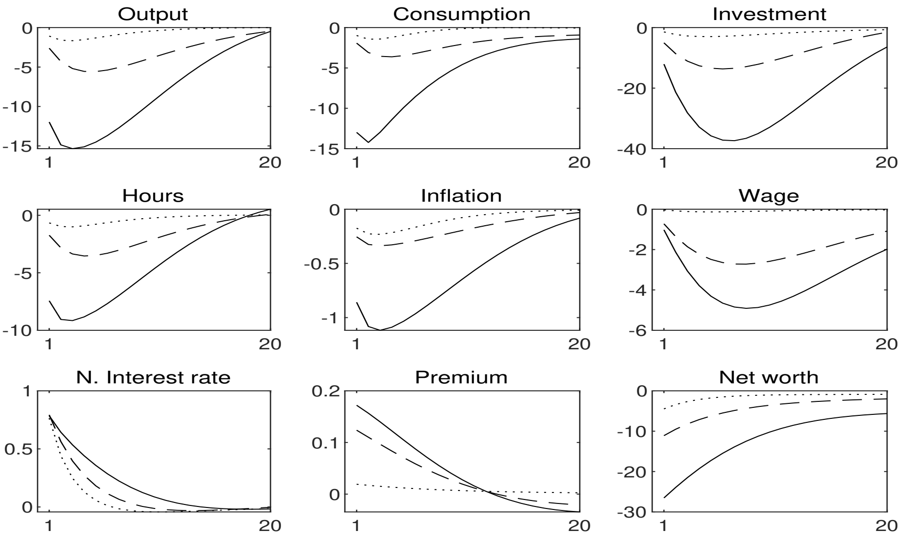


Figure 6.4: IRF net worth shock

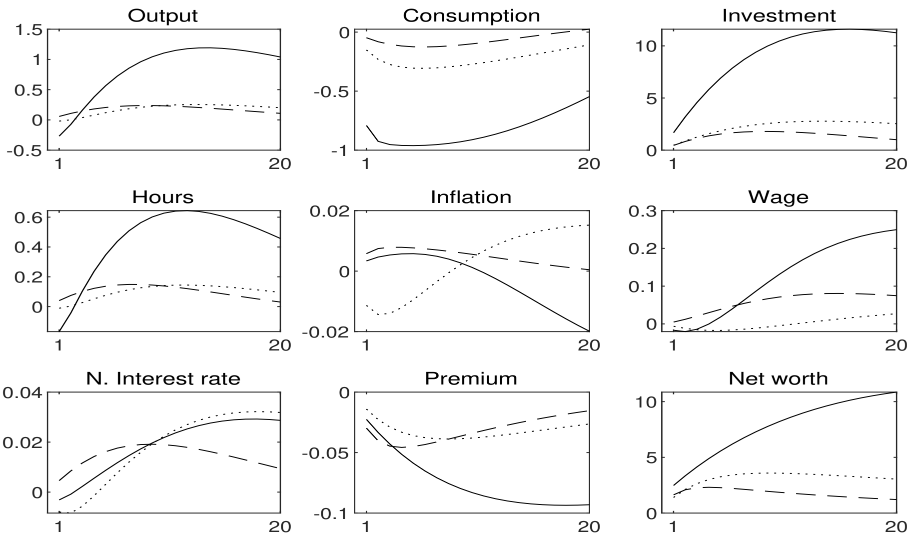
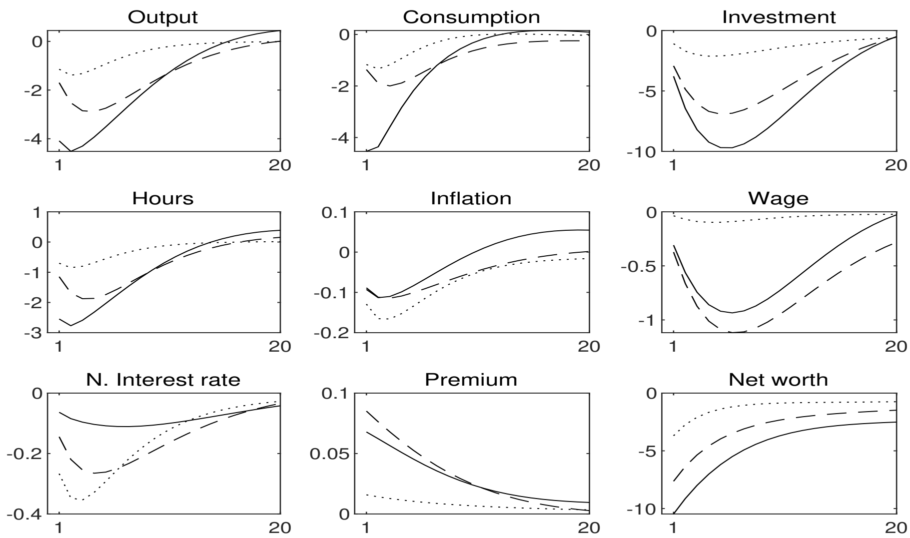


Figure 6.5: IRF risk premium shock



Figures 13-15 show identification test statistics following the methodology suggested by Iskrev (2010). The upper panels of these figures show the identification strength of the parameters based on the Fischer information matrix normalized by either the parameter at the prior mean or by the standard deviation at the prior mean. The lower panel of these figures show the sensitivity of the value of the log-likelihood function to each of the parameters, again, normalized by either the parameter at the prior mean or by the standard deviation at the prior mean. These three figures show that all parameters are identified in the model for the three samples studied.

Figure 6.6: Identification test of parameters in the sample of Great Depression

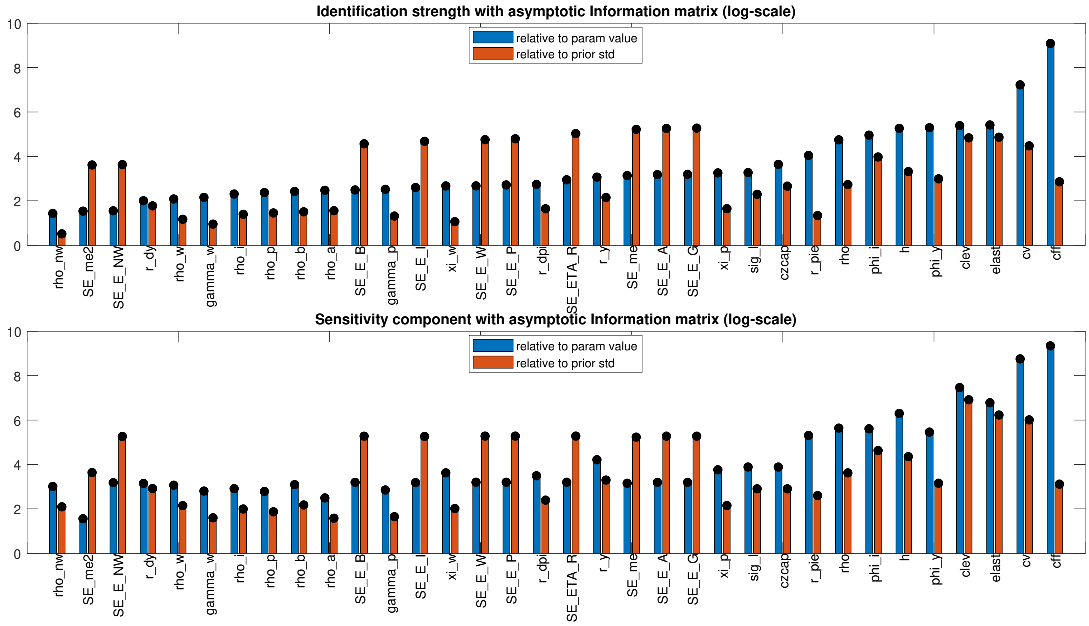


Figure 6.7: Identification test of parameters in the sample of Stagflation

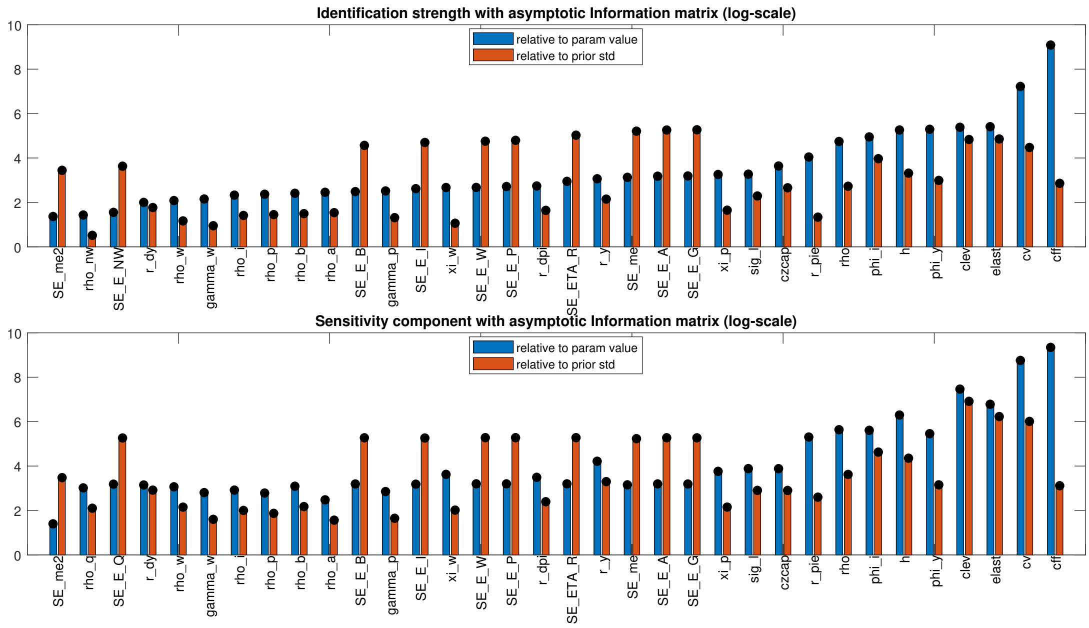
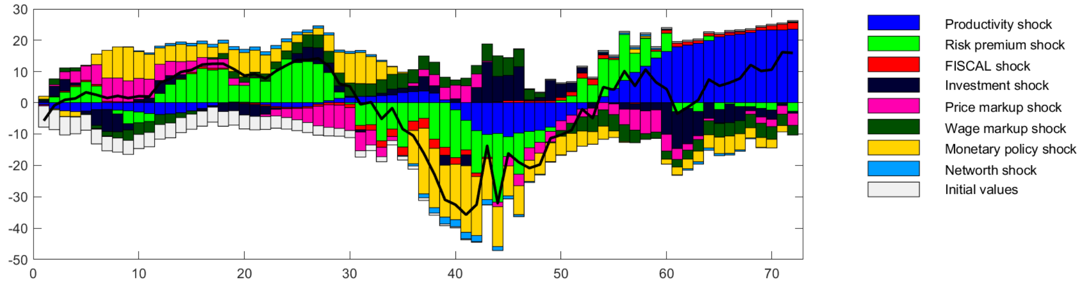


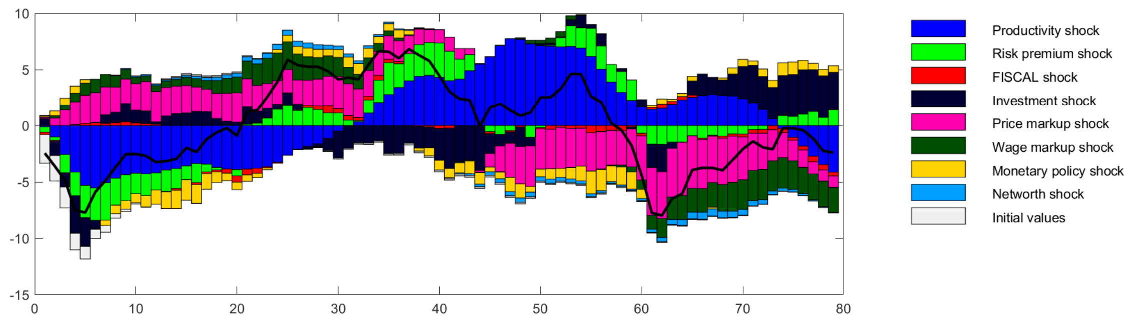
Figure 6.8: Identification test of parameters in the sample of Great Recession

Figure 6.9: Historical variance decomposition of the Great Depression - with fiscal side



Figures 16-17 show the historical variance decomposition of output for the Great Depression and the Stagflation periods, respectively, obtained from the the DSGE model extended with a fiscal size. The two figures show that fiscal shocks play a negligible role in explaining output fluctuations in these two periods.

Figure 6.10: Historical variance decomposition of the Stagflation- with fiscal side



6.2 Appendix: chapter 2

6.2.1 The financial sector in steady state

$$R^k = r^k + (1 - \delta) \tag{6.22}$$

$$\nu = \frac{(1-\theta)\left(R^k - R\right)}{1 - \beta\theta x} \tag{6.23}$$

$$\eta = \frac{(1-\theta)\,R}{1-\beta\theta z} \tag{6.24}$$

$$z = \left(R^k - R\right)\phi + R \tag{6.25}$$

$$x = z \tag{6.26}$$

$$\phi = \frac{\eta}{\lambda - \nu} \tag{6.27}$$

$$N = \frac{K}{\phi} \tag{6.28}$$

$$N^e = \theta z N \tag{6.29}$$

$$N^n = \omega K \tag{6.30}$$

6.2.2 Pin down the values of the spread and the leverage

From previous equations we get the following value for the steady state leverage

$$\phi = \frac{\eta}{\lambda - \nu} \tag{6.31}$$

and using equation (4), equations (7) to (9) and the fact that $N = N^e + N^n$, we get the following expression for the steady state interest rate spread

$$\frac{K}{\phi} = \theta z \frac{K}{\phi} + \omega K$$

$$\frac{1}{\phi} = \theta\left(\left(R^k - R\right)\phi + R\right)\frac{1}{\phi} + \omega$$

$$\left(R^k - R\right) = \frac{\frac{1 - \omega\phi}{\theta} - R}{\phi} \tag{6.32}$$

We calibrate the model to target the following steady state values

$$R^k - R = spread = 0.005 \tag{6.33}$$

$$\phi = 5.5 \tag{6.34}$$

This targeted values of the spread and leverage steady state imply the following calibration:

$$R^k = spread + 1/\beta \simeq 1.0151 \tag{6.35}$$

$$r^k = R^k - (1 - \delta) \simeq 0.0401 \tag{6.36}$$

$$z = \left(R^k - R\right) \phi + R \simeq 1.0376 \tag{6.37}$$

$$x = z \simeq 1.0376 \tag{6.38}$$

$$\nu = \beta \frac{(1 - \theta) \left(R^k - R\right)}{1 - \beta\theta x} \simeq 0.0143 \tag{6.39}$$

$$\eta = \beta \frac{(1 - \theta) R}{1 - \beta\theta z} \simeq 2.8913 \tag{6.40}$$

$$\omega = \frac{\left(1 - \theta \left(\left(R^k - R\right) \phi + R\right)\right)}{\phi} \simeq 0.0007 \tag{6.41}$$

$$\lambda = \frac{\eta + \phi\nu}{\phi} \simeq 0.54 \tag{6.42}$$

$$\frac{N^e}{N} = \frac{\theta z N}{N} = \theta z \simeq 0.996 \tag{6.43}$$

$$\frac{N^n}{N} = \frac{\omega K}{K/\phi} = \omega\phi \simeq 0.004 \tag{6.44}$$

6.2.3 Rest of the required steady state values

The following steady state values depend on previous calibrated values and the estimated value of α. Therefore, they are computed for each Metropolis-Hasting proposal.

$$W = \left(\frac{\alpha^\alpha (1 - \alpha)^{1-\alpha}}{\lambda_p \left(r^k\right)^\alpha}\right)^{\frac{1}{1-\alpha}} \tag{6.45}$$

$$\frac{L}{K} = \frac{(1 - \alpha)}{\alpha} \frac{r^k}{W} \tag{6.46}$$

$$\frac{K}{Y} = \lambda_p \left(\frac{L}{K}\right)^{\alpha-1} \tag{6.47}$$

$$\frac{I}{Y} = \delta_\gamma \frac{K}{Y} \tag{6.48}$$

$$\frac{C}{Y} = 1 - \frac{I}{Y} - \frac{G}{Y} \tag{6.49}$$

6.2.4 Unconditional variance decomposition for the rest of the shocks

Figure 6.11: Unconditional variance decomposition - stationary TFP contribution

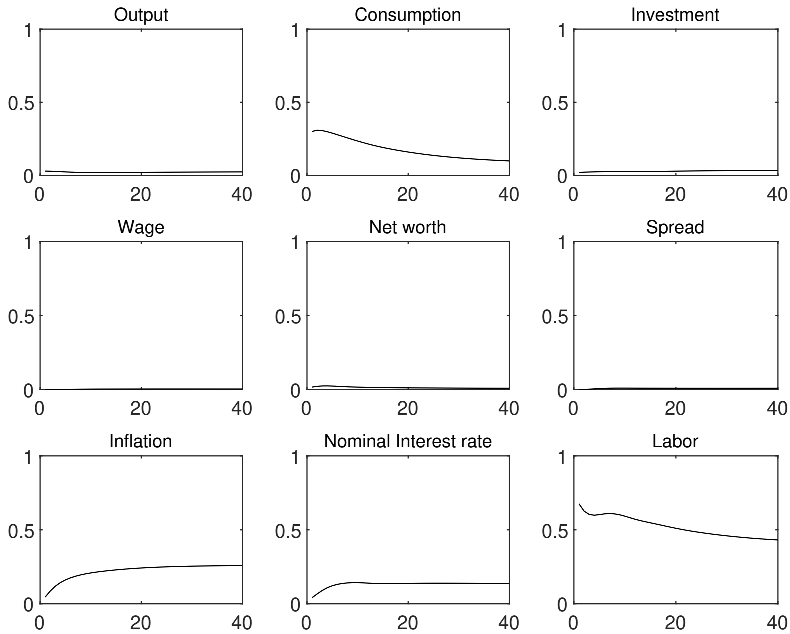


Figure 6.12: Unconditional variance decomposition - govern. spending contribution

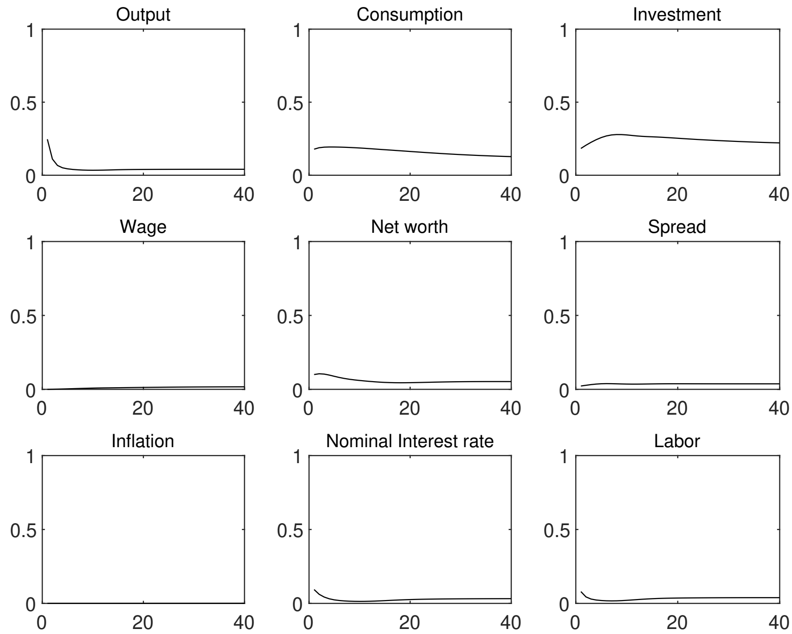


Figure 6.13: Unconditional variance decomposition - monetary policy contribution

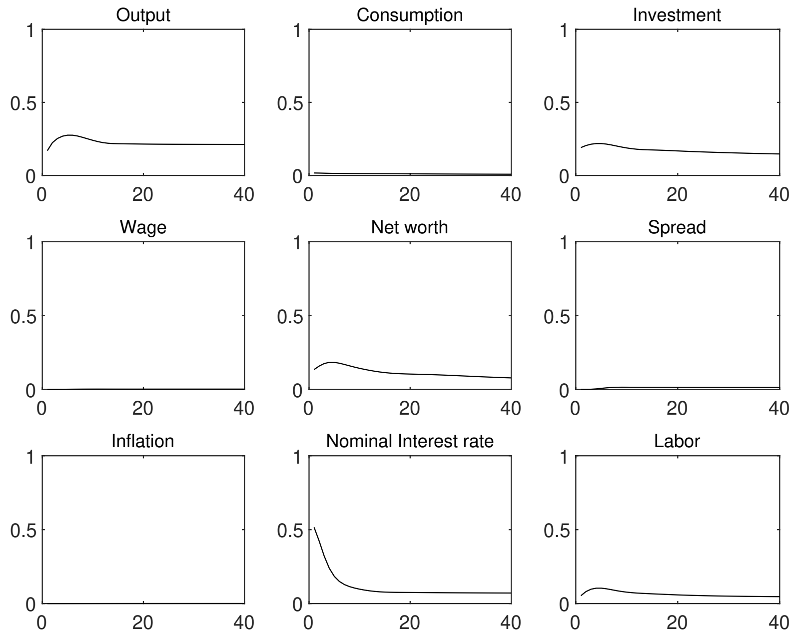


Figure 6.14: Unconditional variance decomposition - nonstationary TFP (surprise) contribution

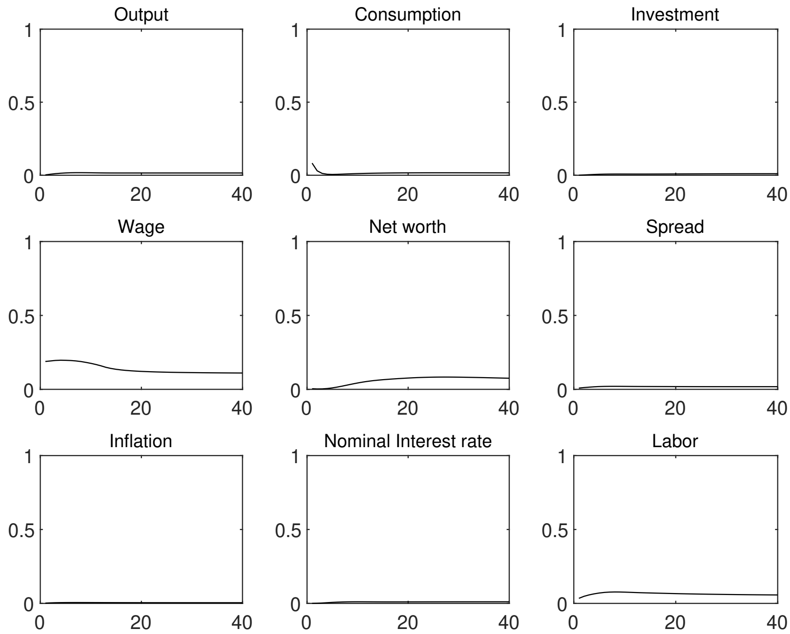


Figure 6.15: Unconditional variance decomposition - quality of capital (surprise) contribution

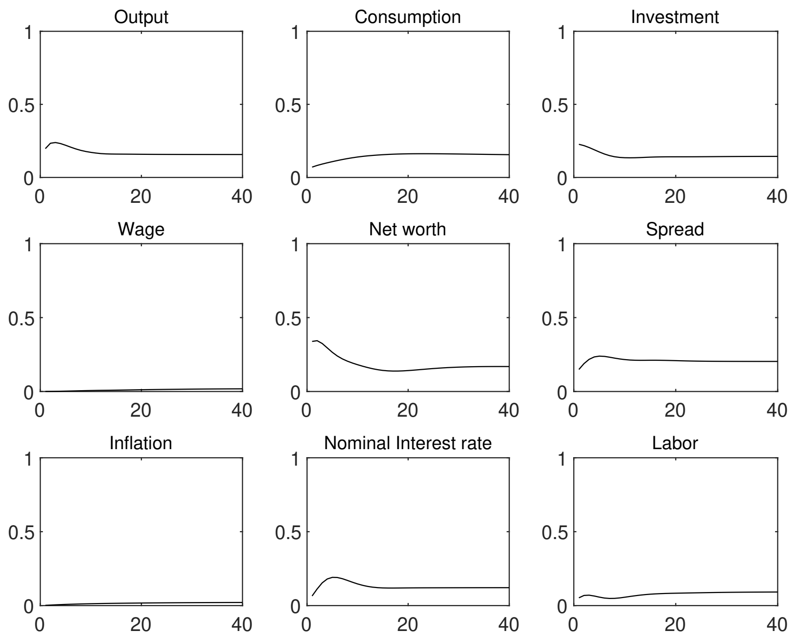


Figure 6.16: Unconditional variance decomposition - price markup contribution

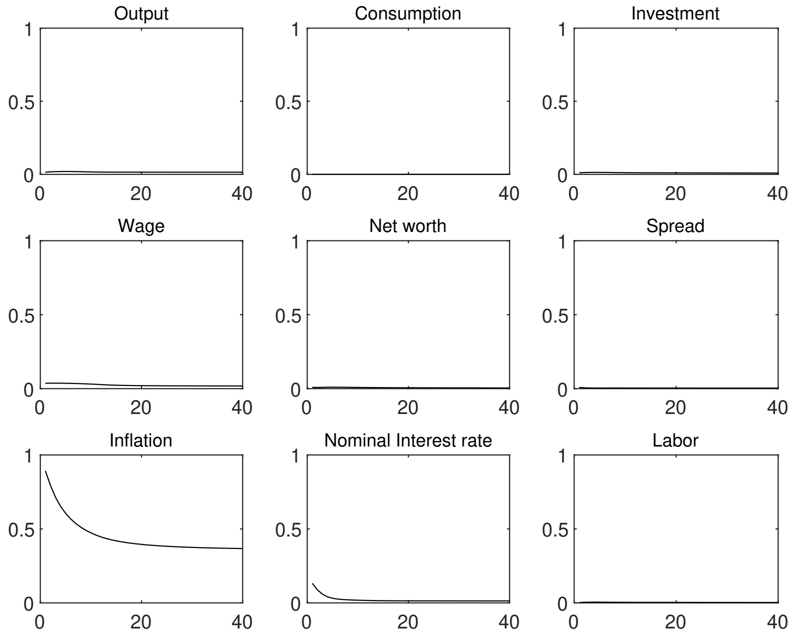


Figure 6.17: Unconditional variance decomposition - wage markup contribution

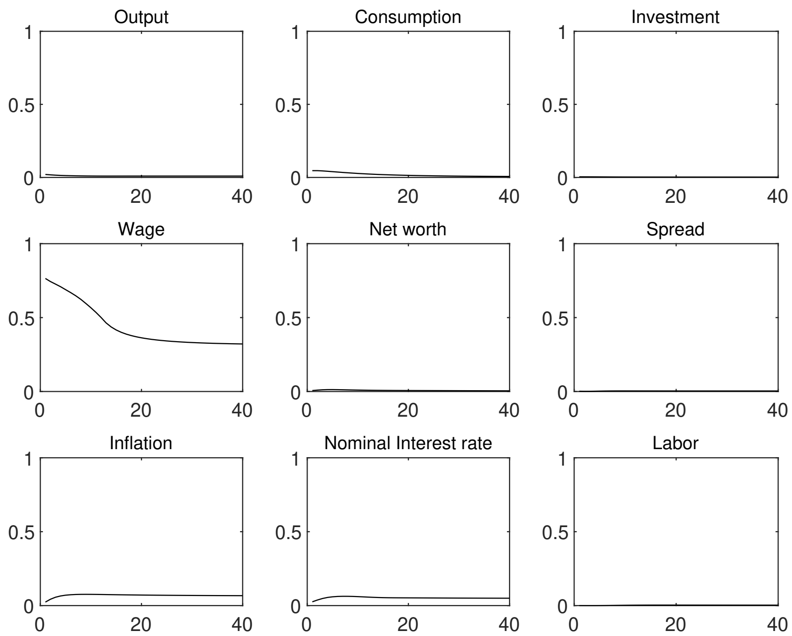


Figure 6.18: Unconditional variance decomposition - preference contribution

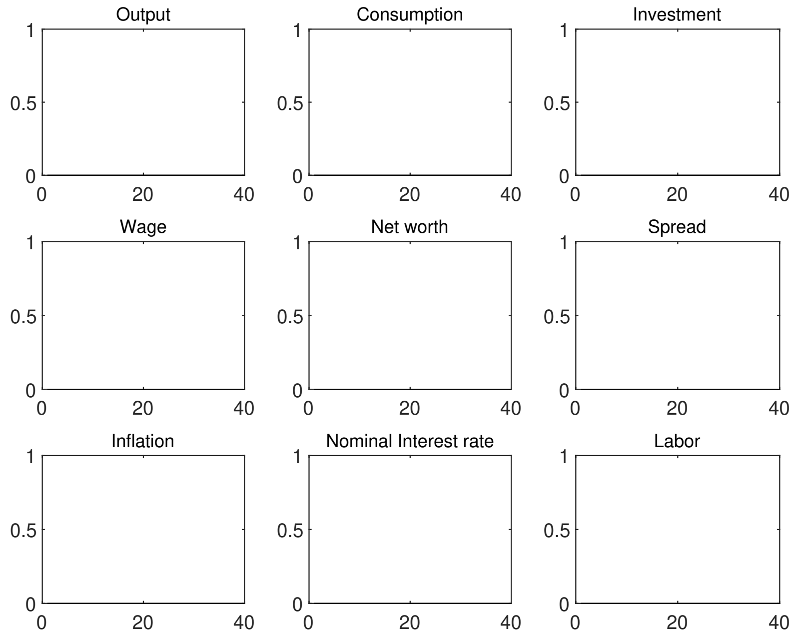


Figure 6.19: Unconditional variance decomposition - IST contribution

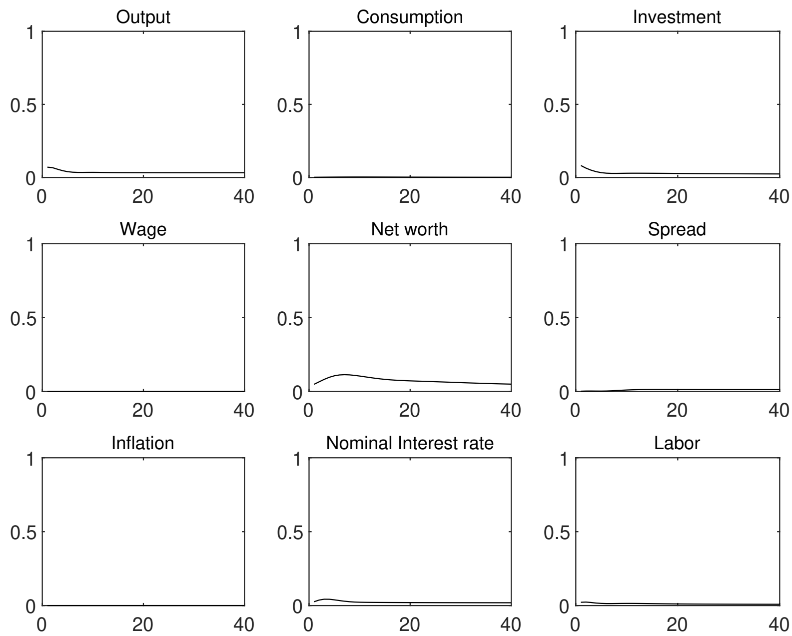
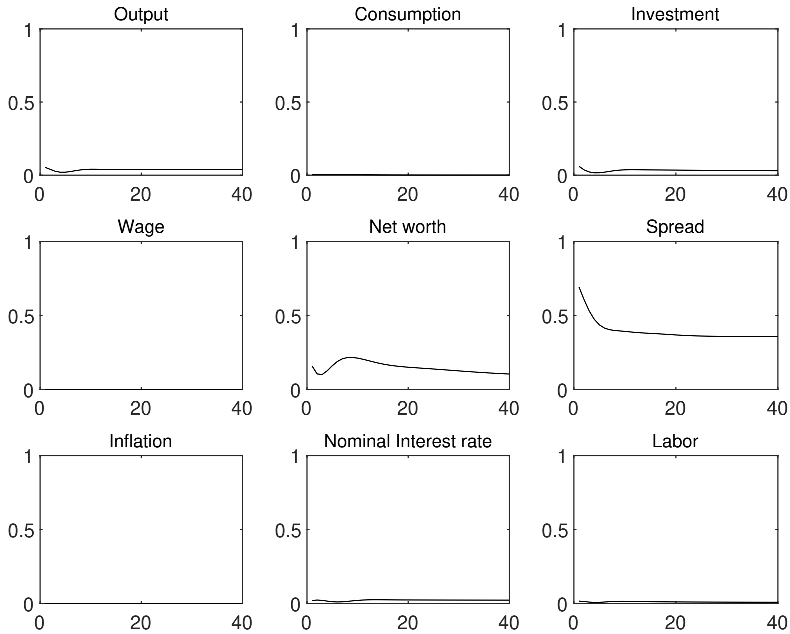


Figure 6.20: Unconditional variance decomposition - net worth contribution



6.2.5 Reduced sample

The results are robust to restricting the sample to 2006. There is a significant improvement of the model fit in terms of marginal data density when considering quality-of-capital news shocks. Similar results are found about the importance of QoC news in explaning the variances of the observables. When QoC news shocks are considered the importance of TFP news shocks are largely reduced in favor of the former. A noteworthy difference when considering this reduced sample is the drop of the importance of the QoC news shock in explaning output fluctuations whereas for the rest of the observables the results are roughtly robust

Table 6.1: Model fit for the reduced sample

	TFP news	QoC news
Marginal data density	-605.76	-566.09

Figure 6.21: Unconditional variance decomposition - TFP news shock (Reduced sample)

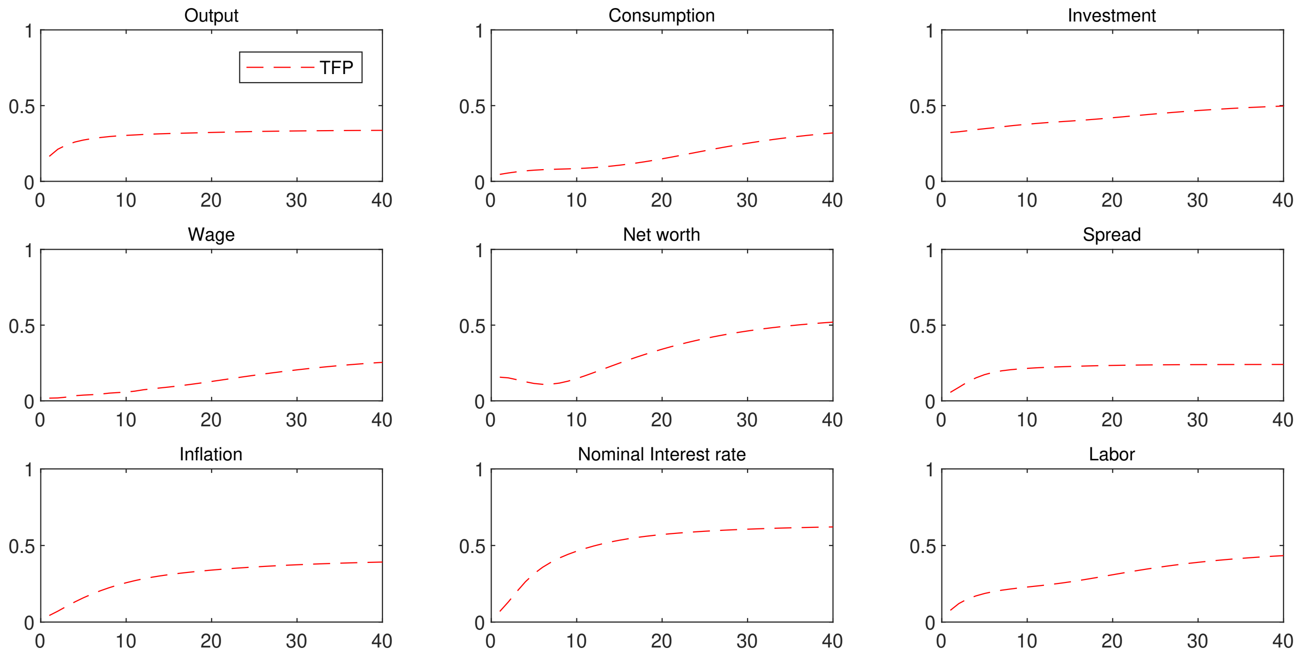
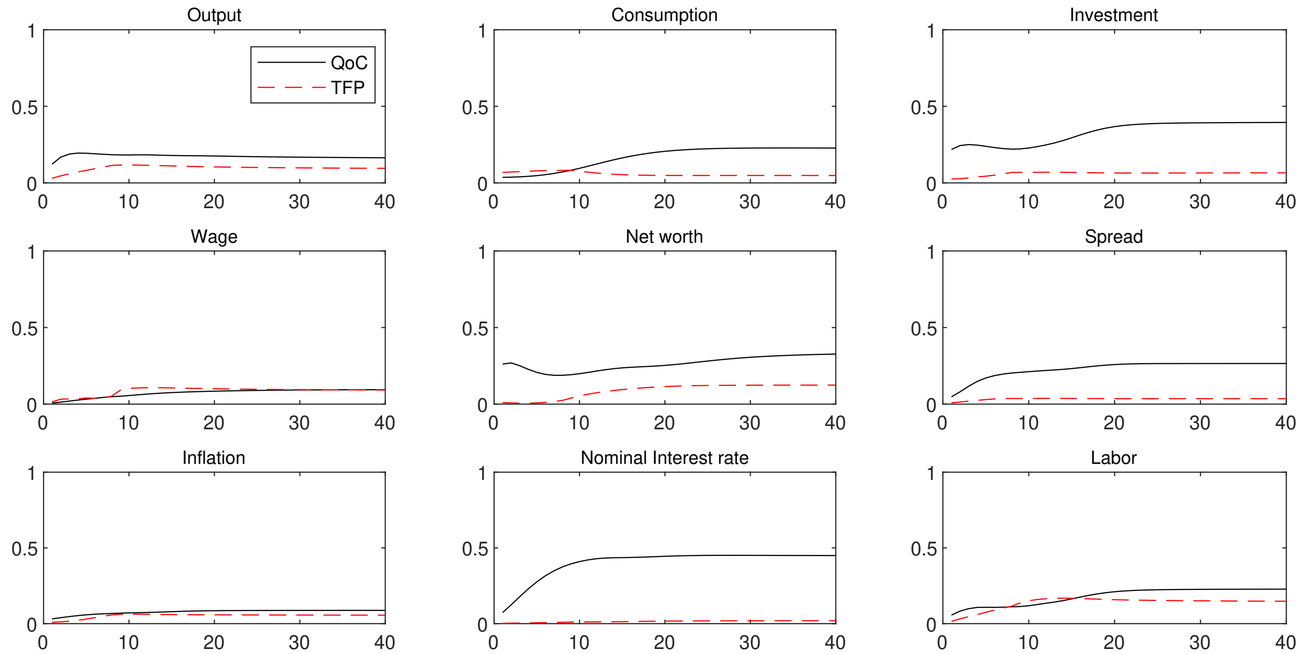


Figure 6.22: Unconditional variance decomposition - TFP vs QoC news shock (Reduced sample)



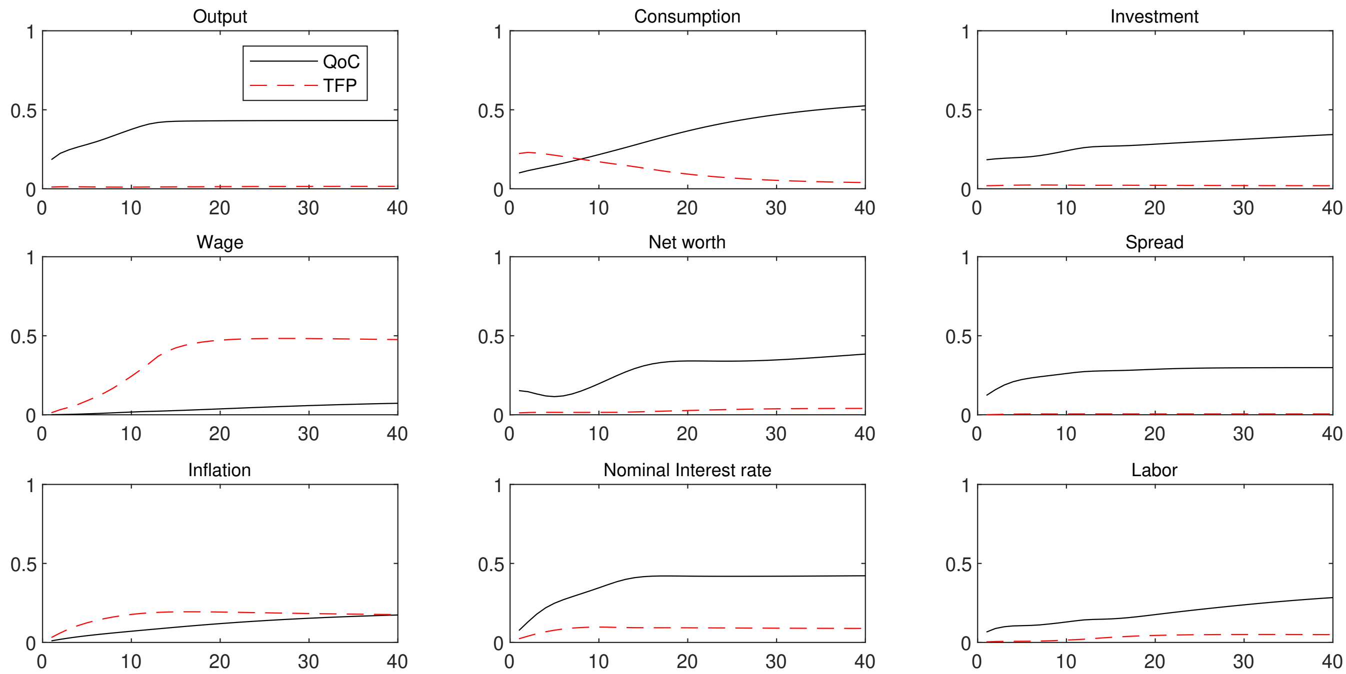
6.2.6 Detrending inside the estimation

This section carries out a robustness exercise regarding the detrending strategy of the observables. We do not detrend the data before the estimation but we estimate the mean of the stationary observables and the mean growth rate of non stationary observables together with the rest of the parameters. We assume a balance growth path, therefore the measurement equations are as follows:

$$\begin{bmatrix} \triangle y_t^o \\ \triangle c_t^o \\ \triangle i_t^o \\ \triangle w_t^o \\ \pi_t^o \\ r_t^o \\ \left(R_t^k - R_t\right)^o \\ \triangle N_t^o \end{bmatrix} = \begin{bmatrix} \triangle y_t + \hat{\gamma} + \epsilon_t^{TFP} \\ \triangle c_t + \hat{\gamma} + \epsilon_t^{TFP} \\ \triangle i_t + \hat{\gamma} + \epsilon_t^{TFP} \\ \triangle w_t + \hat{\gamma} + \epsilon_t^{TFP} \\ \pi_t + \hat{\pi} \\ r_t + \hat{r} \\ R_t^k - R_t + pr\hat{e}m \\ \triangle N_t + \hat{\gamma}_{nw} + \epsilon_t^{TFP} \end{bmatrix} \tag{6.50}$$

Figure 13 shows that the unconditional variance decomposition is robust to this alternative detrending strategy. We prefer to keep as baseline the linear detrending prior to the estimation to be consistent with previous research on the field of news shocks e.g. Schmitt-Grohe and Uribe (2012), Christiano, Motto and Rostagno (2014) and Gortz and Tsoukalas (2017) among others.

Figure 6.23: Unconditional variance decomposition - TFP vs QoC news shock (Alternative detrending)



6.2.7 News in all shocks

In this section we allow all the shocks to follow a AR(1) process with news components. We consider news anticipated 4 and 8 periods in advance in order to reduced the number of estimated parameter that is still largely increased by considering all the news. Table 2 shows the unconditional variance decomposition at the mode.[7] We find that, in addition to the QoC news shocks, other news seem to be rather important. The most remarkable case is the net worth news shocks that is able to explain one forth of output and interest rate fluctuations and more than one third of the financial variables. It is also interesting the role of markup news shocks that anticipate together 32% of the fluctuations of inflation and 20% of the fluctuations of wages. Nevertheless, this results should be taken with caution since the consideration of such a large amount of news shocks without the inclusion of new

[7] We have not run the Metropolis-Hasting algorithm for this specification due to the computational intensity of estimating such a large number of parameters. This should be done in future research when analyzing the role of all types of news in the business cycle.

observables that may allow their identification could result in bias findings. For future research analyzing the role of all types of news in the business cycle more observables capturing expectation changes, such as the Survey of Professional forecasters, should be taken into account.

Table 6.2: Share of variance explained by news components

	non-sTFP	QoC	IST	sTFP	Pref.	Gov. spend.	Monetary pol.	Price markup	Wage markup	NW
Output	0	43	0	0	0	0	8	1	0	23
Consumption	0	66	0	0	0	0	4	0	0	1
Investment	0	28	0	0	0	0	1	0	0	17
Labor	0	37	0	1	0	0	0	0	0	6
Inflation	1	9	0	1	0	0	1	28	4	0
Wage	5	16	0	0	0	0	4	5	15	0
Interest rate	0	50	0	0	0	0	3	3	1	23
Spread	0	39	0	0	0	0	1	1	0	39
Net worth	0	46	0	0	0	0	1	0	0	33

6.2.8 Alternative calibration

In this section we explore the robustness of the results to different calibration of the financial parameters. More specifally, we calibrate ω, $\lambda$and $\theta$to match the same steady state values of the leverage ratio and the interest rate spread proposed in Gertler and Karadi (2011) and Villa (2016). That is an leverage ratio of 4 and a interest rate spread of 150 basis points. Table 3 shows that the estimated parameters are rather robust to this alternative calibration, with an moderate increase of the investment adjustment cost that may compensate the reduction of the financial frictions. Moreover, Figure 14 shows the share of the fluctuations explained by TFP and QoC news shocks. The results are remarkably similar to the baseline calibration. Then, we prefer to keep the 5.5 leverage ratio and the 200 basis points as baseline case since those are the sample means.

Figure 6.24: Variance decomposition with the alternative calibration

Table 6.3: Selected parameter estimates

Parameter	Prior distribution		Posterior Mean	
	Type	Mean/Std	Baseline	Alter. calibration
Structural parameters				
Investment adjustment cost	Normal	4/1.5	0.74 [0.47,0.98]	1.39 [0.85,1.90]
Habit formation	Normal	0.7/0.1	0.94 [0.90,0.98]	0.94 [0.90,0.98]
Calvo probability for wages	Beta	0.5/0.1	0.79 [0.72,0.86]	0.77 [0.70,0.84]
Elasticity of labor supply	Normal	2/0.5	1.69 [0.91,2.40]	1.57 [0.80,2.33]
Calvo probability for prices	Beta	0.5/0.1	0.94 [0.93,0.95]	0.94 [0.93,0.95]
Indexation of past inflation in wages	Beta	0.5/0.15	0.21 [0.08,0.33]	0.22 [0.09,0.35]
Indexation of past inflation in inflation	Beta	0.5/0.15	0.19 [0.07,0.30]	0.19 [0.07,0.31]
Utilization adjustment cost	Gamma	0.5/0.15	0.69 [0.51,0.88]	0.73 [0.56,0.92]
Fixed cost in production	Normal	1.25/0.125	1.65 [1.48,1.81]	1.63 [1.46,1.79]
Capital share in production	Normal	0.3/0.05	0.24 [0.20,0.28]	0.22 [0.18,0.26]
Monetary policy parameters				
Interest rate smoother	Beta	0.75/0.1	0.80 [0.76,0.84]	0.81 [0.77,0.85]
Response to inflation	Normal	1.5/0.25	1.19 [1.00,1.64]	1.24 [1.00,1.48]
Response to output	Normal	0.125/0.05	0.36 [0.30,0.42]	0.32 [0.25,0.39]
Response to output growth	Normal	0.125/0.05	0.15 [0.08,0.22]	0.15 [0.07,0.22]
TFP news shocks				
Persistence of TFP	Beta	0.5/0.2	0.31 [0.18 , 0.44]	0.30 [0.17 , 0.43]
Std of TFP news shock - 1 quarter ahead	Gamma	0.1/2	0.10 [0.02 , 0.19]	0.11 [0.02 , 0.23]
Std of TFP news shock - 4 quarter ahead	Gamma	0.1/2	0.06 [0.02 , 0.10]	0.06 [0.02 , 0.11]
Std of TFP news shock - 8 quarter ahead	Gamma	0.1/2	0.07 [0.02 , 0.11]	0.07 [0.02 , 0.12]
Std of TFP news shock - 12 quarter ahead	Gamma	0.1/2	0.17 [0.08 , 0.27]	0.18 [0.08 , 0.28]
QoC news shocks				
Persistence of QoC	Beta	0.5/0.2	0.93 [0.87 , 0.98]	0.92 [0.86 , 0.98]
Std of QoC news shock - 1 quarter ahead	Gamma	0.1/2	0.05 [0.03 , 0.08]	0.05 [0.03 , 0.08]
Std of QoC news shock - 4 quarter ahead	Gamma	0.1/2	0.05 [0.02 , 0.07]	0.05 [0.03 , 0.07]
Std of QoC news shock - 8 quarter ahead	Gamma	0.1/2	0.06 [0.03 , 0.10]	0.06 [0.02 , 0.10]
Std of QoC news shock - 12 quarter ahead	Gamma	0.1/2	0.11 [0.03 , 0.19]	0.14 [0.03 , 0.23]

6.3 Appendix: Chapter 3

6.3.1 The model

In this appendix, we first describe the DSGE model augmented with financial frictions à la Gertler and Karadi (2011).

Households

The representative household i decides consumption, hours worked, and savings in riskless assets to maximize a utility function that incorporates internal habit formation. Formally,

$$E_t \sum_{k=0}^{\infty} \beta^k \epsilon_{t+k}^b \left[ln\left(C_{t+k}(i) - hC_{t+k-1}\right) - \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l} \right], \tag{6.51}$$

where β is the household subjective discount factor, h represents the degree of habit persistence, σ_l is the elasticity of labor supply (i.e. the Frisch elasticity), and ϵ_{t+k}^b is an exogenous process that affects the intertemporal preferences of households. Household savings are represented by deposit liabilities in banks and government bonds. These riskless assets, B, are perfect substitutes and pay the same nominal interest rate, R^n. Households also receive dividends from intermediate goods firms, capital goods producers, and labor unions, D. Hence, the budget constraint is

$$C_{t+k}(i) + \frac{B_{t+k}(i)}{R_{t+k}^n P_{t+k}} - T_{t+k} = \frac{W_{t+k}(i) L_{t+k}(i)}{P_{t+k}} + \frac{B_{t+k-1}(i)}{P_{t+k}} + \frac{D_{t+k}}{P_{t+k}}, \tag{6.52}$$

where T represents lump-sum taxes, and W is the nominal wage.

Labor unions and wage decision

As in Smets and Wouters (2007), households supply homogeneous labor to intermediate labor unions that differentiate labor services. Intermediate labor unions set wages and sell labor services to a labor packer who aggregates the differentiated labor and resells it to intermediate goods firms. Aggregation of labor services follows

$$L_t = \left[\int_0^1 L_t(i)^{\frac{1}{1+\epsilon_t^w}} di \right]^{1+\epsilon_t^w},$$

where $1+\epsilon_t^w$ is the desired markup of wages over the household's marginal rate of substitution, which is assumed to follow a stochastic process around its steady-state value.

Labor packers maximize profits in a perfectly competitive market. Formally,

$$max_{L_t(i)} W_t L_t - \int_0^1 W_t(i) L_t(i),$$

where W_t is the aggregate wage that intermediate firms pay for labor services, and $W_t(i)$ is the wage that labor packers pay for the differentiated labor. This optimization problem results in the following labor demand function:

$$L_t(i) = \left(\frac{W_t(i)}{W_t}\right)^{-\frac{1+\epsilon_t^w}{\epsilon_t^w}} L_t.$$

The labor demand function and the labor services aggregation function together result in the wage aggregation function:

$$W_t = \left(\int_0^1 W_t(i)^{\frac{1}{\epsilon_t^w}} di\right)^{\epsilon_t^w}. \tag{6.53}$$

Following Calvo's lottery scheme, labor unions are assumed to adjust prices with probability $1-\xi_w$. The fraction of labor unions ξ_w that cannot adjust prices is assumed to follow the indexation rule, $W_{t+1}(i) = W_t(i)\left(\frac{P_t}{P_{t-1}}\right)^{\iota_w}$. Hence, the labor unions choose an optimal W to maximize

$$E_t \sum_{k=0}^{\infty} \beta^k \xi_w^k \left[\Lambda_{t+k} W_t(i) L_{t+k}(i) - \epsilon_{t+k}^b \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l}\right], \tag{6.54}$$

subject to labor demand and the indexation rule.

Final goods firms

Competitive final goods producers buy intermediate goods and combine them to finally sell homogeneous goods to households. The intermediate goods aggregation follows:

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{1}{1+\epsilon_t^p}} di\right]^{1+\epsilon_t^p},$$

where Y_t is the homogeneous good, $Y_t(i)$ is the heterogeneous good supplied by firm i, and $1+\epsilon_t^p$ is the desired markup of prices over firms' marginal cost, which is assumed to follow a stochastic process around its steady-state value.

Final goods firms maximize profits in a perfectly competitive market. Formally,

$$max_{Y_{t(i)}} P_t Y_t - \int_0^1 P_t(i) Y_t(i) di,$$

where Y_t is subject to the goods aggregation function, $P_t(i)$ is the price for differentiated goods, and P_t is the aggregate price index. The optimal condition of this maximization problem results in the following goods demand function for goods:

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\frac{1+\epsilon_t^p}{\epsilon_t^p}} Y_t. \tag{6.55}$$

Hence, the goods demand function and the intermediate goods aggregator result in the following price aggregator

$$P_t = \left[\int_0^1 P_t(i)^{\frac{1}{\epsilon_t^p}} di\right]^{\frac{1}{1-\epsilon_t^p}}. \tag{6.56}$$

Intermediate goods firms

As in the labor market, it is assumed that intermediate goods firms can only adjust prices with probability ξ_p. Those firms which cannot adjust prices in period t simply reset their prices according to the indexation rule: $P_{t+1}(i) = P_t(i)\left(\frac{P_t}{P_{t-1}}\right)^{\iota_p}$. Firms able to set their optimal prices P_t^* at time t choose them by maximizing current and future expected profits. Denoting the marginal costs and the inflation rate by MC_t and π_t, respectively; the price setting optimization problem faced by intermediate goods firms can be written as follows:

$$max_{P_t^*(i)} E_t \sum_{k=0}^{\infty} \beta^k \xi_p^k \Lambda_{t+k} \frac{P_t}{P_{t+k}} \left[P_t^*(i) \prod_{l=1}^{k} \pi_{t+l-1}^{\iota_p} - MC_{t+k} \right] Y_{t+k}(i), \tag{6.57}$$

subject to the price indexation rule, and the demand function for intermediate goods.

In addition to setting prices, intermediate goods firms decide on the output of goods. They choose the amount of production inputs by maximizing the flow of discounted profits

$$E_t \left\{ \beta\Lambda_{t+1} \left[Y_{t+1}(i) - r_{t+1}^k K_{t+1}^s(i) - \frac{W_{t+1}}{P_{t+1}} L_{t+1}(i) \right] \right\}, \tag{6.58}$$

where $\beta\Lambda_{t+1} = \frac{\beta\lambda_{t+1}}{\lambda_t}$ is the stochastic discount factor, λ_t is the marginal utility of consumption for households at time t, r_{t+1}^k is the rental rate of capital, and $K_{t+1}^s(i)$ denotes capital services.

The production function is assumed to follow a Cobb-Douglas technology:

$$Y_t = TFP_t \left(K_t^s\right)^{\alpha} L_t^{1-\alpha} - \Psi_t \phi_p, \tag{6.59}$$

where ϕ_p is the share of fixed costs involved in production, and TFP_t denotes TFP shocks. The optimal inputs decision results in the following optimal conditions:

$$r_t^k = \alpha MC_t TFP_t \left(K_t^s\right)^{\alpha-1} L_t^{1-\alpha}, \tag{6.60}$$

$$\frac{W_t}{P_t} = (1-\alpha) MC_t TFP_t \left(K_t^s\right)^{\alpha} L_t^{-\alpha}. \tag{6.61}$$

Capital services firms

Capital services firms purchase physical capital from capital goods producers and turn it into effective capital by choosing the utilization rate, U_t:

$$K_t^s = U_t K_{t-1}. \tag{6.62}$$

Capital services firms decide the optimal capital utilization rate and face a utilization cost. They solve the following maximization problem:

$$max_{U_t} \left[r_t^k U_t - a\left(U_t\right) \right] K_{t-1},$$

where $a\left(U_t\right)$ is the utilization cost function. The optimal solution implies

$$r_t^k = a'\left(U_t\right). \tag{6.63}$$

This equilibrium condition states that the degree of capital utilization depends on the rental rate of capital. The utilization cost function assumes the following standard properties $U = 1$, $a(U) = 0$, and $\frac{a''(U)}{a'(U)} = \psi$ in the steady state. Hence, the parameter ψ is a positive function of the elasticity of the capital utilization cost, and is normalized to be between zero and one. A higher value of ψ means a higher cost of adjustment in capital utilization.

Capital services firms finance their physical capital acquisition by borrowing from financial intermediaries. At equilibrium, the following condition holds:

$$Q_t K_t = Q_t S_t, \tag{6.64}$$

which states that state-contingent claims, S_t, are equal to the number of units of physical capital acquired, K_t, where firms price their claims at the price of one unit of capital, Q_t. Each claim pays the stochastic return R^k_{t+1} over period t. Capital services firms operate in a perfectly competitive market, so the revenue from renting effective capital must be equal to the cost of purchasing physical capital. Hence, the optimal capital demand satisfies

$$R^k_{t+1} = \frac{r^k_{t+1} U_{t+1} - a\left(U_{t+1}\right) + (1-\delta) Q_{t+1}}{Q_t}, \tag{6.65}$$

which shows that the expected real interest rate on external funds is equal to the marginal return on capital.

Capital goods producers

Capital goods producers turn out physical capital and sell it to capital services firms at price Q_t. Investment goods are purchased from final good producers. Capital goods producers are assumed to face quadratic adjustment costs, $S(I_t/I_{t-1})$. This adjustment costs function is assumed to be a strictly increasing twice differentiable function. The optimization problem of the capital goods producers is

$$max_{I_t} E_t \left\{ \sum_{k=0}^{\infty} \beta^k \Lambda_{t+k} \left[Q_{t+k} I_{t+k} \epsilon^i_{t+k} - I_{t+k} - Q_{t+k} I_{t+k} \epsilon^i_{t+k} S\left(\frac{I_{t+k}}{I_{t+k-1}}\right)\right]\right\}, \tag{6.66}$$

where $S(.)$ is assumed to have the properties $S(1) = S'(1) = 0$, $S''(1) = \varphi > 0$. Therefore, the parameter φ measures the degree of investment adjustment cost, and the disturbance ϵ^i_t is the investment specific-technology shock. Capital accumulation evolves following the standard equation

$$K_t = (1-\delta) K_{t-1} + \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t. \tag{6.67}$$

Financial intermediaries

Görtz and Tsoukalas (2017) find that the financial sector is crucial for identifying TFP news shocks. We closely follow their characterization of financial intermediaries, which was suggested by

Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). A fixed fraction of households includes bankers, who do not supply labor but behave as financial intermediaries. These bankers face a survival probability, θ, and in order to keep the proportion constant further households become bankers in each period.

The financial intermediaries finance the acquisition of physical capital by purchasing claims S_t. These purchases are funded through household liabilities. Hence, the balance sheets of financial intermediaries are

$$Q_t S_t = N_t + B_{t+1},$$

where N_t is the net worth of the bankers. Since the return on financial claims is R^k_{t+1} and the cost of liabilities is R_t, the law of motion of the net worth of intermediaries is given by:

$$N_{t+1} = R^k_{t+1} Q_t S_t - R_t B_{t+1} = \left(R^k_{t+1} - R_t\right) Q_t S_t + R_t N_t.$$

Let $\beta \Lambda_{t+1}$ be the stochastic discount factor of financial intermediaries. The bankers' decisions are endogenously determined in the model through the following problem in which they maximize future expected terminal wealth:

$$V_t = max\ E_t \sum_{i=0}^{\infty} (1-\theta)\, \theta^i \beta^i \Lambda_{t+1+i} N_{t+1+i} =$$

$$max\ E_t \sum_{i=0}^{\infty} (1-\theta)\, \theta^i \beta^i \Lambda_{t+1+i} \left[\left(R^k_{t+1+i} - R_{t+i}\right) Q_{t+i} S_{t+i} + R_{t+i} N_{t+i}\right].$$

However, a moral hazard issue arises in this maximization problem because $\beta^i \left(R^k_{t+1+i} - R_{t+i}\right) \geq 0$. Otherwise bankers would not be willing to purchase assets. Thus, bankers have an incentive to keep borrowing additional funds indefinitely from households. In order to restrict their ability to do this, an enforcement cost is introduced: At the beginning of the period bankers can divert a proportion λ of the funds available. If that is the case, the depositors can then only recover a fraction $(1-\lambda)$ of the assets. Hence, for lenders to be willing to supply funds to bankers the following incentive constraint must be satisfied:

$$V_t \geq \lambda Q_t S_t,$$

where V_t, the gain from not diverting assets, can be expressed as follows

$$V_t = \nu_t Q_t S_t + \eta_t N_t,$$

with

$$\nu_t = E_t \left[(1-\theta)\, \Lambda_{t+1} \left(R^k_{t+1} - R_t\right) + \beta\theta x_{t,t+1} \nu_{t+1}\right], \tag{6.68}$$

$$\eta_t = E_t \left[(1-\theta)\, \Lambda_{t+1} R_t + \beta\theta z_{t,t+1} \eta_{t+1}\right], \tag{6.69}$$

where ν_t is the marginal gain from expanding assets with net worth held constant, η_t is the expected value of one additional future unit of wealth net worth with assets held constant, $x_{t,t+i} = Q_{t+i}S_{t+i}/Q_tS_t$ is the gross growth rate of assets, and $z_{t,t+i} = N_{t+i}/N_t$ is the gross growth rate of net worth.

The incentive constraint holds with equality at equilibrium:

$$Q_tS_t = \frac{\eta_t}{\lambda - \nu_t}N_t = \phi_t N_t, \tag{6.70}$$

where ϕ_t is the leverage ratio of bankers. Thus, from the law of motion of net worth and the incentive constraint, net worth can be rewritten as

$$N_{t+1} = \left[\left(R^k_{t+1} - R_t\right)\phi_t + R_t\right]N_t.$$

Using this equation, the gross growth rates of assets and net worth can be written as

$$z_{t,t+1} = N_{t+1}/N_t = \left(R^k_{t+1} - R_t\right)\phi_t + R_t, \tag{6.71}$$

and

$$x_{t,t+1} = Q_{t+1}S_{t+1}/Q_tS_t = \left(\phi_{t+1}/\phi_t\right)\left(N_{t+1}/N_t\right) = \left(\phi_{t+1}/\phi_t\right)z_{t,t+1}. \tag{6.72}$$

Finally, the law of motion of bankers' net worth is given by the law of motion of the net worth of existing bankers plus the net worth of households that become bankers in this period:

$$\tilde{N}_t = N^e_t + N^n_t, \tag{6.73}$$

with

$$N^e_t = \theta\left[\left(R^k_{t+1} - R_t\right)\phi_t + R_t\right]N_{t-1}, \tag{6.74}$$

$$N^n_t = \omega Q_t S_{t-1}, \tag{6.75}$$

$$\tilde{N}_t = N_t \epsilon^{nw}_t, \tag{6.76}$$

where ω is the fraction of the total assets that households transfer to new bankers, which enable them to start operating in the banking sector, and the disturbance ϵ^{nw}_t captures exogenous variations in the net worth of bankers due, for instance, to exogenous changes in bank profits.

Market clearing condition

The market clearing condition is

$$Y_t = C_t + I_t + a(U_t) + \epsilon^g_t, \tag{6.77}$$

where ϵ^g_t is an exogenous process that captures government spending and exogenous net export shocks.

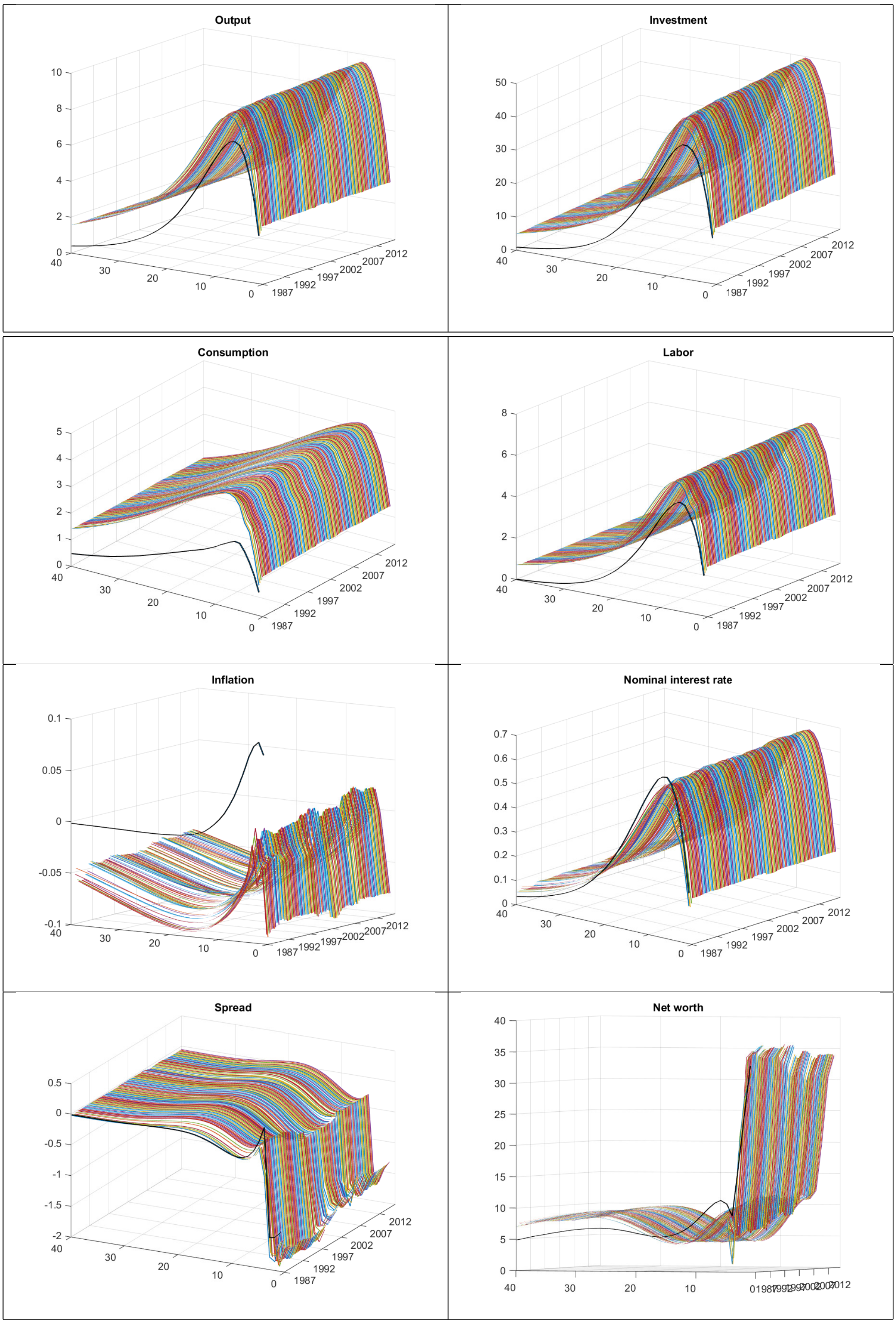
The central bank

The model is closed with a Taylor-type rule in which the nominal interest rate set by the central banker reacts to inflation, output, and output growth (where all variables are measured in deviations from their steady-state values) in addition to a smoothing component, $\left[\frac{R^n_{t-1}}{R^n}\right]^{\rho}$:

$$\frac{R^n_t}{R^n} = \left[\frac{R^n_{t-1}}{R^n}\right]^{\rho} \left\{ \left[\frac{\pi_t}{\pi}\right]^{r_\pi} \left[\frac{Y_t}{Y}\right]^{r_y} \right\}^{1-\rho} \left[\frac{Y_t}{Y_{t-1}}\right]^{r_{\Delta y}} exp(\epsilon^R_t). \tag{6.78}$$

Time-varying AL-IRFs to a TFP news shock

Figure 6.25: Time-varying impulse-response functions to a TFP news shock



6.3.2 Alternative specifications

Table 5 reports the log marginal data density (MDD) statistics for alternative specifications in which news, anticipated 4 and 8 quarters in advance, are placed on alternative shocks. These statistics suggest that the most preferred shock to put news on is the trend TFP shock as considered in the baseline specification. All estimated specifications, but the baseline, include an i.i.d. measurement error term in the measurement equation associated with the GZ spread in order to account for potential measurement errors associated with this variable. It turns out that the model fit barely changes by removing this measurement error, as is shown by a comparison of lines 1 and 2. Moreover, adding news to transitory TFP, government speding, and monetary policy shocks rather than to the trend TFP barely deteriorates model fit, while ignoring news on any shock results in a fall of roughly 20 log points in the log MDD. Table 5 also shows that adding news on all quarters (from 1 to 8) to trend TFP shocks, as shown in line 4, results in a large fall in model fit of roughly 70 log points, which is likely due to the difficulties of identifying news from each of a large number of alternative (anticipated) horizons.

Table 6.4: Log marginal data density (MDD) for alternative news specifications

Trend TFP news (baseline specification)	-847.328
Trend TFP news	-850.475
Transitory TFP news	-854.659
Trend TFP news on all quarters from 1 to 8	-918.894
Risk news	-865.707
Government spending news	-854.847
Investment-specific news	-890.070
Monetary policy news	-854.945
Price markup news	-919.353
Wage markup news	-858.589
Net worth news	-867.540
No news on any shock	-869.621

Notes: The marginal data density is computed using Geweke (1999) modified harmonic mean method. The computations in this table are based on a Monte Carlo Markov chain of length 200,000 draws for each specification and discard the first 20% of the draws. All specifications, but the baseline specification, include a measurement error in the measurement equation associated with the GZ spread.

6.4 Appendix: Chapter 4

6.4.1 Financial shock with and without BBM - QE effects

A credit supply shock is simulated in each economy to produce the same GDP drop in both. This scenario is shown in Figure A2. All macro variables and asset prices have a very similar response on impact to these shocks. In this case, the benefits of QE are remarkably larger in the baseline economy since larger financial frictions amplify the transmission mechanism of QE.

Figure 6.26: Survival probability shock with alternative policies