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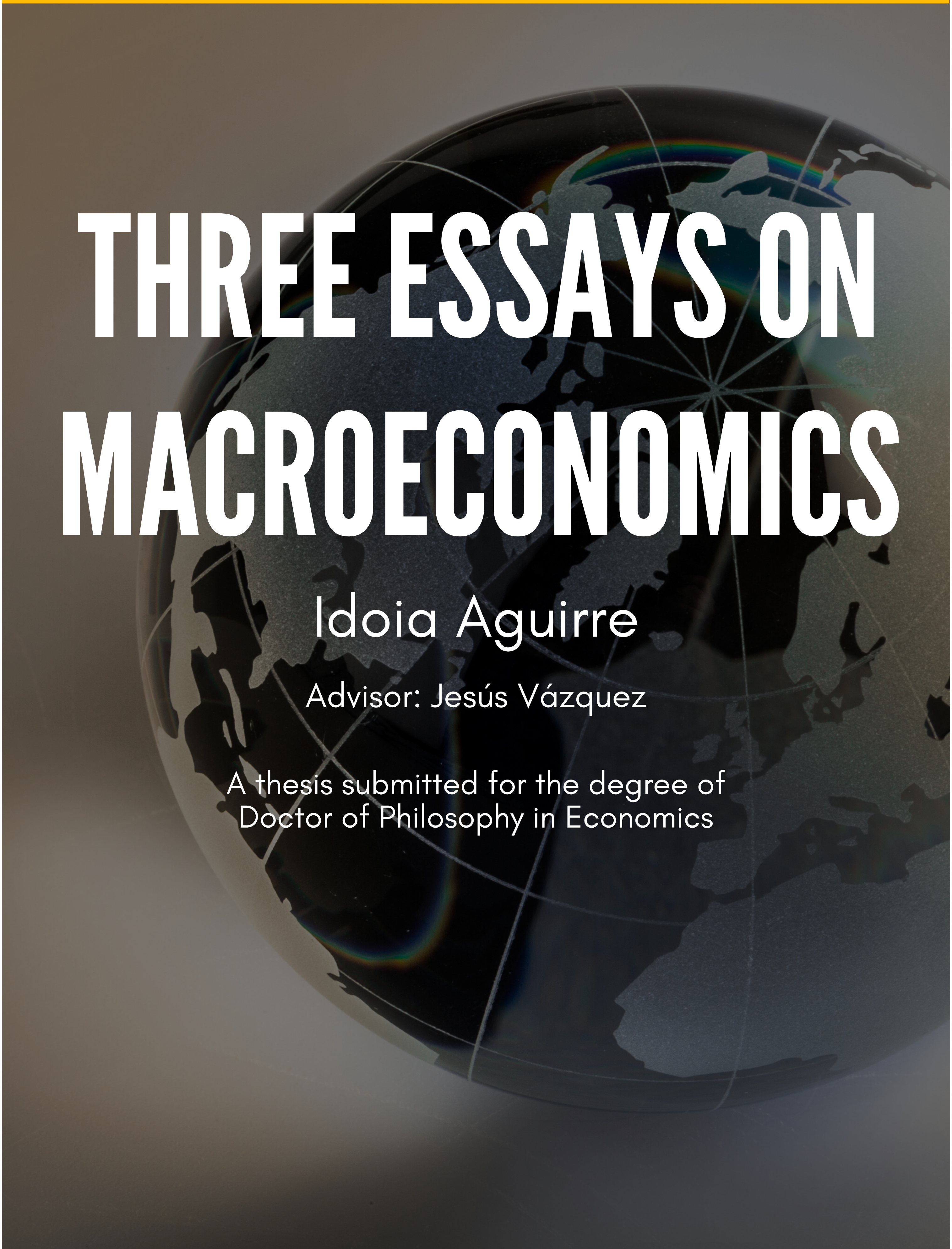

THREE ESSAYS ON MACROECONOMICS

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Three Essays on Macroeconomics

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Ph.D Thesis

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Bilbao, 2020

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Aita, Ama, Aban,
maite zaituztet.

Idoia

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List of Abbreviations

AL	Adaptive Learning.
ARCH	Autoregressive conditional heteroskedasticity model.
CML	Constrained maximum likelihood.
DSGE	Dynamic Stochastic General Equilibrium.
EMU	European Monetary Union.
GARCH	Generalized autoregressive conditional heteroskedasticity model.
LM	Lagrange Multiplier.
OLS	Ordinary Least Square.
RE	Rational Expectations.
VAR	Vector Autoregressive model.

Introduction

1.1 Three Essays on Macroeconomics

The global financial crises has drawn attention to several phenomena at the intersection of macroeconomics and finance. They are: (1) asymmetric information and the optimal use of the available information (i.e. the flash forecasts of GDP and inflation); (2) adjustments in credit supply as a critical channel by which market risk becomes systemic; (3) bank funding conditions as major determinants of bank lending decisions; (4) central bank liquidity as a substitute for market liquidity when private credit vanishes; (5) departure from the standard rational expectation hypothesis towards a benchmark where the agents are able to learn and create their own expectations.

The present thesis aims to study the importance of some of these phenomena from a macroeconomic perspective with a focus on the interaction between the monetary policies and the real economy. This dissertation consists of three chapters, all of them are self-contained works.

The first chapter of the thesis consists of an extension of the asymmetric preference model suggested by Ruge-Murcia (2003a) to investigate the use of real-time data, which roughly measures the type of data available to policy makers when making their decisions, and revised data which more accurately measure economic performance (Croushore, 2011). In the extended model, the central banker monitors a weighted average of revised and real-time inflation. Moreover, the asymmetric central bank can focus on real-time inflation depending on whether the unemployment rate is high or low. It identifies a source of inflation bias due to inflation revisions. The empirical results suggest that the Federal Reserve Bank focuses on monitoring revised inflation during low unemployment periods, but it weights real-time inflation heavily during high unemployment periods. In contrast, the Bank of England seems to focus on an equally-weighted average of real-time and revised inflation when monitoring inflation which is fairly robust over the business cycle.

Monetary policy may reflect the impact of real-time data, which roughly measures the type of data available to central bankers at the time when their decisions are made, as well as revised data which more accurately measure economic performance. First announcements of many macroeconomic variables -e.g. the rate of inflation and GDP- for a given quarter are released around the middle of the following quarter, well before the final release, which takes place roughly three years after the first announcement. Due to these long lags, central bankers face an important conflict. Ideally, they might aim to influence the performance of the actual economy based on optimal forecasts, but because of the long lags associated with the revised data that most accurately measure this performance their actual forecasts might be affected by the most readily available data arriving in real time; this is because market participants' evaluations of monetary policy performance, and by the same token central bank inflation monitoring, are likely to be based at least partially on real-time data components, which do not help to forecast optimally revised data. As noted by Croushore (2011), if the discrepancy between real-time and revised data were characterized by a pure news component-as opposed to a noise component-then the lags associated with data revisions would not be an issue because real-time data would be an optimal forecast of revised data. However this is not the case because revisions usually incorporate both news and noise components (see Aruoba (2008) and references therein), which means that there is some predictability in these data revisions. Moreover, it is extremely difficult, if not impossible to distinguish the news and noise components of expected revisions in real time in an always changing economic environment. All these features may induce policy-makers to make decisions that deviate from decisions that simply reflect revised data.

Our paper contributes to the large body of theoretical literature which investigates the possibility that central bankers may induce an upward bias in inflation. Barro and Gordon (1983) suggest that central bankers might be unable to make long-term policy commitments, which might lead them to pursue policies which create surprise inflation. This proposition generated considerable interest with numerous empirical papers (e.g. Ireland 1999) showing mixed results. More recently, Ruge-Murcia (2003,a, 2004) develop a new theory suggesting that a central banker featuring asymmetric preferences might induce an inflation bias.[1] In the model of Ruge-Murcia (2003a, 2004), the inflation bias arises because the monetary authority takes stronger action when unemployment is above the natural rate than when it is below the natural rate. A similar finding is shown by Cassou, Scott and Vázquez (2012), who posit an asymmetric preference model which focuses on an output asymmetry rather than an unemployment asymmetry. In their model the inflation bias arises because the central banker takes stronger action when output is below its permanent level than when it is above. None of these papers find support for the surprise inflation hypothesis à la Barro and Gordon, but they provide strong evidence in favor of the asymmetric preference hypothesis suggested by Ruge-Murcia (2003a).

We extend the model by Ruge-Murcia (2003a, 2004) by assuming that the monetary authority wants to monitor a weighted average of both revised and real-time inflation forecasts. As motivated above, the inclusion of real-time inflation in the formulation of a central banker objective function is due to the long lag in the releases of final inflation revisions, which might result in a central banker paying attention to real-time inflation forecasts even if they are not rational forecasts of revised inflation. This hypothesis of central bank monitoring of real-time inflation may also reflect the inability of a central banker to make long-term policy commitments as in Barro and Gordon (1983), but the inability studied in this paper is due to a different issue. In particular, here a central banker might be forced to focus on real-time inflation forecasts as a result of short-term pressures from other policy makers, economic pundits of public opinion.[2] Moreover, we explore the hypothesis that the relative importance of real-time inflation forecasts in central bankers' decision-making may be greater during high unemployment periods due to political pressures to react quickly to bad news. Thus, political pressures can also induce asymmetric central bank responses to inflation in real-time decisions making. As

[1]Early papers putting forward central banker asymmetric preferences are Cukierman (2001) and Robert Nobay and Peel (2003). Another approach followed by Surico (2007) focuses on monetary policy rule asymmetries.

[2]That is, the central banker may be more worried about the policy evaluation based on real-time data made in the near future than the one based on revised data, which can be implemented when these data become available only after a long delay.

a result, the importance of an inflation bias induced from the differences between revised and real-time inflation data, as in the traditional inflation bias sources suggested by Barro and Gordon (1983) and Ruge-Murcia (2003a, 2004), is likely to be a consequence of the degree of central bank independence, which can differ from country to country.

Our empirical results clearly show that both the Federal Reserve and the Bank of England take into account real–time inflation forecasts when implementing monetary policy, which induces an important new inflation bias source in both countries, although they do so in quite different ways. The Federal Reserve focuses on monitoring revised inflation during low unemployment periods, but it weights real-time inflation heavily in its decision making during high unemployment episodes. These results are in line with those found in Cassou et al. (2016). In contrast, the Bank of England uses a roughly equally-weighted average of real-time and revised inflation in its decision making which is fairly robust over the business cycle. Moreover, as in Ruge-Murcia (2003a, 2004) and Cassou et al. (2012) we find that the Ruge-Murcia asymmetric preference bias remains significant. In particular, the preferences of the two central banks are asymmetric, with stronger action taken when unemployment (output) is above (below) its natural rate (potential level) than when it is below (above).

As noted above, this new source of inflation bias can be a consequence of the degree of central bank independence that can differ form country to country. In order to compare the different degrees of real-time targeting we extend our analysis to other Central Banks. Specifically, we include two European countries with independent monetary policies and three countries outside the European Union. Our results show that real-time inflation is an important new inflation bias source for all the countries except Sweden. Specifically, the central banks of Australia and New Zealand follow closely the targeting policy of the Fed. This is in contrast to the central banks of Canada and Denmark that seem to be more like to the targeting policy of the Bank of England but they weight less heavily revised data during bad economic times. However, the central bank of Sweden seems not to take into account real-time data in their policy decision making at all.

The second chapter presents and evaluates a model that helps study the role of the financial sector in the Spanish liquidity trap. We find that the agency problems, the liquidity constraints facing banks and risk shocks that hit financial intermediation are primary determinants of economic fluctuations. They have been critical triggers and propagators in the recent financial crisis. The liquidity policies enacted by the European Central Bank (ECB) seem to have greatly attenuated the impact of the spread of financial panic.

Our model is a variant of Christiano et al. (2014), we integrate a foreign sector that supplies government bonds to the Spanish banks of the type studied by Moreno et al. (2014). The real economy is made of households and firms. Households are composed of workers, capital producers and entrepreneurs. The working households consume, supply differentiated work in a monopolistic labour market, and allocate savings as deposits to the bank. Capital producers combine undepreciated physical capital with new investment subject to an idiosyncratic shock that try to emulate the success and the failure of several projects. Entrepreneurial households have a special ability to operate capital. They acquire plant capacity from capital producers, extract production services from it and resell the stock of undepreciated capital at the end of the production cycle, and accumulate net worth in the process. Net worth is used to pay for capital in the next period. But, in order to run their activity entrepreneurs need to borrow a fraction of the value of capital which they are not able to self-finance. The bank provides resources to finance entrepreneurs' investment projects using the deposits placed by households. Firms producing intermediate goods are monopolists and subject to a standard Calvo mechanism with partial indexation for price setting.

Idiosyncratic uncertainty in the financial sector has been introduced in models by Bernanke et al. (1999). More recently, Christiano et al. (2014) make this idiosyncratic uncertainty time-varying through risk shocks that modify the standard deviation of idiosyncratic shocks to the productivity of private borrowers and lead to macroeconomic fluctuations. By doing so, their paper provides a new transmission channel of uncertainty to business cycles through financial frictions that we use in this paper.

We estimate the model for Spain over the period 2000Q1-2017Q4. We use quarterly observations of ten macroeconomic time series that are mainly used in the estimation of DSGE models and three financial series : credit to non financial corporations, entrepreneurial net worth and the risk premium of sovereign bonds. Our results suggest that anticipated risk shocks dominate all the other shocks. Moreover, our results show that 52% of the variability of output and 89% of the variability of credit in the business cycle accounted by anticipated risk shocks in the economy. Those shocks explain the episode of credit crunch and contraction of investment and output. Such a sequence has been observed during the last recession of 2007 in Spain.

In the third chapter we estimate a medium-scale DSGE model both under rational expectations and adaptive learning using a rolling window approach to analyze parameter variability. The different model extension also allows us to explore the hypothesis that the parameters in the DSGE models used to study aggregate fluctuations are in general time-varying (Inoue and Rossi (2011)). Estimation results show that including adaptive learning improves the fit of the model and helps reduce by around 68% the variation in estimated structural parameters. Moreover, our results suggest that the inclusion of adaptive learning helps explaining the recent swings in the comovements between real and nominal US macroeconomic variables.

Recent literature shows evidence that the parameters in the DSGE models used to study aggregate fluctuations are in general time-varying (see, among others, Inoue and Rossi (2011), Canova and Ferroni (2012), Castelnuovo (2012*a*,*b*), Hurtado (2014), Casares and Vázquez (2018), Castelnuovo and Pellegrino (2018), Canova (2019)). These findings have important implications. On the one hand, the instability of structural parameters somewhat weakens the ability of DSGE models to assess policies reliably (Fernández-Villaverde et al. (2007)). On the other hand, parameter variability may be an important source for explaining the macroeconomic dynamic swings observed during the post-WWII era in the US.

This paper analyzes parameter variability by estimating the canonical medium-scale DSGE model suggested by Smets and Wouters (2007) under both RE and AL following Slobodyan and Wouters (2012*a*,*b*) approach to AL. Both versions of the model are estimated for the whole sample and then using a 20-year rolling-window approach. Our estimation results show that learning dynamics help to explain a large proportion of the parameter variability observed under the standard RE hypothesis typically assumed in macroeconomic modelling. The intuition is simple: Under RE, a time-invariant relationship links the endogenous variables to the (predetermined and exogenous) state variables of the economy whenever the structural parameters of the model are constant. Therefore, parameter variability becomes the only source of macroeconomic dynamic swings under RE other than that generated from the exogenous shocks of the model. By contrast, the relationship linking endogenous variables with state variables becomes time varying under

AL even when the structural parameters are time invariant, which might result in much richer macroeconomic dynamics.

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Inflation monitoring in real time: A comparative analysis of the Federal Reserve and the Bank of England

> *"There is no universal best price index, but rather different indexes depending on what you are trying to measure"*
>
> *– Reis (2009)*

2.1 Abstract

This paper extends the asymmetric preference model suggested by Ruge-Murcia (2003*b*) to investigate the use of real-time data which roughly measure the type of data available to policy makers when making their decisions and revised data which more accurately measure economic performance (Croushore, 2011). In our extended model, the central banker monitors a weighted average of revised and real-time inflation. Moreover, we allow for an asymmetric central bank focus on real-time inflation depending on whether the unemployment rate is high or low. Our model identifies a source of inflation bias due to inflation revisions. Our empirical results suggest that the US Federal Reserve Bank focuses on monitoring revised inflation during low unemployment periods, but it weights real-time inflation heavily during high unemployment periods. The Reserve Bank of Australia and the Reserve Bank of New Zealand seem to follow the policies of the US Fed by weighting mainly real-time data in bad economics times. In contrast, the Bank of England seems to focus on an equally-weighted average of real-time and revised inflation when monitoring inflation which is fairly robust over the business cycle. However, the Bank of Canada and the Denmark National Bank target mainly revised data during high unemployment periods. In contrast to the other central banks studied, the estimation results suggest that the Central Bank of Sweden does not take real-time data into account in monitoring their monetary policy.

2.2 Introduction

Monetary policy may reflect the impact of real-time data, which roughly measures the type of data available to central bankers at the time when their decisions are made, as well as revised data which more accurately measures economic performance.[1] First announcements of many macroeconomic variables -e.g. the rate of inflation and GDP- for a given quarter are released around the middle of the following quarter, well before the final release, which takes place roughly 3 years after the first announcement. Due to these long lags, central bankers face an important conflict. Ideally, they might aim to influence the performance of the actual economy based on optimal forecasts, but because of the long lags associated with the revised data that most accurately measure this performance their actual forecasts might be affected by the most readily available data arriving in real time; this is because market participants' evaluations of monetary policy performance, and by the same token central bank inflation monitoring, are likely to be based at least partially on real-time data components, which do not help to forecast optimally revised data. As noted by Croushore (2011), if the discrepancy between real-time and revised data were characterized by a pure news component -as opposed to a noise component- then the lags associated with data revisions would not be an issue because real-time data would be an optimal forecast of revised data. However this is not the case because revisions usually incorporate both news and noise components (see Aruoba (2008) and references therein), which means that there is some predictability in these data revisions. Moreover, it is extremely difficult, if not impossible to distinguish the news and noise components of expected revisions in real time in an always changing economic environment. All these features may induce policy-makers to make decisions that deviate from decisions that simply reflect revised data.

Our paper contributed to the large body of theoretical literature which investigates the possibility that central bankers may induce an upward bias in inflation. Barro and Gordon (1983) suggest that central bankers might be unable to make long-term policy commitments, which might lead them to pursue policies which create surprise inflation. This proposition generated considerable interest with numerous empirical papers (e.g. Ireland 1999) showing mixed results. More recently, Ruge-Murcia (2003*a*,*b*, 2004) develop a new theory suggesting that a central banker featuring asymmetric preferences might induce an inflation bias.[2] In the model of Ruge-Murcia (2003*b*, 2004), the inflation bias arises because the monetary authority takes stronger action when unemployment is above the natural rate than when it is below the natural rate. A similar finding is shown by Cassou, Scott and Vázquez (2012), who posit an asymmetric preference model which focuses on an output asymmetry rather than an unemployment asymmetry. In their

[1] The impact of the revisions process on the empirical evaluation of monetary policy has been widely investigated in the literature -see Croushore (2011) and references therein. A pioneering article by Maravall and Pierce (1986) investigates how preliminary and incomplete data affect monetary policy. They show that even if revisions to measures of money supply are large, monetary policy will not be much different if more accurate data are known whenever policymakers are able to optimally extract the signal from the data. More recently, Orphanides (2001), among others, shows that real-time measurement problems of conceptual variables, such as output gap, may induce policymaking errors. Croushore and Evans (2006) show evidence that the use of a Vector Autoregressive model (VAR) based on revised data may not be a serious limitation for recursive identification of monetary policy shocks. Nevertheless, their analysis also shows that many simultaneous VAR systems identifiable when real-time data issues are ignored cannot be completely identified when these measures are considered. All these studies consider US real-time data. More recently, Fernandez, Branch, Koenig and Nikolsko-Rzhevskyy (2011) assemble a real-time data set for the OECD countries. In line with the US data revisions features reported below, they find that statistical agencies from OECD countries tend to underestimate both real output growth and inflation.

[2] Early papers putting forward central banker asymmetric preferences are Cukierman (2001) and Robert Nobay and Peel (2003). Another approach followed by Surico (2007) focuses on monetary policy rule asymmetries.

model the inflation bias arises because the central banker takes stronger action when output is below its permanent level than when it is above. None of these papers find support for the surprise inflation hypothesis à la Barro and Gordon (1983), but they provide strong evidence in favor of the asymmetric preference hypothesis suggested by Ruge-Murcia (2003*b*).

We extend the model by Ruge-Murcia (2003*b*, 2004) by assuming that the monetary authority wants to monitor a weighted average of both revised and real-time inflation forecasts. As motivated above, the inclusion of real-time inflation in the formulation of a central banker objective function is due to the long lag in the releases of final inflation revisions, which might result in a central banker paying attention to real-time inflation forecasts even if they are not rational forecasts of revised inflation. This hypothesis of central bank monitoring of real-time inflation may also reflect the inability of a central banker to make long-term policy commitments as in Barro and Gordon (1983), but the inability studied in this paper is due to a different issue. In particular, here a central banker might be forced to focus on real-time inflation forecasts as a results of short-term pressures form other policy makers, economic pundits or public opinion.[3] Moreover, we explore the hypothesis that the relative importance of real-time inflation forecasts in central bankers' decision-making may be greater during high unemployment periods due to political pressures to react quickly to bad news. Thus, political pressures can also induce asymmetric central bank responses to inflation in real-time decisions making. As a result, the importance of an inflation bias induced from the differences between revised an real-time inflation data, as in the traditional inflation bias sources suggested by Barro and Gordon (1983) and Ruge-Murcia (2003*b*, 2004), is likely to be a consequence of the degree of central bank independence, which can differ from country to country.

By following Ruge-Murcia (2003*b*, 2004) we are considering a targeting rule approach (e.g. Clarida, Gali and Gertler, 1999 and Svensson, 1999) by first defining a central bank's loss function whose arguments are the monetary policy targets, where these targets in our extended framework can be affected by real-time issues due to the long lags associated with the releases of revised data. This is in contrast with the instrument rule approach (McCallum and Nelson, 2005) usually followed in the related literature to analyze the importance of real-time data (e.g. Orphanides, 2001).[4] The targeting rule and the instrument rule approaches can be viewed as two alternative ways (each with its pros and cons) of dealing with real-time issues. In this perspective, the targeting rule approach adopted in this paper is suitable for identifying potential sources of inflation bias (i.e. those induced by asymmetric central bank preferences à la Ruge-Murcia and those induced by data revisions) in a rather simple framework.

Our model with inflation data revisions identifies a potential source of inflation bias that arises due to two features as suggested in Cassou, Scott and Vázquez (2016): First, the lag of revised inflation measurements with respect to their initial announcements, which may explain why a central banker may pay attention to real-time inflation; and second, the asymmetric central bank focus on real-time inflation may differ depending on whether the economy is doing well or not. The approach followed in this papers is fairly close to the one followed in Cassou et al. (2016) with a few important differences.

[3]That is, the central banker may be more worried about the policy evaluation based on real-time data made in the near future than the one based on revised data, which can be implemented when these data become available only after a long delay.

[4]As emphasized below, an attractive feature of Ruge-Murcia's formulation is that the policy instrument is left unspecified. Hence, the optimal inflation rate is robust to alternative operating procedures and instrument rules used by central bankers, which avoids a potential source of misspecification.

We focus on the asymmetric preference model of Ruge-Murcia (2003*b*, 2004) based on asymmetric preferences on unemployment instead of the asymmetric preference model based on asymmetric preferences on output suggested in Cassou et al. (2012). As explained below, this strategy enables us to better identify the source of bias due to inflation revisions by using a maximum likelihood approach instead of an instrumental variable approach as used in Cassou et al. (2016) . In addition, we extend our analysis to investigate UK data as well as the US data studied in their paper. This enables us to make a comparison between the ways in which the Federal Reserve and the Bank of England deal with non-trivial inflation revisions in the characterization of monetary policy.

Our empirical results clearly show that both the Federal Reserve and the Bank of England take into account real–time inflation forecasts when implementing monetary policy, which induces an important new inflation bias source in both countries, although they do so in quite different ways. The Federal Reserve focuses on monitoring revised inflation during low unemployment periods, but it weights real-time inflation heavily in its decision making during high unemployment episodes. These results are in line with those found in Cassou et al. (2016). In contrast, the Bank of England uses a roughly equally-weighted average of real-time and revised inflation in its decision making which is fairly robust over the business cycle. Moreover, as in Ruge-Murcia (2003*b*, 2004) and Cassou et al. (2012) we find that the Ruge-Murcia asymmetric preference bias remains significant. In particular, the preferences of the two central banks are asymmetric, with stronger action taken when unemployment (output) is above (below) its natural rate (potential level) than when it is below (above).

The rest of the paper is organized as follows. Section 2.3 extends the model of Ruge-Murcia (2003*b*, 2004) by assumming that the central banker wants to monitor a weighted average of both revised an real-time inflation. Section 2.4 shows the estimation results. In Section 2.5 we extend the analysis to several countries. Section 2.6 concludes.

2.3 The model

Following Ruge-Murcia (2003*b*, 2004), the theoretical model consists of a central banker with the dual mandate of stabilizing inflation and unemployment rates around respective targets. These decisions are complicated by the fact that accurate short term measurements for inflation-i.e. revised inflation data-are only available after a long delay. We regard the revised inflation time series, that is data that appear in conventional databases such as Federal Reserve Economic Data (FRED), as more accurately measuring actual inflation, but because of the long lags associated with revising these inflation data, real-time inflation data may affect the central banker's decision-making. Furthermore, the extent to which the monetary authority considers real-time inflation in its decision-making may depend on whether the economy is doing well or not.

To investigate the extent to which real-time inflation releases potentially matter in central bank decision-making and possibility that this extent may be different in low and high unemployment periods, we build on the inflation-unemployment asymmetric preference model suggested in Ruge-Murcia (2003*b*, 2004). This model begings with a short run Phillips curve given by:

$$u_t = u_t^n - \mu\left(\pi_t - \pi_t^e\right) + \eta_t \tag{2.1}$$

where u_t is observed unemployment at time t, u_t^n is the natural rate of unemployment at time t, π_t is the-actual or revised-inflation rate at time t, π_t^e is the public's forecast of inflation at time t constructed at time $t-1$, and η_t is a supply disturbance. The natural rate of unemployment changes over time according to

$$\Delta u_t^n = \psi - (1-\delta)\, u_{t-1}^n + \theta \Delta u_{t-1}^n + \xi_t \tag{2.2}$$

where ξ_t is serially uncorrelated and normally distributed with mean zero and standard deviation σ_ξ. Note that this formulation is rather general. Thus, when $\sigma = 1$ the model imposes a unit root process for the rate of unemployment, while when $\sigma \neq 1$ there is no stochastic trend.

In the Ruge-Murcia model, the central banker monitors actual inflation. More precisely, actual inflation for the period is assumed to be simply determined as the sum of a policy instrument, i_t, chosen by the monetary authority and a control error, ϵ_t, so that

$$\pi_t = i_t + \epsilon_t \tag{2.3}$$

where ϵ_t is serially uncorrelated and normally distributed with mean zero and standard deviation σ_ϵ. An attractive feature of Ruge-Murcia's formulation is that the policy instrument, i_t, is left unspecified. The optimal inflation rate is thus robust to alternative operating procedures used by central bankers over long sample periods, which avoids a potential source of misspecification. In particular, this formulation accommodates the alternative ways that central bankers may have used to implement monetary policy over the years. From instrument rules that set the rate of growth of nominal money as the policy instrument in the 60's and 70's to interest rate rules -e.g. the Taylor rule- used during the great moderation periods, and the unconventional monetary polices used by central bankers when dealing with the great recession and the zero lower bound issue.

Since our main objectives are, first, to investigate the degree to which the central banker weights real-time versus revised inflation data and, second to analyze whether the weighting or real-time inflation depends on whether the economy is doing well or not, we assume that the central banker wishes to monitor a weighted average of these two data types instead of monitoring only actual-revised-inflation as assumed by (2.3) in the Ruge-Murcia model. Formally, we introduce a parameter $\lambda_j^\pi \in [0,1]$ for $j = b, g$ to index whether the economy is in a good or low unemployment state ($j = g$) or in a a bad or high unemployment state ($j = b$).[5] To be more specific, when the economy is in state j, $\lambda_j^\pi = 0$ indicates that the central banker focuses only on real-time inflation, $\lambda_j^\pi = 1$ indicates that the central banker focuses only on revised inflation and $\lambda_j^\pi \in (0,1)$ indicates that policy monitoring is determined by an average of these two inflation data types. Under this formulation one can interpret $(1-\lambda_j^\pi)$ as a measure of the short-term pressure extended on the central banker by the government and other economic agents to focus on the real-time inflation forecast when the economy is in regime j. One reasonable prior is that the monetary authority might weight real-time data more heavily than revised data in high unemployment periods (i.e. $(1-\lambda_b^\pi) > (1-\lambda_g^\pi)$ or $\lambda_g^\pi > \lambda_b^\pi$) because during such periods it might be under stronger short-term pressure from other policy makers, economic pundits or public opinion to fulfil its dual mandate of stabilizing both inflation and unemployment.

[5] We use the unemployment rate as a measure for economic performance because it is a major economic variable targeted by the Federal Reserve Bank. Moreover, it is observed in real-time and is not revised beyond a few seasonal adjustments. Furthermore, the choice of the rate of unemployment as the threshold variable is in line with the role played by the rate of unemployment in the asymmetric preference model of Ruge-Murcia (2003*b*, 2004) of signalling whether the economy is in good times (low unemployment) or in bad times (high unemployment).

We use the weighting structure outlined above to extend the policy structure in Ruge-Murcia (2003*b*, 2004). In particular, rather than simply choosing the policy instrument i_t to monitor revised inflation, the central bank chooses the policy instrument to monitor a weighted average of both revised and real-time inflation. Furthermore, also as noted above, we allow the degree to which these two inflation measures are weighted to differ depending on whether the economy is currently in a low unemployment period or a high unemployment period. This means that our modified equation linking the policy instrument, i_t, and the average inflation measure monitored by the central banker, $\tilde{\pi}_t$, is given by

$$\tilde{\pi}_t = i_t + \epsilon_t \tag{2.4}$$

where $\tilde{\pi}_t$ is given by

$$\tilde{\pi}_t = I_t[\lambda_b^\pi \pi_t + (1 - \lambda_b^\pi)\pi_t^r] + (1 - I_t)[\lambda_g^\pi \pi_t + \left(1 - \lambda_g^\pi\right) \pi_t^r] \tag{2.5}$$

π_t^r is the first announcement-real-time observation-of inflation, ϵ_t is serially uncorrelated disturbance with mean zero and standard deviation σ_ϵ as in (2.3) and I_t is a dummy indicating the strength of the economy in period t given by

$$I_t = \begin{cases} 0 & \text{if } u_t \leq u^T \\ 1 & \text{if } u_t > u^T \end{cases} \tag{2.6}$$

where u_t is the unemployment rate and u^T is the threshold value. Equation (2.6) shows that the dummy variable takes a value of 1 during high unemployment periods and 0 otherwise.

The remaining blocks of the model are identical to those in Ruge-Murcia's model, with the difference of considering the average of inflation, $\tilde{\pi}_t$, instead of revised inflation, π_t. Thus, the central banker selects i_t in an effort to minimize her expected loss function that penalizes variations of unemployment and average inflation of the two types of data around target values according to

$$E_{t-1}\left(\frac{1}{2}\right)\left(\tilde{\pi}_t - \pi_t^*\right)^2 + \left(\frac{\phi}{\gamma^2}\right)\left(exp\left(\gamma\left(u_t - u_t^*\right)\right) - \gamma\left(u_t - u_t^*\right) - 1\right) \tag{2.7}$$

where $\gamma \neq 0$ and $\phi > 0$ are preference parameters, and π_t^* and u_t^* are target rates of inflation and unemployment, respectively. As in Ireland (1999) and Ruge-Murcia (2003*b*, 2004), it is assumed that π_t^* is constant denoted by π^*. The linex function characterizing unemployment allows for asymmetric preferences on unemployment by assigning different weights depending on the sign of deviations from the target in unemployment.[6] In particular, for $\gamma > 0$ positive deviations in unemployment from the target are weighted more than negative ones in the monetary authority's loss function. Also notice that the asymmetric loss function on unemployment nests the symmetric (quadratic) loss function whenever γ goes to zero. Thus, the presence of asymmetric central bank preferences on unemployment can be uncovered by running a test on whether γ is significant.

As in the model in Ruge-Murcia (2003*b*), we define ξ_t to be the 3×1 vector that contains the model's structural shocks at time t. It is assumed that ξ_t is serially uncorrelated, normally distributed with zero mean, and (possibly) exhibiting conditional

[6] The lines function was introduced by Varian (1975) in the context of Bayesian econometric analysis. More recently, Robert Nobay and Peel (2003) introduced it into the optimal monetary policy analysis.

heteroskedasticity,

$$\xi_t \;/\; I_{t-1} = \begin{bmatrix} \eta_t \\ \zeta_t \\ \epsilon_t \end{bmatrix} \Big/ I_{t-1} \to N(0, \Omega_t) \tag{2.8}$$

where Ω is a 3×3 positive-definitive variance-covariance matrix. The conditional heteroskedasticity of ξ_t relaxes the more restrictive assumption of constant conditional second moments and captures temporary changes in the volatility of structural shocks.

The unemployment level targeted by the central banker is proportional to the natural rate value according to

$$u_t^* = kE_{t-1}u_t^n \quad \text{for} \quad 0 < k \leq 1 \tag{2.9}$$

Applying a first-order Taylor series expansion to linearize this first-order condition, after some small algebra involving (2.2), (2.4) and (2.5), and using the fact that $i_t = E_{t-1}[i_t]$, one arrives at the two key econometric equations given by

$$\pi_t = a + bE_{t-1}u_t + c\sigma_{u,t}^2 + \left(1 - \lambda_g^\pi\right)(1 - I_t)\, r_t^\pi + (1 - \lambda_b^\pi)\, I_t r_t^\pi + e_{ut} \tag{2.10}$$

where $\sigma_{u,t}^2$ is the conditional variance of unemployment based on the information at time t, $r_t^\pi (= \pi_t = \pi_t^r)$ denotes the final revisions of inflation, $a = \pi^*$, $b = \phi\mu(1-k) \geq 0$, $c = \frac{\phi\mu\gamma}{2} \leq$, and e_{ut} is a reduced form disturbance, and

$$\Delta u_t = \psi - (1-\delta)u_{t-1} + \theta\Delta u_{t-1} + \zeta_t + \eta_t - \mu\epsilon_t + \delta(\mu\epsilon_{t-1} - \eta_{t-1}) + \theta(\mu\Delta\epsilon_{t-1} - \Delta\eta_{t-1}) \tag{2.11}$$

Equations (2.10) and (2.11) are an extension of the system of equations estimated by Ruge-Murcia (2003*b*, 2004). Indeed, when $\lambda_j^\pi = 1$ for all $j = g, b$ - indicating that policy monitoring focuses only on revised inflation - equation (2.10) becomes equations (3.1) in Ruge-Murcia (2003*b*). Stationary and nonstationary versions of the model can be investigated by placing different restrictions on δ. When $\delta = 1$, equation (2.11) implies that u_t is an ARIMA(1,1,2) process, while for $\delta < 1$, u_t is an ARIMA(2,0,2) process.

The coefficients associated with the conditional expectations of unemployment and the conditional unemployment volatility - $b = \phi\mu(1-k)$ and $c = \frac{\phi\mu\gamma}{2}$, respectively - are functions of deep model parameters characterizing central bank preferences (ϕ, k and γ) and the slope. of the Phillips curve, μ. Since ϕ and μ are positive parameters, the sign of c perfectly identifies the sign of γ - the asymmetric shape of central banker preferences regarding deviations in unemployment from its target. Similarly, the sign of b perfectly identifies the presence of surprise inflation à la Barro and Gordon (1983) featured by a $k \neq 1$.

Following similar reasoning, the output-inflation asymmetric preference model suggested in Cassou et al. (2012) can be extended to obtain the following bivariate system which enables the presence of an inflation bias due to inflation revisions to be assessed further:

$$\pi_t = a - bE_{t-1}uY_t + c\sigma_{Y,t}^2 + \left(1 - \lambda_g^\pi\right)(1 - I_t)\, r_t^\pi + (1 - \lambda_b^\pi)\, I_t r_t^\pi + e_{Yt} \tag{2.12}$$

$$\Delta Y_t = \psi' + (1-\delta)^2 t - (1-\delta)Y_{t-1} + \theta\Delta Y_{t-1} + \zeta_t + \eta_t + \mu\epsilon_t - \delta(\mu\epsilon_{t-1} + \eta_{t-1}) - \theta(\mu\Delta\epsilon_{t-1} + \Delta\eta_{t-1}) \tag{2.13}$$

where Y_t is output produced at time t, $\sigma_{Y,t}^2$ is the conditional variance of output at time t, and μ, η_t and ζ_t now interpret the slope of the supply curve, the supply curve disturbance term and the potential output process disturbance term, respectively. Equation (2.12) is a special case of the inflation equation derived in Cassou et al. (2016), which considered the possibility of real-time output monitoring in addition to real-time inflation monitoring. In this paper we have decided to ignore real-time output monitoring and focus on only revised output for various reasons: It enables us to focus only on the inflation bias resulting from a central banker wishing to monitor real-time inflation. This focus is rationalized because the central banker in our model is able to exercise direct control over inflation, whereas its control over output (unemployment) is exercised indirectly through the aggregate supply (Phillips curve) in the inflation-output (inflation-unemployment) model. It also enables a more straightforward comparison to be made with the extended unemployment-inflation model, where unemployment revisions are ignored since they are small and mostly due to seasonal statistical adjustments, as emphasized above. Furthermore, the possibility that output revisions may behave differently depending on whether the economy is performing well or bad as suggested in Cassou et al. (2016) might be hard to distinguish from a central banker preference asymmetry à la Ruge-Murcia (2003*b*, 2004). In short, the presence of two type of asymmetry associated with deviations in output from its target can be difficult to identify separately.

We now describe the econometric strategy followed in this paper to estimate the bivariate models (2.10)-(2.11) and (2.12)-(2.13), and then discuss the empirical results.

2.4 Estimation strategy and empirical results

This section discusses the estimation approach considered and the empirical results. To keep things organized and clear, we have broken the section down into six subsections: the first describes the sources of the data. The second subsection studies the inflation revision series. Here, among other things, we show that inflation revisions processes are predictable. As noted by Croushore (2011) and emphasized above, this is a necessary condition for real-time data to have an effect on policy decision making. Third, we report tests results providing support for conditional volatility in both the unemployment and output time series for the US and the UK, which is a necessary condition for having asymmetric central bank preferences à la Ruge-Murcia. Fourth, we address the issue of estimating an unobservable unemployment threshold. Fifth, we show the (CML) estimation results of the two bivariate empirical models given by equations (2.10) and (2.11) and equations (2.12) and (2.13) for the two countries. The last subsection shows two tests for further assessment of real-time inflation monitoring.

2.4.1 Data

To estimate the two empirical models revised and real-time data for inflation are needed as well as data for the unemployment rate and output. The US revised data used here include, the quarterly GDP deflator, the unemployment rate and Gross Domestic Product (GDP). These series were obtained from the Federal Reserve Economic Data (FRED) base maintained by the ST. Louis Federal Reserve Bank. The real-time GDP deflator time series was obtained from the real-time data bank maintained by the Philadelphia Federal Reserve Bank (Croushore and Stark 2001).

UK revised data were taken from the OECD database and the real-time UK GDP deflator time series was taken from the OECD time database. Because the models require inflation rates rather than price indexes, the inflation rates were obtained as the first difference of the log of the GDP deflator, which was then multiplied by 4 to obtain annualized rates.

Table 2.1: Estimation of inflation revision processes

Countries	US		UK	
	linear	non-linear	linear	non-linear
Estimated threshold		7.4		2.7
Constant-low unemp.	0.398***	0.494***	2.14***	5.837***
	(0.103)	(0.117)	(0.482)	(1.041)
Constant-high unemp.		0.137		0.871*
		(0.205)		(0.537)
AR(1)-low unemp.			-0.26***	-0.36***
			(0.067)	(0.086)
AR(1)-high unemp.				-0.136*
				(0.092)
Real-time π low unemp.	-0.084***	-0.12***	-0.332***	-0.583***
	(0.024)	(0.028)	(0.06)	(0.083)
Real-time π high unemp.		0.009		-0.15**
		(0.046)		(0.079)
F statistic		3.29		8.72

Notes: *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

The sample periods considered for the two countries in our empirical analysis are determined by the availability of real-time inflation data. Thus, we consider US data from the first quarter of 1866 and UK data from the first quarter of 1968. Although data that is called revised data was available up to 2017:1 when we started to carry out our empirical analysis, the earlier end data for the long sample was chosen so as to be consistent with the timing of the last revisions for the data, ignoring any comprehensive or benchmark revisions that may be carried out in the future. In particular, there are three-year lag before GDP and the GDP deflator are revised for the last time. This lag means that only the data up to 2013:4 can be considered as truly revised data.

As emphasized above, having predictable inflation revision processes is a necessary condition for real-time data affecting policy decision making. Hence, we now study the features of inflation revision processes.

2.4.2 Properties of inflation revision processes

Before estimating the empirical models, we carried out a preliminary analysis of the inflation revisions processes for the US and the UK in order to determine (i) whether revisions of inflation are white noise; and (ii) whether inflation revisions processes look different depending on whether the economy is doing well or not. This analysis is important because if revisions are unpredictable then, as noted in Croushore (2011) and elsewhere, the distinction between real-time and revised inflation data would not be an issue as long as revisions are not large.

For the US and the UK, we estimate linear and nonlinear models of inflation revisions. The estimated linear model is an AR(4) augmented with real-time inflation as an explanatory variable:

$$r_t^{\pi} = \beta_0 + \sum_{k=1}^{4} \beta_k r_{t-k}^{\pi} + \psi \pi_t^r + u_t \tag{2.14}$$

Using the Bayesian Information Criterion (BIC) as a guide we choose the best linear model. For the US the best fitting model implies that $\beta_k = 0$ for all k, whereas for the UK the best fitting model is an AR(1) augmented with real-time inflation. Based on these linear models, we estimate a threshold model augmented with real-time inflation as an explanatory variable:

$$r_t^{\pi} = \beta_0 I_t + \beta_1 I_t r_{t-1}^{\pi} + \psi I_t \pi_t^r + \beta_0'(1 - I_t) + \beta_1'(1 - I_t) r_{t-1}^{\pi} + \psi'(1 - I_t)\pi_t^r + \epsilon_t \tag{2.15}$$

where we assume that I_t is a dummy indicating the strength of the economy at period t given by (2.6). The threshold, u^T, is endogenously chosen so as to obtain the best fit. Moreover, in line with the best fitting linear model, we assume $\beta_1 = \beta_1' = 0$ for the US.

Table 2.1 shows the results of this investigation into whether the various revisions processes are predictable. In order to save space, the estimates of the linear model coefficients are displayed in the same row as the coefficients of the nonlinear model associated with low unemployment rate periods -i.e. $I_t = 0$. Table 2.1 shows that the coefficients of real-time inflation are highly significant in the two countries.Moreover, the first-lag of inflation revisions is also significant in the UK, The nonlinear model basically reproduces the results of the linear model when the unemployment rate is below its threshold. However, inflation revisions behave rather differently when the unemployment rate is above its threshold. Thus, US inflation revisions do not display any structure -all coefficients are non-significant-, which suggests that real-time inflation is a rational predictor of revised inflation in high unemployment periods. In contrast, UK real-time inflation also marginally anticipates inflation revisions when the unemployment rate is high.

Table 2.2: LM tests for neglected ARCH

Panel A: Unemployment							
				No. of lags			
Squared residuals	Country	1	2	3	4	5	6
Original	US	15.89***	23.31***	23.65***	23.62***	23.48***	23.6***
	UK	15.77***	16.52***	16.46***	16.34***	16.36***	17.72***
Standardized	US	0.14	0.3	0.36	0.53	3.07	8.49
	UK	0.62	0.9	0.9	1.11	2.78	5.31
Panel B: Output							
				No. of lags			
Squared residuals	Country	1	2	3	4	5	6
Original	US	1.34	6.23**	6.15	9.93**	10.79*	10.85*
	UK	15.6***	17.37***	20.82***	20.62***	20.99***	21.74***
Standardized	US	0.51	0.6	0.6	0.94	2.45	3.39
	UK	1.45	2.16	2.17	2.22	2.11	3.17

Notes: *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

The test to determine whether this model fits no better than the linear model, as indicated by the row labeled F-statistic, has an F-statistic of 3.290 for the US, which is lower than the 10% critical value of 4.706, so this null hypothesis cannot be rejected. Notice that these test results are somewhat in contrast with the different estimated coefficients of real-time inflation found above and below the unemployment threshold.[7] For the UK, the F-statistic is 8.735, which is above the 5% critical values of 4.419, so the null hypothesis is easily rejected.

There are two issues associated with the estimation of the inflation-unemployment model and the inflation-output model given by equations (2.10) and (2.11) and equations (2.12) and (2.13), respectively. First, the conditional variances entering into the inflation equations in the two models -equations (2.10) and (2.12) - are hard to identify for two reasons. Namely, they are identified only if they are not constant. Moreover, they cannot be observed directly, so they have to be estimated. Second, the unemployment threshold defined in (2.6) cannot be observed directly either. These two issues are addressed below.

2.4.3 Conditional volatility of output and unemployment

Following Ruge-Murcia (2003*b*) and others, we first perform neglected ARH tests to check whether there is conditional volatility in both the unemployment and output time series. Here the residuals from a four-lag VAR -a time trend is also included in the case of output -were collected. These residuals were then squared and an regression was run on a constant and one to six lags. These test statistics have χ_1^2 distribution, where q is the number of lags.

Then, the two conditional variances -$\sigma_{u,t}^2$ and $\sigma_{Y,t}^2$ - were estimated using a parsimonious (1,1) model. Following the line of argument in Pagan and Ullah (1988) and Ruge-Murcia (2003*b*), if we wish to use these estimates as generated regressors in equations (2.10) and (2.12), we first have to verify that the ARCH model chosen is correctly specified. A standard misspecification test for ARCH models is the LM test for neglected ARCH described above, but applied to the standardized squared residuals -i.e. the residuals corrected for heteroskedasticity. That is, if the ARCH model is correctly specified, then the standardized squared residuals must be serially uncorrelated.

Table 2.2 contains the results of various neglected ARCH tests. This table is broken down into two panel (Panels A and B), which show the results for unemployment and output series, respectively. In each panel, the first two rows show the results using the original series for the US and the. UK. The last two rows show the results using the standardized residuals from the Generalized autoregressive conditional heteroskedasticity model (GARCH)(1,1) model for the two countries. Theses results show evidence that the original unemployment an output series do have conditional heteroskedasticity, while the two conditional variance series do not.

We now examine the issue of estimating the unemployment threshold.

2.4.4 Unobservable unemployment threshold

To address the issue of dealing with an unobservable unemployment threshold, we first estimate each of the two models for alternative values of the unemployment threshold using a constrained maximum likelihood (CML) procedure on a predefined grid interval for

[7] The critical values do not come from a conventional F distribution table. We computed the critical values by using the bootstrap simulation procedure describe in Hansen (1997), which showed that the F-statistics in TR models do not have standard F distributions and that. proper critical values can be found using a bootstrap procedure.

each country. The model specification with the largest log-likelihood value thus provides the estimated unemployment threshold and the remaining parameter estimates. The threshold unemployment grid intervals considered for the US and the UK are defined by the vectors (6.2, 7.8, 0.1) and (6.5, 8.5, 0.1), respectively, where the first two components denote the lower and upper bounds.

2.4.5 Empirical results

Table 2.3: CML estimation results

Countries	US		UK	
	Unemployment	Output	Unemployment	Output
Threshold	7.4	7.4	7.3	8.4
Bad times/total	48/184	48/183	51/174	37/175
a	3.193***	1.909***	5.108***	3.139***
	(0.207)	(0.178)	(0.58)	(0.42)
c	5.421***	2.628***	2.542**	2.767***
	(2.057)	(0.326)	(1.525)	(0.469)
λ_g^π	1	1	0.441***	0.565***
	-	-	(0.136)	(0.084)
λ_b^π	0.047	0	0.563***	0.392***
	(0.402)	-	(0.103)	(0.106)
Log-likelihood	-424.852	259.68	-464.793	77.238

Note: Standard errors in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors of estimated parameters of λ_j^π reaching corner points cannot be reported.

This subsection discusses the empirical results. In order to simplify the exposition, we focus our discussion on the empirical results for the case of $\delta = 1$. Thus, equations (2.11) and (2.13) imply that u_t and Y_t are both ARIMA(1,1,2) processes.[8] Table 2.3 shows the maximum likelihood estimation results of the unemployment-inflation and the output-inflation models for the US (left panel) and the UK (right panel). In each panel, unemployment model results are displayed in the left column and output model results in the right column. The first row of Table 2.3 shows the unemployment thresholds that maximize the log-likelihood function in each case. Interestingly, the estimated unemployment threshold is the same at 7.4 in the two models for the US. However, for the UK the estimated threshold of the unemployment rate is higher (8.4) in the output model than in the unemployment model (7.3), which is similar to the estimated value in the US.

Several noteworthy conclusions emerge from Table 2.3.[9] Namely, the two models provide evidence of a strong asymmetric Fed monitoring of real-time inflation depending

[8]Similar results are found if $\delta < 1$ is assumed, i.e. if equations (2.11) and (2.13) imply that u_t and Y_t are both ARIMA(2,0,2) processes. Estimation results under the alternative assumption are available from the authors upon request.

[9]Preliminary CML estimates ob the bivariate models (2.10)-(2.11) and (2.12)-(2.13) always result in a corner estimate $b = 0$, which implies $k = 1$, indicating the absence of surprise inflation à la citebarro. Hence, we do not report the corner estimate $b = 0$ in Table 2.3.

on the state of the economy. Thus, the corner estimates of $\lambda_g^\pi = 1$ suggest that the Fed only monitors revised inflation during "good economic times" when unemployment is low. However, the Fed focuses only on real-time inflation, $\lambda_b^\pi \approx 0$, when unemployment is high -i.e. above the estimated unemployment rate threshold. The finding that the Federal Reserve mainly focuses on real-time inflation during "bad economic times" may reflect the need to react quickly to the initial announcements of inflation in these periods due to poltical pressures, but may also reflect the fact that real-time inflation data is a less noisy predictor of revised inflation in high-unemployment periods than in low-unemployment periods, as shown in Table 2.1 above.

In contrast to the US, the estimated inflation weights for the UK indicate that the Bank of England uses a roughly equally-weighted-average of revised and real-time inflation when monitoring inflation-that is $\lambda_g^\pi \approx \lambda_b^\pi \approx 0.5$. Moreover, this feature is fairly robust across the two bivariate models in the UK. The absence of asymmetric monitoring in the case of the Bank of England is also in line with the absence of a non-linear patter in UK inflation revisions, as shown in Table 2.1.

The estimated positive value of c also provides additional support for the findings in Ruge-Murcia (2003*b*), Cassou et al. (2012) and Cassou and Vázquez (2014), supporting the hypothesis that the Federal Reserve takes stronger action when the rate of unemployment (output) is above (below) its natural rate (potential level) than when it is below (above). in the case of the Bank of England, the significance of c is somewhat sensitive across models. Thus, the null hypothesis $c = 0$ is weakly rejected at the 10% significance level in the unemployment model, which is in line with the findings in Ruge-Murcia (2004). However, this null hypothesis is strongly rejected in the output model, which provides evidence that the Bank of England takes stronger action when output is below its potential level than when it is above.

We now formally test the hypothesis of real-time inflation monitoring for the two central banks.

2.4.6 Tests of real-time inflation monitoring

Although estimation results suggest that $\lambda_g^\pi \neq \lambda_b^\pi$ for the US and $\lambda_g^\pi = \lambda_b^\pi$ for the UK, a formal test of the null hypothesis $\lambda_g^\pi = \lambda_b^\pi$ can be rather cumbersome in the contest of the bivariate models and the CML estimation approach followed above because the conventional critical values are not useful when the threshold is estimated. Fortunately, this test can be easily implemented in our estimated model because the CML estimates imply that $b = 0$. Hence, we can use ordinary least squares (OLS) to estimate the single-equation models (2.10) and (2.12) by imposing $b = 0$:

$$\pi_t = a + c\sigma_{u,t}^2 + \left(1 - \lambda_g^\pi\right)(1 - I_t)r_t^\pi + (1 - \lambda_b^\pi)I_t r_t^\pi + e_{ut} \tag{2.16}$$

$$\pi_t = a + c\sigma_{Y,t}^2 + \left(1 - \lambda_g^\pi\right)(1 - I_t)r_t^\pi + (1 - \lambda_b^\pi)I_t r_t^\pi + e_{Yt} \tag{2.17}$$

and considering the estimated threshold values obtained from the CML of the bivariate models. Similarly, a test of the (un)importance of inflation revisions (i.e. $H_o : \lambda_g^\pi = \lambda_b^\pi = 1$) can be implemented.

Table 2.4: OLS estimation results

Countries	US		UK	
	Unemployment	Output	Unemployment	Output
Threshold	7.4	7.4	7.3	8.4
Bad times/total	48/184	48/184	51/176	37/176
a	3.233***	1.894***	4.796***	3.210***
	(0.227)	(0.219)	(0.632)	(0.386)
c	5.171***	2.684***	3.807*	2.696***
	(1.960)	(0.261)	(1.955)	(0.240)
$1-\lambda_g^\pi$	0.020	-0.071	0.504**	0.600***
	(0.240)	(0.194)	(0.211)	(0.197)
$1-\lambda_b^\pi$	0.746*	1.033***	0.555***	0.438***
	(0.407)	(0.326)	(0.085)	(0.063)
F-stat: $\lambda_g^\pi = \lambda_b^\pi$	2.387	8.509	0.052	0.607
	[6.404,10%]	[7.959,5%]	[6.134,10%]	[6.092,10%]
F-stat: $\lambda_g^\pi = \lambda_b^\pi = 1$	1.682	5.096	24.435	28.789
	[4.044,10%]	[4.899,5%]	[6.754,1%]	[6.714,1%]

Note: Standard errors in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Each term in brackets below the F-statistics contains two entries: the first indicates the critical value obtained using Hansen (1997) bootstrapping procedure whereas the second shows the associated significance level.

Table 2.4 shows the estimation results of the two univariate models of inflation (2.16) and (2.17) for the two countries. A comparison of Table 2.3 and Table 2.4 shows that the two econometric approaches lead to rather robust results. The test of the null hypothesis $\lambda_g^\pi = \lambda_b^\pi$, as indicated by the row labeled F-statistic: $\lambda_g^\pi = \lambda_b^\pi$ in Table 2.4, shows an F-statistic of 2.387 for the US using the univariate model (2.16), which is lower than the 10% critical value of 6.404, implying that the null hypothesis of symmetry cannot be rejected. Howerver, an F-statistic of 8.509 using the conditional variance of output as a regressor in the model (2.17), which is larger than the 5% critical value of 7.959, indicates that the threshold model clearly fits better than the linear model.[10] Furthermore, the low values of the F-statistics for the two UK univariate models clearly indicate the non-rejection of this null hypothesis.

A test of the hypothesis positing the absence of inflation bias due to inflation data revisions: $\lambda_g^\pi = \lambda_b^\pi = 1$, as indicated by the row labeled F-statistic: $\lambda_g^\pi = \lambda_b^\pi = 1$ in Table 2.4, shows that this null hypothesis cannot be rejected at any standard significance level for the US using the univariate model (2.16). However, an F-statistic of 5.096 using the conditional variance of output as a regressor in the model (2.17), which is larger than te 5% critical value of 4.899, suggests the presence of inflation bias due to inflation data revisions. The evidence against the null hypothesis $\lambda_g^\pi = \lambda_b^\pi = 1$ is much stronger for the UK.

[10] Again, critical values are computed using Hansen (1997) bootstrapping procedure.

2.5 Analysis of other Central Banks

We extend the analysis to a larger number of countries. Specifically, we include two European countries that are outside the European Monetary Union: Sweden and Denmark; and three non-european countries: Australia, New Zealand and Canada. The revised inflation and output data series of the counties included in this extension were taken from the OECD database and the real-time deflator time series was taken from the OECD time database. Because the models require inflation rates rather than price indexes, the inflation rates were obtained as the first difference of the log of the GDP deflator, which was then multiplied by 4 to obtain annualized rates. The sample periods for each country are determined by the availability of real-time inflation data. The starting period for Denmark is the most recent period considered, starting at the third-quarter of 1995, and therefore is the smallest sample included in this analysis. All the data is considered up to 2013:4 in order to have truly revised data. Table 2.5 shows the main results obtained for those six countries.

Table 2.5: Summary of the main results

Countries	Non-linear revisions	Heterosked.	Sym. targeting in good and bad times	Hyp. no RT targeting
Australia	Yes	Output model	Not rejected	Rejected
Switzerland	Yes	Output model	Not rejected	Rejected
Canada	Yes	Unemp. model	Not rejected	Rejected
New Zealand	Yes	Output model	Not rejected	Rejected
Sweden	No	Output model	Not rejected	Not rejected
Denmark	Yes	None	Rejected	Rejected

As shown in the summary Table 2.5 of the main results of the extended empirical analysis, the absence of real-time data targeting is rejected for all countries but for Sweden. The revisions of Sweden seem not to display a non-linearity and this can be the source of the finding of no real-time data inclusion in the decision making of the Swedish Central Bank policy. However, the rest of the countries of our analysis seem to take into account real-time data targeting in good or/and bad economic times in their decision making process. In order to distinguish furthermore the sources of those differences in the targeting rules of the Central Banks we will discuss the steps of the analysis more in deep in the next lines.

Table A.1 shows the results of the analysis of the predictability of the revisions processes for each country. As mentioned above, in order to save space the estimates of the linear model coefficients are displayed in the same row as the coefficients of the nonlinear model associated with low unemployment rate periods -i.e. when the dummy is $I_t = 0$. Table A.1 shows that the coefficients of real-time inflation are highly significant in all the countries. The first-lag of inflation revision is also significant for Australia, New Zealand, Canada and Denmark, as happened for UK. Therefore, we conclude that the distinction of real-time and revised inflation data for those countries is crucial. The test to determine whether this model fits no better than the linear model, as indicated by the row labeled F-statistic, shows that with a F-statistic of lower than the 10% critical value of 4.706, this null hypothesis cannot be rejected for Australia, New Zealand, Sweden and Denmark. However, it seems that we cannot reject this hypothesis for Canada.

Table A.2 displays the results for the LM test. Maintaining the structure of the previous analysis, the table is divided in two Panels: Panel A above shows the results from the unemployment model and Panel B from the output model. Each Panel is divided in two sections. The first five rows show the results using the original series for each country. The last five rows of each panel show the results using the standardized residuals from the GARCH(1,1) model. These results show evidence that the original unemployment series shows heteroskedasticity in Canada. However, the output series show heteroskedasticity for the rest of the countries: Australia, New Zealand, Canada, Sweden and Denmark.

As for US and UK we estimate the unobservable unemployment threshold using a CML procedure on a grid interval for each country. The model specification with the largest log-likelihood values is chosen as the unemployment threshold and the remaining parameters. Table A.3 shows the results for this analysis. It is divided in two panels, above the results from the output analysis and below the results from the unemployment model. The two models provide evidence of a strong asymmetric monitoring of real-time inflation depending on the state of the economy in Australia in New Zealand. In contrast to these results, the Central Banks of Canada, Denmark and Sweden seems to put more weight in the targeting of revised data independently of the state of the economy. However, as happened for the UK, there is evidence of an equally-weighted average of real-time and revised inflation targeting for Sweden during the business cycle. The Bank of Canada and the National Bank of Denmark seem to put more weight on real-time data targeting during good times and it only targets revised data during bad economic times. Those results are consistent in both specifications of the model.

Comparing Table A.3 and Table A.4 leads to rather robust results. The test of the null hypothesis of symmetric inflation targeting, indicated by the row labeled F-statistic: $\lambda_g^\pi = \lambda_b^\pi$, cannot be rejected for Australia, New Zealand, Canada and Sweden. However, Denmark with a F-statistic of 14.658, which is larger than the 1% critical value of 12.055, indicates that the threshold model clearly fits better than the linear model. The results of the test of the absence of inflation bias due to inflation data revisions, shown in the row labeled F-statistic: $\lambda_g^\pi = \lambda_b^\pi = 1$, with a F-statistic larger than the 1% critical value, suggest that there is real-time inflation targeting in Australia, New Zealand, Canada and Denmark. The null hypothesis of non real-time inflation targeting cannot be reject for Sweden with a F-statistic of 1.213 using the conditional variance of output as a regressor in the model (2.17), which is lower than te 10% critical value of 4.096. The results are robust under the two univariate models of inflation (2.16) and (2.17) for the all the countries.

These results suggest that the importance of real-time inflation monitoring may reflect whether the inflation revisions are well behaved (i.e. whether real-time inflation is a rational forecast of revised inflation). As we have seen, for the US, Australia and New Zealand, the importance of real-time inflation monitoring increases in bad times (i.e. when the rates of unemployment are high), which are characterized by well-behaved inflation revisions (i.e. intercepts and lagged real-time inflation have no explanatory power on inflation revisions). Meanwhile, inflation monitoring mainly focus on revised inflation in good times (i.e. when the rates of unemployment are low) when inflation revisions are not well behaved.

In contrast, inflation revisions in Canada behave better in good times than in bad times. The estimation results of the Canadian inflation equation suggest that real-time inflation monitoring is more important in good times than in bad times, also providing support to the hypothesis stated above. For Sweden, inflation revisions behaved poorly both in good and bad times. Estimation results of the Swedish inflation equation show that real-time inflation monitoring is not important at any time in this country, which also supports the hypothesis.

Finally, the hypothesis cannot be tested for the two remaining countries in this analysis (UK and Denmark). The reason is that the estimated thresholds of the unemployment rate in the inflation revision equation and the inflation equation are very different to each other in order to establish a relationship between the quality of inflation revisions and real-time inflation monitoring. In order to test the hypothesis we re-estimate the CML model using the thresholds that better define the revision processes in theses countries (displayed in Table 2.1 and Table A.1).

Table 2.6: CML estimation results with the revision process threshold: UK and Denmark

Panel: Unemployment	UK	DENMARK	Panel: Output	UK	DENMARK
Threshold	2.7	7.3	Threshold	2.7	7.3
Bad times/total	151/174	12/66	Bad times/total	151/173	12/67
a	5.233***	1.951***	a	3.287***	1.949***
	(0.577)	(0.214)		(0.413)	(0.209)
c	2.035	0	c	2.606***	0
	(1.672)	(0)		(0.463)	(0)
λ_g^π	0.64***	0.704***	λ_g^π	0.713***	0.69***
	(0.167)	(0.236)		(0.098)	(0.236)
λ_b^π	0.275**	0.192	λ_b^π	0.367***	0.293
	(0.141)	(0.297)		(0.113)	(0.267)
Log-likelihood	-462.143	-149.582	Log-likelihood	80.132	77.147

Note: Standard errors in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.6 shows the results for UK and Denmark for both models, unemployment and output, respectively. The estimation results provide evidence of a strong asymmetric monitoring of real-time inflation depending on the state of the economy in UK and Denmark. The Bank of England and the National Bank of Denmark mainly focus on real-time inflation during "bad economic times" and they focus on mainly revised data on good economic times. As happened for US, this may reflect a need to react quickly to bad news. Thus, political pressures can also induce asymmetric central bank responses to inflation in real-time decisions making. As a result, the importance of an inflation bias induced from the differences between revised an real-time inflation data, as in the traditional inflation bias sources suggested by Barro and Gordon (1983) and Ruge-Murcia (2003*b*, 2004), is likely to be a consequence of the degree of central bank independence, which can differ from country to country.

2.6 Conclusion

This paper adds to the growing body of literature on monetary policy and real-time data analysis. Here, we show how to extend the Ruge-Murcia (2003*b*) type of asymmetric monetary planning models to study real-time issues faced by a central banker. By assuming that the central banker aims at monitoring a weighted average of both revised and real-time inflation data, our model identifies another source of inflation bias due to inflation revisions in addition to that featured by asymmetric central bank preferences as suggested by Ruge-Murcia (2003*b*). This analysis is implemented by estimating two parallel models. In one case, we estimate a bivariate inflation-unemployment model and in the other we estimate a bivariate inflation-output model.

The two models are estimated by implementing a constrained maximum likelihood procedure and considering several countries data. Our empirical results suggest that the Federal Reserve focuses only on monitoring revised inflation during low unemployment periods, but focuses heavily on real-time inflation during high unemployment periods, inducing an important source of inflation bias. This asymmetric attention in regards to real-time inflation may be related to the long lags associated with the final revised inflation releases and pundits or public opinion. The Reserve Banks of Australia and New Zealand seems to follow closely the targeting policy of the Fed, but they also consider revised data when the unemployment is high.

In contrast to these findings, the Bank of England seems to use a roughly equally-weighted-average of real-time and revised inflation when monitoring the deviations of this average from its inflation target. The Central Banks of Canada and Denmark however, seem to weight less more heavily revised data during bad economic times. However, when the economy is doing well they seem to put more weight on real-time inflation targeting. On the other hand, the results for Sweden suggest an absence of real-time data targeting.

Moreover, the empirical results in the US show that the inflation bias induced by asymmetric central banker preferences in our augmented model with data revisions remains significant. However, this empirical evidence is not as clear-cut in the UK. Overall, these results reinforce those found by Ruge-Murcia (2003*b*, 2004) using revised unemployment and inflation data and by Cassou et al. (2012) using output and inflation data.

Our analysis also tentatively suggests a relationship between the quality of the initial announcements of inflation as a predictor of final revised inflation and the weight given to real-time inflation in the policy function. Thus, US, Australia and New Zealand seem to focus only on real-time inflation during bad economic times, but also when real-time inflation is a rational predictor of inflation. However, the Central Bank of Sweden seems to focus only on revised inflation, as real-time inflation seems not to be a rational predictor of revised inflation. For the rest of the countries, UK and Denmark, the empirical evidence -including a threshold that better characterizes the revision processes- supports this relationship. Needless to say that this relationship is suggestive and further research is warranted.

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Analysis of other countries

Table A.1: Estimation of inflation revision processes

Countries	AUSTRALIA	
	linear	non-linear
estimated threshold		8.5
constant-low unemp.	1.748***	2.037***
	(0.326)	(0.363)
constant-high unemp.		0.47
		(0.836)
AR(1)-low unemp.	-0.33***	-0.326***
	(0.058)	(0.059)
AR(1)-high unemp.		-0.363*
		(0.238)
Real-time π low unemp.	-0.311***	-0.332***
	(0.043)	(0.045)
Real-time π high unemp.		-0.177
		(0.197)
F statistic		1.117

Countries	NEWZEALAND	
	linear	non-linear
estimated threshold		8.1
constant-low unemp.	0.842***	0.989***
	(0.33)	(0.353)
constant-high unemp.		-0.208
		(0.864)
AR(1)-low unemp.	-0.32***	-0.392***
	(0.077)	(0.082)
AR(1)-high unemp.		0.102
		(0.206)
Real-time π low unemp.	-0.363***	-0.363***
	(0.072)	(0.073)
Real-time π high unemp.		-0.084
		(0.298)
F statistic		2.118

Countries	CANADA	
	linear	non-linear
estimated threshold		10.6
constant-low unemp.	0.776***	0.523***
	(0.191)	(0.2)
constant-high unemp.		2.018***
		(0.439)
AR(1)-low unemp.	0.122*	0.169**
	(0.079)	(0.093)
AR(1)-high unemp.		-0.156
		(0.141)
Real-time π low unemp.	-0.245***	-0.16***
	(0.046)	(0.049)
Real-time π high unemp.		-0.622***
		(0.1)
F statistic		6.021

Countries	SWEDEN	
	linear	non-linear
estimated threshold		9
constant-low unemp.	1.662***	1.647***
	(0.24)	(0.266)
constant-high unemp.		1.794***
		(0.681)
AR(1)-low unemp.	-0.034	-0.035
	(0.027)	(0.029)
AR(1)-high unemp.		-0.039
		(0.088)
Real-time π low unemp.	-0.987***	-0.988***
	(0.028)	(0.03)
Real-time π high unemp.		-0.962***
		(0.114)
F statistic		0.031

Countries	DENMARK	
	linear	non-linear
estimated threshold		7.3
constant-low unemp.	1.325***	1.408***
	(0.273)	(0.291)
constant-high unemp.		0.797
		(1.045)
AR(1)-low unemp.	-0.154*	-0.198**
	(0.096)	(0.103)
AR(1)-high unemp.		0.136
		(0.329)
Real-time π low unemp.	-0.525***	-0.549***
	(0.092)	(0.097)
Real-time π high unemp.		-0.355
		(0.345)
F statistic		0.701

Table A.2: LM Tests for neglected ARCH

Panel A: Unemployment							
		No. of lags					
Squared residuals	Country	1	2	3	4	5	6
Original	AUSTRALIA	1.66	1.9	1.87	5.19	5.91	6.45
	NEWZEALAND	1.02	2.92	5.16	5.15	8.84	8.2
	CANADA	4.55**	5.34*	7.41*	7.51	7.44	7.53
	SWEDEN	2.17	3.14	3.47	3.61	3.7	3.89
	DENMARK	0.01	0.17	3.27	3.47	3.82	3.66
Standardized	AUSTRALIA	-	-	-	-	-	-
	NEWZEALAND	-	-	-	-	-	-
	CANADA	0.39	1.15	1.24	3.8	3.87	8.52
	SWEDEN	-	-	-	-	-	-
	DENMARK	-	-	-	-	-	-

Panel B: Output							
		No. of lags					
Squared residuals	Country	1	2	3	4	5	6
Original	AUSTRALIA	3.27*	5.31*	9.07**	9.79**	11.08**	11.11*
	NEWZEALAND	1.71	0.47	2.45	2.37	5.22	29.68***
	CANADA	1.37	1.47	2.61	1.95	2.26	2.44
	SWEDEN	0.27	1.58	13.39***	13.27**	12.98**	14.64**
	DENMARK	0.04	0.14	1.54	2.01	2.42	2.39
Standardized	AUSTRALIA	0.18	0.74	0.52	1.7	1.75	1.75
	NEWZEALAND	0	0.01	0.71	1.15	1.39	2.41
	CANADA	-	-	-	-	-	-
	SWEDEN	0.02	0.87	2.83	2.79	2.99	3.26
	DENMARK	-	-	-	-	-	-

Table A.3: CML estimation results

Panel: Output					
Countries	AUSTRALIA	NEWZEALAND	CANADA	SWEDEN	DENMARK
Threshold	7.4	7.3	10.4	9.1	5.7
Bad times/total	55/182	21/90	21/122	7/74	22/66
a	1.114**	2.087***	2.402***	1.553***	1.862***
	(0.512)	(0.357)	(0.263)	(0.245)	(0.234)
c	5.239***	0	0	0	0
	(0.627)	-	(0)	(0)	(0)
λ_g^π	0.775***	0.619***	0.548***	0.951***	0.379***
	(0.102)	(0.169)	(0.219)	(0.024)	(0.089)
λ_b^π	0.35***	0.217*	0.92***	0.838***	1
	(0.135)	(0.138)	(0.321)	(0.077)	-
Log-likelihood	81.066	45.512	154.435	-155.985	-144.812

Panel: Unemployment					
Countries	AUSTRALIA	NEWZEALAND	CANADA	SWEDEN	DENMARK
Threshold	6.9	8	9.5	10.2	5.7
Bad times/total	61/182	17/94	36/122	2/74	22/66
a	5.477***	2.06***	2.394***	1.171*	1.862***
	(0.351)	(0.346)	(0.257)	(0.872)	(0.234)
c	0	0	0	5.613	0
	(0)	(0)	-	(15.07)	(0)
λ_g^π	0.804***	0.626***	0.463**	0.961***	0.379***
	(0.128)	(0.159)	(0.247)	(0.027)	(0.089)
λ_b^π	0.28**	0.068	0.913***	0.774***	1
	(0.149)	(0.145)	(0.176)	(0.064)	-
Log-likelihood	-563.63	-275.577	-305.023	-159.046	-144.812

Table A.4: OLS estimation results

Panel: Output					
Countries	AUSTRALIA	NEWZEALAND	CANADA	SWEDEN	DENMARK
Threshold	7.4	7.3	10.4	9.1	5.7
Bad times/total	55/182	20/90	20/122	7/74	22/66
a	1.155**	3.283	2.349***	2.123***	1.887***
	(0.554)	(4.2)	(0.256)	(0.732)	(0.244)
c	5.198***	-13.076	0	-0.806	0
	(0.57)	(45.375)	(0)	(0.908)	(0)
$1-\lambda_g^\pi$	0.24***	0.358***	0.529***	0.041*	0.627***
	(0.085)	(0.14)	(0.171)	(0.028)	(0.123)
$1-\lambda_b^\pi$	0.703***	0.843***	0.249	0.063	-0.214
	(0.194)	(0.281)	(0.28)	(0.188)	(0.184)
F-stat: $\lambda_g^\pi = \lambda_b^\pi$	4.782	2.353	0.737	0.014	14.658
	[6.261,10%]	[6.183,10%]	[5.914,10%]	[6.416,10%]	[12.055,1%]
F-stat: $\lambda_g^\pi = \lambda_b^\pi = 1$	10.665	8.123	5.235	1.213	14.175
	[6.81,1%]	[6.988,1%]	[6.526,1%]	[4.096,10%]	[7.222,1%]

Panel: Unemployment					
Countries	AUSTRALIA	NEWZEALAND	CANADA	SWEDEN	DENMARK
Threshold	6.9	8	9.5	10.2	5.7
Bad times/total	61/182	17/94	35/122	2/74	22/66
a	5.474***	2.062***	2.394***	1.458***	1.887***
	(0.351)	(0.364)	(0.286)	(0.237)	(0.244)
c	0	0	-303.796	0	0
	(0)	(0)	(1107.753)	(0)	(0)
$1-\lambda_g^\pi$	0.214**	0.375***	0.586***	0.042*	0.627***
	(0.104)	(0.133)	(0.18)	(0.027)	(0.123)
$1-\lambda_b^\pi$	0.684***	0.939***	0.204	-24.405**	-0.214
	(0.219)	(0.24)	(0.249)	(13.969)	(0.184)
F-stat: $\lambda_g^\pi = \lambda_b^\pi$	3.751	4.222	1.572	3.063	14.658
	[6.233,10%]	[6.073,10%]	[5.955,10%]	[6.338,10%]	[12.055,1%]
F-stat: $\lambda_g^\pi = \lambda_b^\pi = 1$	7.064	11.883	5.686	2.858	14.175
	[6.756,1%]	[6.792,1%]	[6.587,1%]	[4.03,10%]	[7.222,1%]

Risk news, financial frictions and the Spanish recession

"These senior claims were supposed to be very low-risk; after all, how likely was it that a large number of people would default on their mortgages at the same time? The answer, of course, is that it was quite likely in an environment where homes were worth 30, 40, 50 percent less than the borrowers originally paid for them. So a lot of supposedly safe assets, assets that had been rated AAA by Standard & Poor's or Moody's, ended up becoming "toxic waste", worth only a fraction of their face value."

– Paul Krugman *End This Depression Now!*

3.1 Abstract

After the recent banking crisis in 2008, financial market conditions have turned out to be a relevant factor for economic fluctuations. This paper provides a quantitative assessment of the impact of financial frictions on the Spanish economy. We augment the model of Christiano et al. (2010, 2014) to a small economy model with a banking sector able to diversify portfolio choices between loans and risk-free German bonds (Bunds). Our model also includes, the inflation differential between Spain and the European Monetary Union (EMU) in order to quantify the influence of the implementation of the single monetary policy in Spain. Our results show that anticipated risk shocks, measured as the volatility of idiosyncratic uncertainty in the financial sector, are key in the evolution of the economic crisis in Spain.

3.2 Introduction

The global financial crisis of 2007-2010 has underlined the need for researchers to include and explicitly model the financial sector as a trigger and propagator of the financial crisis. Moreover, it has drawn attention to the role of financial frictions as key mechanisms to explain business fluctuations.

In this paper we present and evaluate a model that helps study the role of the financial sector in the Spanish liquidity trap. We find that the agency problems, the liquidity constraints facing banks, risk shocks that hit financial intermediation and the ineffectiveness of the single monetary policy are prime determinants of economic fluctuations. Altogether, they have been critical triggers and propagators in the recent financial crisis.

Our model is a variant of Christiano et al. (2010, 2014), we integrate a foreign sector that supplies government bonds to the Spanish banks of the type studied by Moreno et al. (2014). The real economy is made of households and firms. Households are composed by workers, capital producers and entrepreneurs. The working households consume, supply differentiated work in a monopolistic labour market, and allocate savings as deposits on the bank. Capital producers combine undepreciated physical capital with new investment subject to a shock in the investment efficiency process. Entrepreneurial households acquire plant capacity from capital producers, extract production services from it, they resell the stock of undepreciated capital at the end of the production period. Firms buy capital production services from entrepreneurs and produce intermediate goods in a monopolist market.

Entrepreneurs' net worth is subject to a financial wealth shock and is used to pay for capital in the next period. But, in order to run their activity, entrepreneurs need to borrow a fraction of the value of capital which they are not able to self-finance through their net worth. The bank provides the sources to finance entrepreneurs' investment projects using the deposits placed by households. They can also diversify their portfolio investment having access to foreign sovereign debt (Bunds).

Idiosyncratic uncertainty in the financial sector has been introduced in DSGE models by Bernanke et al. (1999). More recently, Christiano et al. (2010, 2014) make this idiosyncratic uncertainty time-varying through risk shocks that modify the standard deviation of idiosyncratic shocks to the productivity of private borrowers and lead to macroeconomic fluctuations. By doing so, the authors provide a new transmission channel from uncertainty to business cycles through financial frictions that we use in this paper. The model also includes an inflation differential between Spain and the EMU. This differential helps to analyze the effects of single-monetary policy and its effectiveness in Spain.

We estimate the model for Spain over the period 2000Q1-2017Q4. We use quarterly observations of ten macroeconomic series that are commonly used in the estimation of DSGE models and three financial series: credit to non financial corporations, the risk premium of sovereign bonds and entrepreneurial net worth. First, we show that 52% of the variability of output and 89% of the variability of credit in the business cycle is accounted by anticipated risk shocks in the economy. Moreover, they explain the variations in the stock market and the interest premium as well. These shocks explain the episode of credit crunch and contraction of investment and output. Such a sequence has been observed during the last crisis of 2007 in Spain which was anticipated by several economic agents. Our results show that anticipated risk shocks dominate all the other shocks.

The rest of the paper is structured as follows. Section 3.3 clarifies the empirical motivation for our analysis. Section 3.4 discusses the related literature. Section 3.5 provides a brief summary of the model. The data used in our analysis and the empirical results are discusses in section 3.6. Finally, section 3.7 concludes.

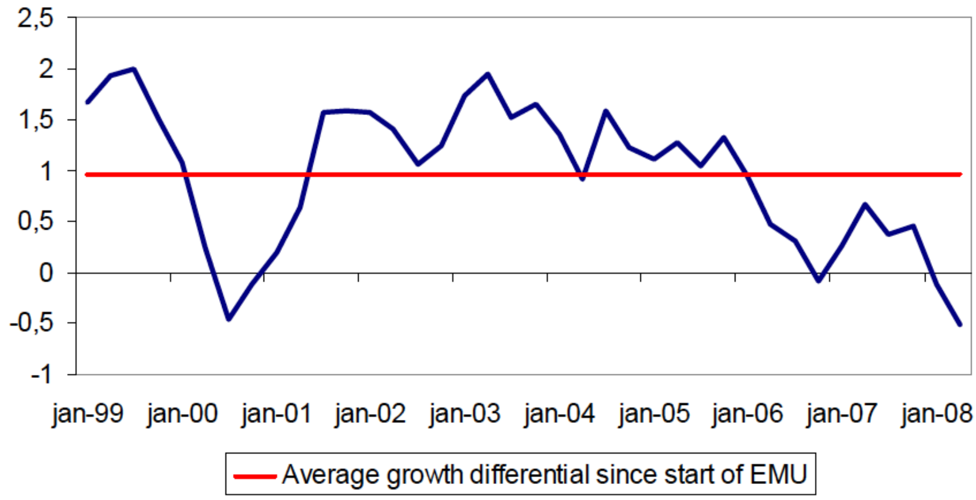
3.3 Motivation

The global financial crisis of 2007, originated by the sub-prime crisis in the US, had a major impact worldwide. The influence on the Spanish economy has been deeper and more long-lasting due to the state of the financial system when the crisis began.

With the establishment of the single currency in 2002, the exchange rate risk disappeared and Spain started to receive capital inflows from abroad. This produced a dramatic fall in the Spanish interest rates. Figure 3.1 shows that the integration of Spain into the

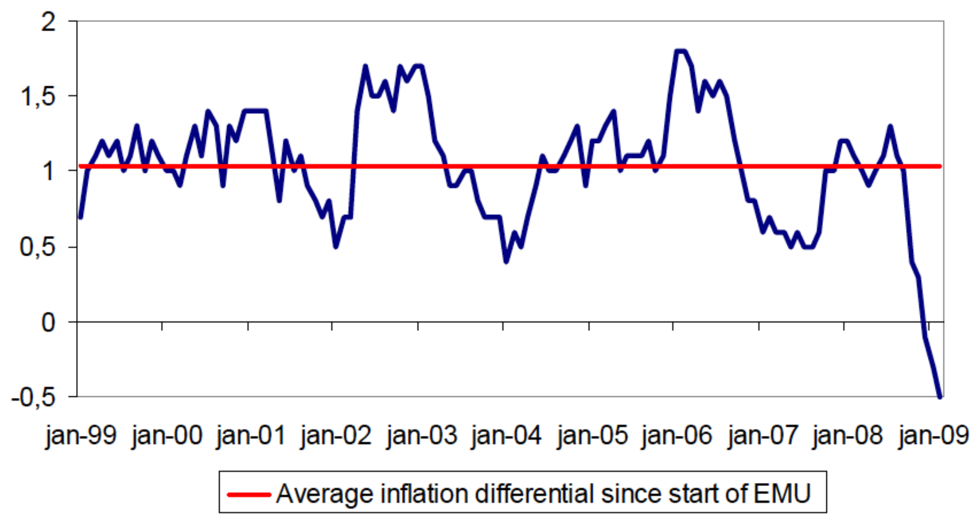
European Union led to a higher economic growth in Spain relative to the Euro Area (2.3 points on average). During this period of economic boom, credit flowed and created a process of excessive indebtedness of public and private sectors and a high dependence on credit to generate economic activity. As a consequence the Spanish inflation was on average higher than the EMU's inflation as shown in Figure 3.2.

Figure 3.1: GDP growth rate compared to previous quarter between Spain and the EMU, s.a.



Graph taken from Andrés et al. (2010)

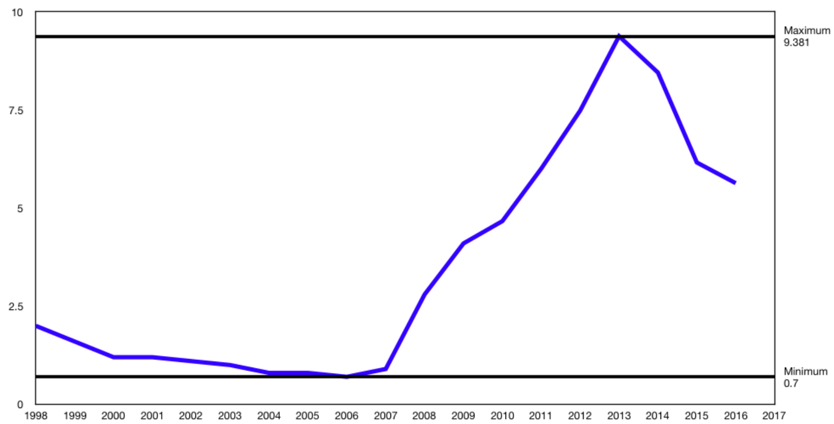
Figure 3.2: Inflation differential between Spain and the EMU



Graph taken from Andrés et al. (2010)

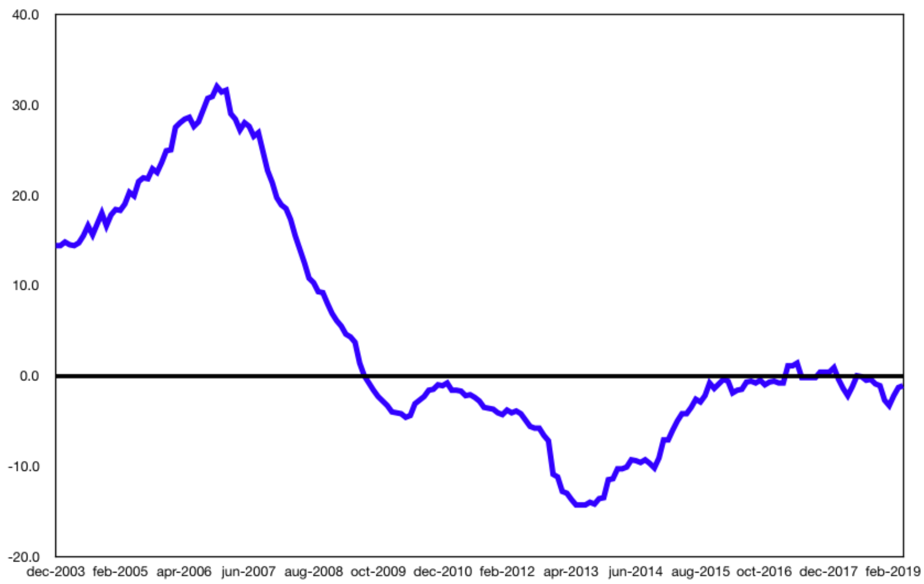
At the time the financial crisis struck, Spain was vulnerable to monetary and financial shocks. The Spanish economy entered into a recession and the number of firms that went bankrupt rapidly escalated. As a result, the number of non-performing loans increased dramatically during this period, as shown in Figure 3.3. With the increase in the number of non-performing loans, banks tightened their collateral constraints and started lending less to the private sector as shown in Figure 3.4.

Figure 3.3: Non-performing loans to the total gross loans (percentage)



Source: World Bank. Source Code: GFDD.SI.02.

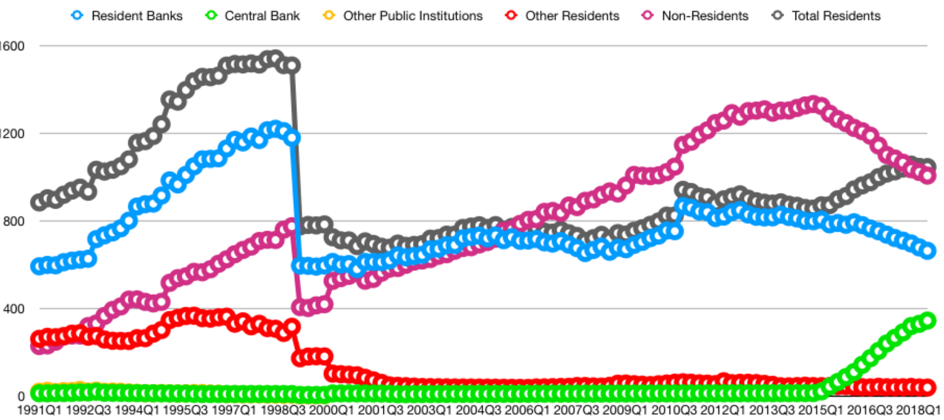
Figure 3.4: Loans from Spain to Euro Area non-financial corporations (anual growth rate)



Graph taken from the Bank De France database

Due to the increase in loan risk, the banks started allocating their investments to other assets. As a consequence, the international demand for German bonds, rated as minimum risky assets (AAA rating), increased as shown in Figure 3.5.

Figure 3.5: Billions of euros of German sovereign debt holding by nationals and non-nationals



Graph taken from the Bruegel database

3.4 Related Literature

In the recent empirical macroeconomics literature, there are different approaches for modelling the Spanish economy. Andrés et al. (2006) estimate a DSGE model developed by the Spanish Central Bank (BdE) as two regions of the same EMU: Spain and the rest of the Euro area. They include housing, as a durable good, and the level of disaggregation for each region is adjusted to the Quarterly National Accounts (QNA). They show that the shocks differ in magnitude in Spain and in the rest of the Euro Area having higher effects on the Spanish macroeconomic variables including inflation. As a consequence, Spain will face more difficulties in fulfilling the Maastricht inflation criterium. More recently, Boscá et al. (2010) present a Rational Expectations Model for the Spanish economy (REMS model). This is a small open economy model that incorporates financial frictions. Specifically, they include adjustment costs in consumption and investment. They estimate this rational expectation DSGE model using Bayesian techniques. Their results show that this models helps better understanding the effects of several policies on the Spanish economy, but it falls short in explaining the recent crisis. Boscá et al. (2015) modelled a specific financial sector for the Spanish economy. They estimate a small open economy model of Spain in a currency union. The model can be used to evaluate ex-ante and ex-post policies, structural reforms and to decompose the evolution of macroeconomic aggregates according to different shocks. In contrast, our model includes signals on risk shock that helps explain better the linkages between the financial and real sectors in the Spanish economy during the recent financial crisis.

Recent studies show different approaches to include the contribution of anticipated shocks in explaining the business cycles. There is a widespread belief that changes in expectations may be an important independent driver of economic fluctuations. The news view of business cycles offers a formalization of this perspective. Our paper relates to a few strands of the literature investigating these macroeconomic phenomena using Bayesian estimation of DSGE models. We find that anticipated shocks account for about 52% of the predicted fluctuations in output whereas the unanticipated shocks do not have any explanatory power. Also, they account for 100% of the variation in the risk premium.

Recently, Beaudry and Portier (2007); Schmitt-Grohé and Uribe (2012) estimate a DSGE model where forward-looking agents react to anticipated technological changes. They show that these anticipated shocks account for half of the aggregate fluctuations in output, consumption, employment and investment over the business cycle. Fujiwara et al. (2011) estimate a DSGE model using Bayesian methods. They show that in the United States the news shock with a longer forecast horizon has a larger effect on nominal variables. Another approach analyzed in the literature by Beaudry and Portier (2004), is the effect of agents-forecasting the economy's future needs in term of capital. Their results show that a model that includes agents having difficulties forecasting the future helps better understanding the recent US recession.

In our model, we also analyze the effect of the single monetary policy has on Spain. With the establishment of the Euro Zone in 1999, Spain lost the ability to conduct independently its monetary policy and handed over this power to the European Central Bank. The recent crisis had different effects across the European Monetary Union (EMU) due to the different institutional features (e.g. labor market institutions). Several authors have analyzed the inconveniences and inequalities that a single monetary policy has across the EMU member countries. Canzoneri et al. (1996) analyze the inflation differentials between the EMUcountries. Their results show that countries like Spain and Italy face more difficulties into fulfilling the Maastricht convergence criteria due to the different productivity trends. In particular, the different productivity trends have generated higher inflation in Spain than in other countries as Germany. Sinn and Reutter (2001) analyze the changes in price and show that a common monetary policy that stabilises the prices in all EMU countries is not feasible due to structural differences across countries. Gomez-Gonzalez and Rees (2018) go a step beyond, and analyze the hypothetical case of the performance of Spain if it would have retained an independent monetary policy. They show that the Spanish economic growth would have been 0.8 points higher during the first years of the crisis but that the economic activity would have slowed down by the late 2016, following the global trend. Our results show that the inflation differential between Spain and the EMU can account for 11% of the variability of output and 63% of the variability on the interest rates.

3.5 The Model

This section provides a brief overview of the model.[1] The model includes households, intermediate good firms, final good firms, a government, a bank and a foreign unlimited supplier of risk-free assets[2]. The households are composed by workers, capital producers and entrepreneurs.

The model belongs to the class of DSGE models with real and nominal rigidities developed by Smets and Wouters (2003) augmented to include a financial accelerator

[1]The detailed maximization and conditions that the agents face are available upon request from the author.

[2]Think of German short-term bongs as risk-free foreign bonds for Spanish banks.

mechanism à la Bernanke et al. (1999).

Households are composed by workers, capital producers and entrepreneurs. At the beginning of the period the households make their optimal choices: provide deposits to the bank, supply labor to the intermediate good firms and consume. Prices and wages are subject to nominal rigidities à la Calvo. Monopoly suppliers of labor and of intermediate goods can reoptimize their wage and price, respectively, only periodically (with an exogenous probability).

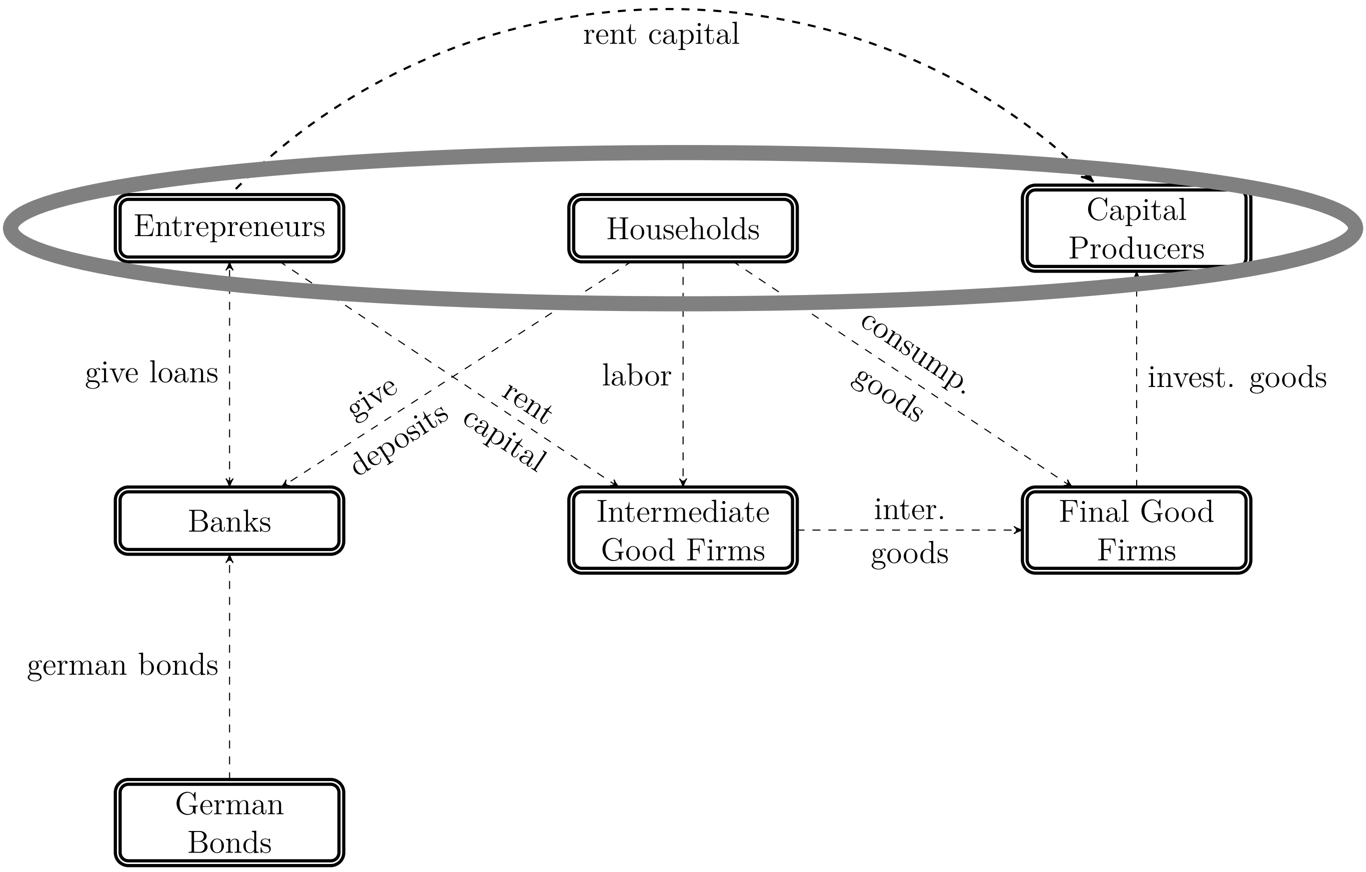
The capital producers use the investment goods to invest in capital. They sell the new capital to the entrepreneurs. To buy raw capital, entrepreneurs need to borrow a fraction of the capital value as they are not able to completely self-finance their purchase. They use their personal wealth as well as loans obtained from a financial intermediary. Raw capital cannot be directly used in the production sector that uses effective capital. Entrepreneurs extract production services from the purchased raw capital and transform it into effective capital. They resell this effective capital to intermediate firms.

The monopolistic intermediate firms produce intermediate goods using the labor of the households and the rented capital of the entrepreneurs. They sell their production to a final good producer. This competitive final good producer aggregates the intermediate goods and converts the output into consumption goods, investment goods, goods used up in capital utilization and in bank monitoring.

The bank is a competitive bank that makes portfolio investment decisions. It allocates the savings across loans to entrepreneurs and foreign bonds. The loan contract is characterized by agency problems subject to financial shocks: the entrepreneurs can observe their shock realization, but the bank needs to verify the state of the entrepreneur and pay the implied state verification cost.

The monetary authority sets the nominal interest rate of the European Monetary Union (EMU hereon) given its past value, the deviations of inflation respect to their steady-state values, and a stochastic disturbance, which is referred as the monetary policy shock. Following Fernández-Villaverde et al. (2010), the deviation of Spanish inflation from EMU's inflation is described as a zero mean idiosyncratic shock. We can see the representation of our economy in Figure 3.6.

Figure 3.6: The Small Economy



3.5.1 Firms

Goods Production

The final good producer aggregates the intermediate firms goods and produces the final output, Y_t, using the technology (Dixit-Stiglitz aggregator):

$$Y_t = \left[\int_0^1 Y_{j,t}^{\frac{1}{\lambda_{f,t}}} dj\right]^{\lambda_{f,t}}, \text{ where} 1 \leq \lambda_{f,t} < \infty \tag{3.1}$$

where $Y_{j,t}$ are the intermediate goods and $\lambda_{f,t}$ is the substitution rate between the intermediate goods.

We assume that there is a unit of intermediate good producers, denoted by j where $j \in (0, 1)$, that produce with the following technology:

$$Y_t = \begin{cases} \epsilon_t K_{j,t}^{\alpha}(z_t l_{j,t})^{1-\alpha} - \Phi z_t^* & \text{if } \epsilon_t K_{j,t}^{\alpha}(z_t l_{j,t})^{1-\alpha} > \Phi z_t^* \\ 0 & \text{otherwise} \end{cases}$$

where ϵ_t is a transitory productivity shock, $K_{j,t}$ is the capital, z_t is a persistent component of technology, $l_{j,t}$ denotes the homogeneous labor, $0 < \alpha < 1$ denotes the capital income share and Φ denotes the fixed cost of production. The persistent technology shock is given by $z_t = \mu_{z,t} z_{t-1}$. In order to assure a non-stochastic steady-state, we assume that z_t^* follows:

$$z_t^* = z_t \Upsilon^{\frac{\alpha}{1-\alpha}t},$$

where Υ has to be greater than one in order to capture the increasing growth rate of the economy.

The homogeneous labor employed by the firms is an aggregate of the differentiated labor supplied by individual households:

$$l_t = \left[\int_0^1 (h_{j,t})^{\frac{1}{\lambda_w}} dj\right]^{\lambda_w}, \tag{3.2}$$

where $1 < \lambda_w$, where λ_w is the substitution rate between the differentiated labor.

The firm chooses $Y_{j,t}$ and Y_t to maximize profits taking prices as given:

$$\alpha = \int_0^1 P_{j,t} Y_{j,t} d_j + P_t \left(Y_t \left(\int_0^1 Y_{j,t}^{\frac{1}{\lambda_{f,t}}} d_j \right)^{\lambda_{f,t}} \right), \tag{3.3}$$

Using the the first order condition and substituting it in equation (3.1) we obtain the aggregate price index:

$$P_t = \left[\int_0^1 P_{j,t}^{\frac{1}{1-\lambda_{f,t}}} d_j\right]^{1-\lambda_{f,t}}, \tag{3.4}$$

In equilibrium, the ratio of the marginal productivity of the producing factors has to be equal to the ratio of the cost of renting the factors. Using this equilibrium condition we can write the marginal cost of labor as:

$$s_t = \left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} \frac{1}{\epsilon_t z_t^{1-\alpha}} \left[\tilde{r}^k\right]^{\alpha} \left[\frac{w_t}{p_t}\right]^{1-\alpha}, \tag{B1}$$

The real marginal cost of renting one unit of capital divided by its marginal productivity derives the following condition:

$$s_t = \frac{\left[\tilde{r}^k\right]}{\alpha \epsilon_t \left(\frac{z_t l_{j,t}}{k_{j,t}}\right)^{1-\alpha}}, \tag{B2}$$

The ratio of marginal productivities has to be equal to the ratio of the cost of renting in equilibrium. Therefore, using the ratio of the marginal productivity of capital and labor, we obtain the next condition:

$$r_t^k = \frac{\alpha \epsilon_t}{(1+\Psi_{k,t} R_t)} \left(\frac{\Upsilon \mu_{z,t}^* L_t (w_t^*)^{\frac{\lambda_w}{\lambda_w - 1}}}{u_t k_t} \right)^{1-\alpha} s_t \tag{B3}$$

Sticky Prices

The model uses a variant of Calvo sticky prices. We assume that $(1-\xi_p)$ of intermediate firms can reoptimize their price: $P_{i,t} = \tilde{P}_t$. The other ξ_p will set their price according to the following partial indexation rule:

$$P_{i,t} = \tilde{\pi}_t P_{i,t-1},$$

$$\tilde{\pi}_t = (\pi^{target})^{\iota}(\pi_{t-1})^{1-\iota},$$

where $\pi_{t-1} = \frac{P_{t-1}}{P_{t-2}}$ is the inflation rate at time $t-1$.

A firm able to change its price, will choose a price that maximizes the discounted profits in the expected future taking into account the demand curve of goods.

$$\max_{\tilde{P}_t} E_t \sum_{j=0}^{\infty} (\beta\xi_p)^j \lambda_{t+j} P_{t+j} [(x_{t+j}\tilde{P}_t)^{1-\frac{\lambda_{f+j}}{\lambda_{t+j}-1}} Y_{t+j} - s_{t+j} Y_{t+j} (x_{t+j}\tilde{P}_t)^{-\frac{\lambda_{f,t+j}}{\lambda_{f+j-1}}}] \tag{3.5}$$

$$\text{s.t. } x_{t+j} = \frac{\tilde{\pi}_{t+j}, \ldots, \tilde{\pi}_{t+1}}{\pi_{t+j}, \ldots, \pi_{t+1}} \tag{3.6}$$

From the first order condition of the above problem and using the assumption that $K_{p,t}$ and $F_{p,t}$ have convenient recursive representations when $\lambda_{f,t}$ is non-stochastic, we obtain the next two conditions:

$$E_t \left[\lambda_{z,t} Y_{z,t} + \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}} \right)^{\frac{1}{1-\lambda_{f,t+1}}} \beta\xi_p F_{p,t+1} - F_{p,t} \right] = 0, \tag{B4}$$

$$E_t \left[\lambda_{f,t} \lambda_{z,t} Y_{z,t} s_t + \beta\xi_p \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}} \right)^{\frac{-\lambda_{f,t+1}}{\lambda_{f,t+1}-1}} K_{p,t+1} - K_{p,t} \right] = 0, \tag{B5}$$

where the relation between $K_{p,t}$ and $F_{p,t}$ is: $K_{p,t} = F_{p,t} \left[\frac{1-\xi_p \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}} \right)^{\frac{1}{1-\lambda_{f,t+1}}}}{1-\xi_p} \right]^{1-\lambda_{f,t}}$. These two optimality conditions characterize the stickiness of the prices in the model.

Using the conditions above we can rewrite the time t aggregate price index (equation 3.4) as:

$$P_t = \left[(1-\xi_p)\tilde{P}_t^{\frac{1}{1-\lambda_{f,t}}} + \xi_p(\tilde{\pi}_t P_{t-1})^{\frac{1}{1-\lambda_{f,t}}} \right]^{1-\lambda_{f,t}} \tag{3.7}$$

Using equations B4 and B5 and substituting the above equation 3.7 we obtain the optimal price equation:

$$P_t^* = \left((1-\xi_p) \left(\frac{1-\xi_p \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}} \right)^{\frac{1}{1-\lambda_{f,t+1}}}}{1-\xi_p} \right)^{1-\lambda_{f,t}} + \xi_p \left(\frac{\tilde{\pi}_t}{\pi_t} p_{t-1}^* \right)^{\frac{\lambda_{f,t}}{1-\lambda_{f,t}}} \right)^{\frac{1-\lambda_{f,t}}{\lambda_{f,t}}}, \tag{B6}$$

Rewriting the intermediate firms' production function using the new notation the following expression obtains:

$$Y_{z,t} = (P_t^*)^{\frac{\lambda_{f,t}}{\lambda_{f,t}-1}} \left\{ \epsilon_t \nu_t^l (\bar{k}_t)^{\alpha} \left[(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}} h_t \right]^{1-\alpha} - \Phi \right\}, \tag{3.8}$$

3.5.2 Banks

Lending

There is a representative competitive bank that receives deposits from the households and gives loans to entrepreneurs. It also can diversify its portfolio buying risk-free foreign bonds.

It is assumed that the entrepreneurs cannot completely self-finance the capital acquisiton therefore they ask a loan to the bank. An entrepreneurs signs a contract with the bank in which if the shock is less than the threshold value the entrepreneur bankrupts and the bank needs to pay some monitoring costs in order to observe the default of the entrepreneur (there is a costly verification state (CVS) of bankruptcy). The contract also states that the entrepreneurs pay a gross interest Z_{t+1} on their bank loans.

The cutoff value that sets the default of the entrepreneur is defined by:

$$\bar{\omega}_{t+1}(1+R^k_{t+1})Q_{\bar{K},t}\bar{K}_{t+1} = Z_{t+1}B_t \tag{3.9}$$

where the loans are equal to the price of purchasing capital that the entrepreneurs cannot self-finance: $B_{t+1} = Q_{\bar{K},t}\bar{K}_{t+1} - N_{t+1}$.

The loans to the entrepreneurs, B_t, are set in a contract that maximize the entrepreneurs expected state. This condition establishes that the payback to entrepreneurs can not be higher than what the banks receives from them:

$$[1 - F_t(\bar{\omega})]\, Z_{t+1}B_{t+1} + (1-\mu)\int_0^{\bar{\omega}_{t+1}} \omega dF_t(1+R^k_{t+1})Q_{\bar{K},t}\bar{K}_{t+1} = (1+R^e_{t+1})B_{t+1}, \tag{3.10}$$

where the left hand side of the equation expresses the total payback from the entrepreneurs as the the payback of the surviving entrepreneurs and assets of the bankrupt entrepreneurs net of monitoring costs. The right hand side is the gross nominal payback of the loans. We set this interest rate to R^e_{t+1}. This interest rate is set in the period in which the contract is signed therefore it is not contemporaneous to the shock.

Taking the previous expression and substituting equation 3.9 we obtain:

$$\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})] = \frac{B_{t+1}}{Q_{\bar{K},t}\bar{K}_{t+1}}, \tag{3.11}$$

where,

$$\Gamma_t(\bar{\omega}_t) = \bar{\omega}_{t+1}[1 - F_t(\bar{\omega}_{t+1})] + G_t(\bar{\omega}_{t+1}),$$

$$G_t(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega),$$

$\Gamma_t(\bar{\omega}_{t+1})$ is the share of entrepreneurial earnings, $(1+R^k_{t+1})Q_{\bar{K}_t}\bar{K}_{t+1}$, received by the bank subsidiary before monitoring costs. The object, $\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})$ is the share net of monitoring costs. Also, $1 - \Gamma_t(\bar{\omega}_{t+1})$ denotes the share of gross entrepreneurial earnings obtained by entrepreneurs.

The entrepreneurial earnings are given by the entrepreneurs that do not bankrupt and payback the bank the gross interest rate on the loans:

$$[1 - \Gamma_t(\bar{\omega}_t)]\, Z_{t+1}B_{t+1} = \int_{\bar{\omega}_{t+1}}^{\infty} Z_{t+1}B_{t+1}dF_t(\omega), \tag{3.12}$$

Substituting the definition of the loans and after some algebra, we obtain:

$$E_t\left\{[1 - \Gamma_t(\bar{\omega})]\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)(B_{t+1}+N_{t+1})\right\}, \tag{3.13}$$

The standard debt contract has two parameters, the loan amount B_{t+1} and a non-default interst rate Z_{t+1} (or equivalently $\bar{\omega}$). The two parameters are chosen to maximize the end-of-contract level of net worth for the entrepeneur, equation 3.13, subject to the bank subsidiary's zero profits condition, equation 3.11:

$$\max_{B_{t+1},\bar{\omega}_{t+1}} E_{t+1}\begin{Bmatrix}[1-\Gamma_t(\bar{\omega})]\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)(B_{t+1}+N_{t+1})+ \\ \eta_{t+1}\left([\Gamma_t(\bar{\omega})-\mu G_t(\bar{\omega})]\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)(B_{t+1}+N_{t+1})-B_{t+1}\right),\end{Bmatrix} \tag{3.14}$$

where η_{t+1} represents the Lagrange multiplier, which is a function of the period $t+1$ state of nature.

The setting of the optimal contract for the entrepreneur leads to the following first order condition:

$$E_t\left\{[1-\Gamma_t(\bar{\omega}_{t+1})]\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)+\frac{\Gamma'(\bar{\omega}_{t+1})}{\Gamma'(\bar{\omega}_{t+1})-\mu G'(\bar{\omega}_{t+1})}\left[\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)(\Gamma'(\bar{\omega}_{t+1})-\mu G'(\bar{\omega}_{t+1}))\right]\right\}=0, \tag{B7}$$

and their respective derivatives are:

$$\Gamma'_t(\bar{\omega}_{t+1})=1-\Gamma_t(\bar{\omega}_{t+1})-\bar{\omega}_{t+1}\Gamma'_t(\bar{\omega}_{t+1})+G'_t(\bar{\omega}_{t+1})=1-\Gamma_t(\bar{\omega}^N_{t+1})$$

$$G'_t(\bar{\omega}_{t+1})=\bar{\omega}_{t+1}\Gamma'_t(\bar{\omega}_{t+1})$$

Rewriting the zero profit condition with the new terminology it gives:

$$(1+R^k_{t+1})\left[\Gamma(\bar{\omega}_{t+1})-\mu G(\bar{\omega}_{t+1})\right]=(1+R^e_{t+1})B_{t+1}, \tag{B8}$$

Funding

There is representative competitive bank. The bank's net source of funds at the end of period, Π^b_t, is:

$$\Pi^b_t=(1+R^e)B_t+(1+R^b)BO_t+D_{t+1}-(1+R_t)D_t-B_{t+1}-BO_{t+1} \tag{3.15}$$

The bank's sources of fund at this point in time are: interest and principal on entrepreneurial loans extended in the previous period, the interest and the principal of the bonds, and the deposits the banks has received at the start of this period. The bank uses these funds to extend new loans, to buy news foreign bonds and to pay the interest and the principal of the deposits. In solving this problem, the bank takes rates of return as given. In addition, B_{t+1} is determined by the bank's lending channel of the sub-section 3.5.2, and so here B_{t+1} is also taken as given. At date t, the banks chooses BO_{t+1}.

From the maximization of the bank's expected profits we obtain the next Euler equation:

$$\lambda_{zt}=E_t\{\frac{\beta}{\pi_{t+1}\mu^*_{z,t+1}}\lambda_{zt+1}\left(1+R^{BO}_{t+1}\right)\} \tag{B9}$$

where the left hand side of the equation shows the lost in the marginal utility of using the extra units to buy foreign bonds, λ_{zt}. The right side shows the discounted utility of the future, where the bank will have $\frac{1+R^{BO}_{t+1}}{\pi_{t+1}\mu^*_{z,t+1}}$ units to diversify in its portfolio.

3.5.3 Households

Households are composed by workers, capital producers and entrepreneurs. The working households consume, supply differentiated work in a monopolistic labour market, and allocate savings as deposits on the bank. Capital producers combine undepreciated physical capital with new investment subject to a marginal efficiency of investment shock. Entrepreneurial households have a special ability to operate capital. For simplicity purposes we divide each kind of household decision-making process below.

Consumption and Deposits decision

There is a continuum of households, $j \in (0,1)$ that consume, save as deposits and supply a differentiated labor, $h_{j,t}$. The instantaneous utility function of the household is given by:

$$log(c - bc_{t-1}) - \psi_L \int_0^1 \frac{h_{it}^{1+\sigma_L}}{1+\sigma_L} d_i + a_d log\left(\frac{d_{t+1}}{P_{t+1}}\right),$$

where b is the internal habit on consumption, σ_L is the disutility parameter of labor and a_d is the utility parameter of deposits.

The households budget constraint is:

$$(1-\tau^l)\int_0^1 w_{j,t}h_{j,t}dj + (1-\Theta)(1-\gamma_t)V_t + Lump_t + (1+R_t^e)d_t = d_{t+1} + w^e + (1+\tau^c)p_t c_t, \tag{3.16}$$

where, τ^l, τ^c are the taxes on labor earnings and consumption, respectively. On the left side of the above equation there are the wages net of taxes, the net fraction of the bankrupt net worth, the lump sum transfers and the gross nominal returns on deposits. On the right hand side there are the new deposits, the fixed transfers to the new entrepreneurs and the consumption expenses.

From the maximization of the households, we obtain the next two Euler equations:

$$E_t[(1+\tau^C)\zeta_{c,t}\lambda_{z,t} - \frac{\mu_{z,t}^*\zeta_{c,t}}{c_t\mu_{z,t}^* - bc_{t-1}} + b\beta\frac{\zeta_{c,t+1}}{c_{t+1}\mu_{z,t+1}^* - bc_t}] = 0 \tag{B10}$$

where the continue here

$$E_t\{-\zeta_{c,t}\lambda_{zt} + \frac{\beta}{\pi_{t+1}\mu_{z,t+1}^*}\zeta_{c,t+1}\lambda_{zt+1}\left(1+R_{t+1}^k\right)\} = 0 \tag{B11}$$

where the continue here

Wage process

A representative, competitive labor contractor aggregates differentiated labor services, $h_{i,t}$, $i \in [0,1]$ into homogeneous labor, l_t, using the production function in equation 3.2.

The demand for labor is the solution to the following problem:

$$\max W_t \left[\int_0^1 (h_{j,t})_{\lambda_w}^1 d_j\right]^{\lambda_w} - \int_0^1 W_{t,j}h_{j,t}d_j \tag{3.17}$$

The jth household faces the following demand for its labor:

$$h_{j,t} = l_t\left(\frac{W_t}{W_{j,t}}\right)^{\frac{\lambda_w}{\lambda_w - 1}} \tag{3.18}$$

We assume that $(1-\xi_w)$ fraction of households can re-optimize their wage, $w_{j,t} = \tilde{w}_{j,t}$. The other fraction, ξ_w cannot reoptimize their wage and set their wage as:

$$w_{j,t} = \tilde{\pi}_{w,t}(\mu_z^*)^{1-\vartheta}(\mu_{z,t}^*)^{\vartheta} w_{j,t-1},$$

$$\tilde{\pi}_{w,t} = (\pi^{target})^{\iota_w}(\pi_{t-1})^{1-\iota_w},$$

where $0 < \iota_w < 1$.

In choosing $\tilde{W}_t$, the household considers the discounted utility of future cases when it cannot reoptimize:

$$\max_{\tilde{W}_t} E_t \sum_{j=0}^{\infty}(\beta\xi_w)^j \left\{-\zeta_{c,t+i}\zeta_{t+i}z(h_{j,t+i} + \lambda_{t+i}(1-\tau_{t+i}^l)W_{j,t+i}h_{j,t+i}\right\} \tag{3.19}$$

where, $z(h) = \Psi_L \frac{h^{1+\sigma_L}}{1+\sigma_L}$.

Substituting we obtain the demand for labor:

$$\frac{\tilde{W}_{t+i}}{W_{t+i}} = X_{t,i}W_t\tilde{W}_t \tag{3.20}$$

The workers choose to optimize their wages, solve the maximization of equation 3.17 subjet to the demand of labor, equation 3.20. From the wage optimization of the firms we obtain the next two relations:

$$E_t\left\{\varsigma_{c,t}(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}l_t\frac{(1-\tau^l)\lambda_{z,t}}{\lambda_w} + \beta\xi_w(\mu_z^*)^{\frac{1-\vartheta}{1-\lambda_w}}(\mu_{z,t+1}^*)^{\frac{\vartheta}{1-\lambda_w}-1}\left(\frac{1}{\pi_{w,t+1}}\right)^{\frac{\lambda_w}{1-\lambda_w}}\frac{\tilde{\pi}_{w,t+1}^{\frac{1}{1-\lambda_w}}}{\pi_{t+1}}F_{w,t+1} - F_{w,t}\right\} = 0, \tag{B12}$$

$$E_t\left\{\left[(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}l_t\right]^{1+\sigma_L}\varsigma_{c,t}\varsigma_t + \beta\xi_w\left(\frac{\tilde{\pi}_{w,t+1}}{\pi_{w,t+1}}(\mu_z^*)^{1-\vartheta}(\mu_{z,t+1}^*)^{\vartheta}\right)^{\frac{\lambda_w}{1-\lambda_w}(1+\sigma_L)}K_{w,t+1} - K_{w,t}\right\} = 0, \tag{B13}$$

We can write the aggregate wage level as:

$$w_t^* = \left[(1-\xi_w)\left(\frac{1-\xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_z^*)^{1-\vartheta}(\mu_{z,t+1}^*)^{\vartheta}\right)}{1-\xi_w}\right)^{\lambda_w} + \xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_z^*)^{1-\vartheta}(\mu_{z,t+1}^*)^{\vartheta}w_{t-1}^*\right)^{\frac{\lambda_w}{1-\lambda_w}}\right]^{\frac{1-\lambda_w}{\lambda_w}}, \tag{B14}$$

Capital production decision

The capital producer takes the used capital from the entrepreneur $(1-\delta)\bar{k}_t$ and decides how much to invest taking into account the technology to transform used capital and investment into new capital. This technology function, $F(I_t, I_{t-1}, \zeta_{i,t})$, is expressed as $(1 - S(I_t, I_{t-1}, \varsigma_{i,t}))I_t$. The function $S(I_t, I_{t-1}, \varsigma_{i,t})$ measures the investment adjustment costs. It is a strictly increasing function in deviations of the investment from the steady state. This function S is chosen because in the steady state the function and the first derivative are equal to zero. This function is:

$$S(\varsigma_{i,t}, I_t, I_{t-1}) = exp\left(\sqrt{\frac{S''}{2}}\left(\frac{\varsigma_{i,t}I_t\mu_z^*\Upsilon}{I_{t-1}} - \Upsilon\mu_z^*\right)\right) + exp\left(-\sqrt{\frac{S''}{2}}\left(\frac{\varsigma_{i,t}I_t\mu_z^*\Upsilon}{I_{t-1}} - \Upsilon\mu_z^*\right)\right) - 2.$$

In order to obtain market equilibrium, we assume that the last period depreciated capital is reacquired completely by the entrepreneurs. They also choose, taking this quantity as given, the amount of investment they want to pursue. Therefore, the capital evolves as:

$$\bar{k}_{t+1} = (1-\delta)\bar{k}_t + F(I_t, I_{t-1}, \varsigma_{i,t}) = (1-\delta)\bar{k}_t + (1 - S(I_t, I_{t-1}, \varsigma_{i,t}))I_t. \tag{B15}$$

From the maximization of the capital producer we obtain the next condition:

$$E_t\left[\lambda_t Q_{\bar{k},t}F_{1,t} - \lambda_t \frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}} + \beta\lambda_{t+1}Q_{\bar{k},t+1}F_{2,t+1}\right] = 0, \tag{B16}$$

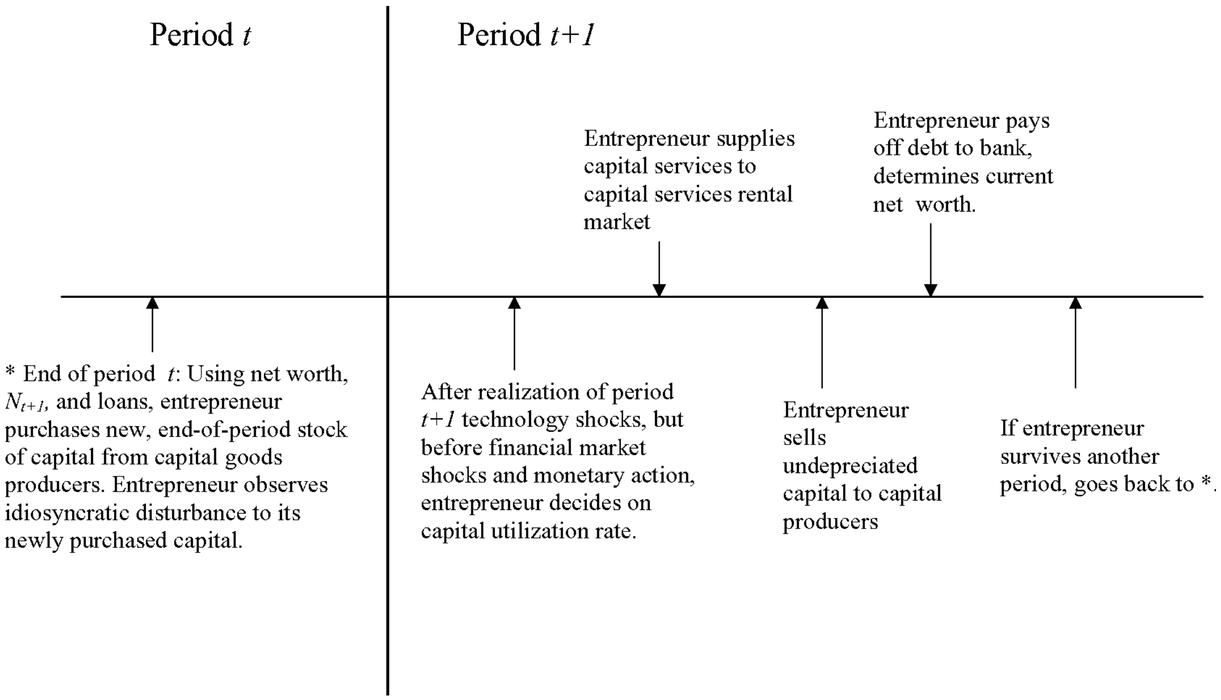
where the derivatives are:

$$F_{1,t} = -\frac{\partial S}{\partial I_t}I_t + (1 - S(I_t, I_{t-1}, \varsigma_{i,t})),$$

$$F_{2,t+1} = -\frac{\partial S}{\partial I_{t+1}}.$$

Entrepreneurial households

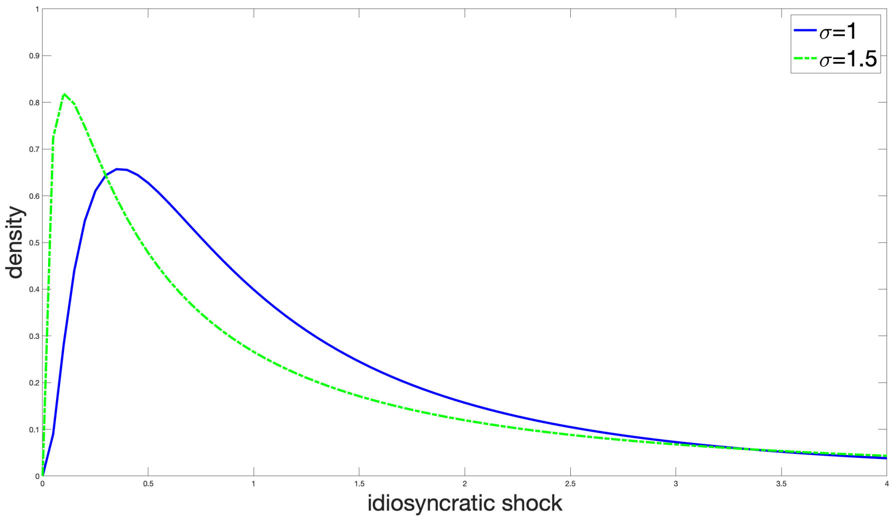
Figure 3.7: One period in the life of an entrepreneur



Taken from Christiano et al. (2010)

There is a unity of entrepreneurs in each period that borrows, resell their acquired capital and sells them to the intermediate good firms for production. Figure 3.7 states clearly the timeline of the decisions taken by the entrepreneur. As stated above, the entrepreneurs buy new capital from the capital producers and receive a random shock, denoted by ω, in their capital acquisition. This shock follows a log normal distribution with mean 1 and σ_t stochastic variance. The variance captures the risk aversion of the entrepreneurs. Figure 3.8 shows the effect of an increase in the variance of the idiosyncratic shock process. When the variance increases the probability of entrepreneurs in the left tail increases. This makes the investment riskier and as a consequence the interest rate on loans increases. Therefore, the entrepreneur borrows less and the economy tanks due to the decrease in investment.

Figure 3.8: Log Normal Distribution: 20 percent jump in standard deviation



The capital utilization adjustment cost is:

$$a(u_t) = \frac{r^k}{\sigma_a}\left\{exp(\sigma_a(u_{t-1})) - 1\right\} \tag{3.21}$$

where $\sigma_a > 0$, and r^k is the steady-state rental rate of capital in the model. This function is designed so that utilization is unity in steady-state, independent of the value of the parameter σ_a. Due to the formulation of $a(u)$, higher utilization rates have higher costs.

The user cost-function:

$$P_{t+1}\Upsilon^{-(t+1)}\tau^{oil}_{t+1}a(u_{t+1})\omega\tilde{K}_{t+1} \tag{3.22}$$

It maximizes the profits as:

$$\max_{u_{t+1}} \left[u_{t+1}r^k_{t+1} - \tau^{oil}_{t+1}a(u_{t+1})\right]\omega\tilde{K}_{t+1}P_{t+1}\Upsilon^{-(t+1)} \tag{3.23}$$

After observing the shock at $t+1$ they decide the level of capital utilization u_{t+1} and rent the capital services, $\omega k_{t+1} = \omega u_{t+1}\bar{k}_{t+1}$. The first order condition of the capital utilization rate derives:

$$r^k_{t+1} = \tau^{oil}_{t+1}a'(u_{t+1}) = \tau^{oil}_{t+1}exp(\sigma_a(u_{t-1})) \tag{B7}$$

where the function a is $a(u_t) = \frac{r^k}{\sigma_a}\left\{exp(\sigma_a(u_{t-1})) - 1\right\}$ and τ^{oil}_{t+1} is meant to capture the costs of production linked to the oil use in the production.

The total payoff at period $t+1$ of an entrepreneur is given by:

$$\left[u_{t+1}\tilde{r}^k_{t+1} - \Upsilon^{-(t+1)}\tau^{oil}_{t+1}a(u_{t+1})\right]p_{t+1} + (1-\delta)Q_{\bar{k}_{t+1}}\omega\bar{k}_{t+1}$$

Averaging the above expression across all the entrepreneurs at period $t+1$:

$$\frac{\left[u_{t+1}\tilde{r}^k_{t+1} - \Upsilon^{-(t+1)}\tau^{oil}_{t+1}a(u_{t+1})\right]p_{t+1} + (1-\delta)Q_{\bar{k}_{t+1}}}{Q_{\bar{k},t}} + \tau^k\delta = 1 + R^k_{t+1} \tag{B17}$$

where $1+R^k_{t+1}$ is the average nominal interest rate across entrepreneurs, τ^k is the tax rate on capital income and δ is the depreciation rate on capital.

The entrepreneurs do not have enough net worth to buy the capital and therefore, they finance a part of their capital acquisition by the loans of the bank. They sign a contract in which there is set a threshold value, $\bar{\omega}$. If their shock is below this threshold, they will go bankrupt and they will give their assets to the bank. If their shock realization is above this threshold they will pay a interest Z_{t+1} on their loan. The threshold value is defined as:

$$\bar{\omega}_{t+1}(1+R^k_{t+1})Q_{\bar{k},t}\bar{k}_{t+1} = Z_{t+1}B_{t+1}$$

where the loans are expressed as the difference between the rental price of capital and the net worth:

$$B_{t+1} = Q_{\bar{k},t}\bar{k}_{t+1} - n_{t+1}$$

As mentioned above, if $\omega < \bar{\omega}$ they will go bankrupt and they will turn over their assets to the bank. The entrepreneurs know the realization of their shock but the Bank can not observe it. Due to this asymmetry of information the bank will need to pay a fraction of the assets of the bankrupt entrepreneurs as a monitoring cost, $\mu(1+R^k_{t+1})\omega Q_{\bar{k},t}\bar{k}_{t+1}$. Upon exiting the economy the net worth of the bankrupt entrepreneurs is divided. A fraction of their net worth, $(1-\gamma_t)\Theta V_t$, will be consumed upon the exit and the remaining, $(1-\gamma_t)(1-\Theta)V_t$, will be transferred as a lump-sum payment to the households. Each period there is a unity of entrepreneurs and $(1-\gamma_{t+1})$ of them will exist the economy. Therefore, every period the same fraction of entrepreneurs will enter the economy in order to keep the mass of entrepreneurs unchanged. The new entrepreneurs will receive a transfer from the households, denoted by w^e, to have net wealth and be able to borrow from the bank when they enter the economy. The law of motion of the net worth across entrepreneurs is:

$$\bar{n}_{t+1} = \gamma_t((1+R^k_{t+1})Q_{\bar{k}_{t-1}}\bar{k}_t - \left[1 + R^e_t + \mu\int_0^{\bar{\omega}}\frac{\omega dF_t(1+R^k_t)Q_{\bar{k},t-1}\bar{k}_t}{Q_{\bar{k},t-1}\bar{k}_t - \bar{n}_t}\right]\left(Q_{\bar{k},t-1}\bar{k}_t - \bar{n}_t\right)) + w^e, \tag{B18}$$

where γ_t is the financial wealth shock capturing the part of value of the entrepreneurs that do not go bankrupt, $\mu\int_0^{\bar{\omega}}\frac{\omega dF_t(1+R^k_t)Q_{\bar{k},t-1}\bar{k}_t}{Q_{\bar{k},t-1}\bar{k}_t-\bar{n}_t}$ is the premium cost of external finance, the left hand side of the square brackets are the paybacks of renting the capital, the next terms between brackets are the average payments by entrepreneurs to banks per unit of currently borrowed multiplied by the loans, the last term, w^e, is the transfer from the households.

We compute the goods used as monitoring costs as:

$$d_t = \frac{\mu G(\omega_t)(1+R^k_t)q_{t-1}k_t}{\pi_t\mu^*_{z,t}} \tag{B19}$$

Signals

In our analysis we include a more complex risk shock process in order to include the advance information that agents acquire about the future. In this way we have included the agents perceptions and forecasts about risk. As we have seen, the crisis in Spain was forecasted by some agents. Therefore, our empirical exercises is based in well motivated micro facts that are supported on the recent financial crisis.

The risk shock is different to the other shock due to its more complex structure. We explicitly include advanced information in risk shocks before the innovation is realized. The shock representation is:

$$\sigma_t = \rho_\sigma \sigma_t - 1 + \underbrace{\xi_{0,t} + \xi_{1,t-1} + ... + \xi_{p,t-p}}_{=v_t} \tag{B*}$$

where ρ is an autoregressive parameters. σ_t is innovation to the risk shock process and v_t is the i.i.d. statistical innovation in σ_t. We expresss the variable v_t as a sum of i.i.d., mean zero random variables. We assume that in period t, agents observe $\xi_{j,t,}, j = 0, 1, ..., 8$. We refer to $\xi_{0,t}$ as the unanticipated component of v_t and to $\xi_{j,t}$ as the anticipated, or news, components of v_{t+j} for $j > 0$.

For the sake of parameter parsimony, we place the following structure on the variances of the shocks: $(E\xi^2_{0,t}) = \sigma^2_x$, $(E\xi^2_{1,1}) = (E\xi^2_{2,1}) = ..., (E\xi^2_{p,1}) = \sigma^2_{x,\eta}$.

3.5.4 Closing the Model

The National Account identity of this small open economy is:

$$\begin{aligned} Y_t = \mu \int_0^{\bar{\omega}_t} \omega dF(\omega)(1+R^k_t)\frac{Q_{k,t-1}\bar{k}_t}{p_t} + \frac{\tau^{oil} a(u_t)}{\Upsilon^t}\bar{k}_t + \frac{\Theta(1-\gamma_t)}{p_t}V_t + g_t + c_t \\ + \left(\frac{i_t}{\Upsilon^t \mu_{\Upsilon,t}}\right) i_t + BO_{t+1} - \frac{(1+R^b_t)}{P_t}BO_t, \end{aligned} \tag{B20}$$

where the left hand side is the total output of the economy. On the right hand side, we have the monitoring cost of bankrupt entrepreneurs, the capital utilization cost, the fraction consumed by the bankrupt entrepreneurs upon exiting the economy, the government spending, the consumption, the investment with its adjustment costs, the return on previous bonds and the bonds bought in this period.

Our model is a small open economy with incomplete asset markets. Therefore, the steady state will depend on the equilibrium dynamics that posses a random walk component. In order to close the model and assure convergence we apply the elastic interest process proposed by Schmitt-Grohé and Uribe (2003):

$$R^b_{t+1} = R^b + \psi_2\left(e^{BO_t - BO} - 1\right). \tag{B21}$$

where the German bond interest rate depends slightly on the bond holding by the Spanish bank.

The nominal interest rate is set by the ECB which takes into account inflation in the monetary union (EMU):

$$R_t - R = \rho_p\left(R_{t-1} - R\right) + (1-\rho_p)\left[\alpha_\pi\left(\pi^{EA}_t - \pi^{EA*}\right)\right] + \frac{1}{400}\epsilon^p_t. \tag{3.24}$$

where ϵ^p_t is a monetary policy shock, $0 < \rho_p < 1$ is the smoothing parameter in the policy rule and $\alpha_\pi > 0$. $\pi^{EA}_t - \pi^{EA*}$ is the deviation of quarterly inflation from the ECB inflation target.

As in Fernández-Villaverde et al. (2010), we assume that the deviations of inflation with respect to its Euro Area counterpart is described by zero mean idiosyncratic shocks. Formally,

$$\pi_t - \pi = \left(\pi_t^{EA} - \pi^{EA*}\right) + \epsilon_t^{\pi} \tag{B22}$$

where ϵ_t^{π} is an AR(1) idiosyncratic shock. Using this condition the policy rule can be rewrriten as

$$R_t - R = \rho_p \left(R_{t-1} - R\right) + \left(1 - \rho_p\right) \left[\alpha_\pi \left(\pi_t^{EA} - \pi^{EA*}\right)\right] + \frac{1}{400}\epsilon_t^p - \left(1 - \rho_p\right) \alpha_\pi \epsilon_t^{\pi} \tag{B23}$$

3.6 Data and estimation results

We use data on thirteen variables covering the period 2000Q1-2017Q4. These include ten time series that are standard in Bayesian estimation of DSGE models: GDP, consumption, investment, inflation, EMU inflation, wage, price of investment, hours worked, real interest rate and short-term risk-free interest rate. As Christiano et al. (2014), we also use three financial variables: credit, entrepreneurial net worth and credit spread.[3] All data are quarterly and, except for the short-term interest rate, inflation, hours worked and the external finance premium, they are logged and first-differenced. Moreover, before the estimation, data are demeaned by removing their sample mean, with the exception of inflation, the short-term interest rate, which are demeaned in the model by subtracting their estimated steady-state values.

Table 3.1: Calibrated Parameters (Time unit of model: quarterly)

β	Discount rate	0.99
σ_L	Curvature of disutility of labor	1
ψ_L	Disutility weight on labor	0.7705
λ_w	Steady-state markup, suppliers of labor	1.05
λ_f	Steady-state markup, intermediate good firms	1.2
μ_z	Growth rate of the economy	1.0041
Υ	Trend rate of investment-specific technological change	1.0042
δ	Depreciation rate on capital	0.025
α	Power on capital in production function	0.4
$1-\gamma$	Fraction of entrepreneurial net worth transferred to households	1-0.985
W^e	Transfer received by entrepreneurs	0.005
η_g	Steady-state government spending-GDP ratio	0.22
τ^c	Tax rate on consumption	0.13
τ^k	Tax rate on capital income	0.32
τ^l	Tax rate on labor income	0.241

We partition the model parameters into two sets. The first set contains parameters that are calibrated using data of Spain between the first quarter of 2000 and the fourth quarter of 2017.[4] Therefore, each period in the model represents one quarter. Some

[3]See Appendix B for details about the different time series used in the Bayesian estimation procedure.
[4]A detailed description of the data sources used in this analysis are available in Appendix B .

parameters are borrowed from the literature. Table 3.1 shows the calibrated values of all the fixed parameters of the model. The discount rate parameter, β, has a value of 0.99 that is standard in the literature. The Frisch elasticity of labor supply σ_L is set to 1. There are no natural units for the measurement of hours worked in the model, so we arbitrarily set υ_L as in Christiano et al. (2014) so that hours worked is unity at the steady state. Following Christiano et al. (2014), we fix the steady-state markups in the labor market λ_w and in the product market λ_f at 1.05 and 1.2, respectively.

The depreciation rate that we use is slightly higher at $\delta = 0.025$ than the one used in Burriel et al. (2010) ($\delta = 0.0175$). Also, the output-capital elasticity used in the production function is 0.04 points higher. However, the tax rate on consumption and labor, $0.13, 0.34$ are borrowed from Burriel et al. (2010). We set the mean growth rate μ_z of the unit root technology shock and the quarterly rate of investment-specific technological change υ to 0.41 percent and 0.42 percent, respectively. These values are chosen to ensure that the model steady state is consistent with the mean growth rate of per capita, real GDP in our sample, as well as the average rate of decline in the price of investment goods.

The steady-state value of the parameter controlling the rate at which the household tranfers equity from entrepreneurs to itself, $1 - \gamma$, is set to 1-0.985. This is fairly close to 1-0.973 value used by Christiano et al. (2014). The steady-state value of η_g is set to ensure that the ratio of government consumption to GDP is 0.22 in steady state. Our settings of the consumption, labor, and capital income tax rates, τ_c, τ_l, τ_k, respectively, are taken from Burriel et al. (2010).

The remaining parameters are estimated through a Bayesian procedure. The priors and posteriors of estimated structural parameters and shock processes, are detailed in Table 3.2. Our estimated parameter values are reasonably close to the ones obtained in the literature on the Spanish economy. For example, our estimated habit parameter value is 0.712 close to the estimated value of 0.795 in Burriel et al. (2010). $F(\bar{\omega})$ and μ_p are the parameters characterizing the entrepreneur bankruptcy. The estimated probability of default and the monitoring cost estimated values are similar to the ones obtained in Christiano et al. (2014) and seem to be well identified.

The Calvo price setting probability has an estimated value of 0.778 compared with the higher value obtained in Burriel et al. (2010) (0.904). The wage setting probability has an estimated value of 0.677, which is more standard than the low estimate of 0.235 in Burriel et al. (2010). Apparently, the more complex representation of our economy, it is able to capture the high stickiness of the economy and consequently, the wage and price setting probabilities, ζ_w and ζ_p, take more reasonable values. The rest of the parameters characterizing wage and price settings are the weights on steady state inflation in the indexation rules of wages and prices, ι_w and ι_p, respectively. Their estimated values are similar to the values estimated by Christiano et al. (2014). The parameters controlling the investment process of the entrepreneur, σ_a, S' and $\rho_{\tau^{oil}}$, are the capital utilization rate, the investment adjustment cost and the oil price shock parameters, respectively. The estimated capital utilization rate is higher, 1.864, than the 0.248 estimated in Burriel et al. (2010). However, note that the 90% posterior probability interval is large. The investment adjustment cost is estimated with a value of 15.893 in contrast with the 28.995 value obtained by Burriel et al. (2010). The estimated oil price shock parameter is 0.859 and significantly lower than the one estimated by Christiano et al. (2014). Our model includes several sticky mechanisms necessary to assure the uniqueness of the rational expectation equilibrium (i.e. the fulfillment of the Blanchard and Khan (1980) conditions). In regards to the monetary policy rule, the estimated value of the parameter featuring the reaction of the nominal interest rate to inflation shows a sound value of 2.05. With a estimated coefficient greater than one, the Taylor rule satisfies the Taylor principle

The estimated autoregressive parameters of the shocks show a high inertia and thus a strong long-run response to shocks, with the exceptions of the estimated autoregressive parameter of the persistent productivity shock, $\rho_{\mu^*_{z,t}}$, and the government consumption shock, ρ_{g_t}, that are close to zero in line with the findings of Christiano et al. (2014). The posterior standard deviations of shocks, show that sample information helps identify them, as can be seen in the narrow estimated 90% posterior probability intervals.

Table 3.2: Model priors and posteriors

	Prior			Posterior	
Parameter	Type	Mean	SD	Mean	90% CI
ξ_w: Calvo wages	Beta	0.75	0.1	0.677	0.651- 0.697
b: Habit parameter	Beta	0.5	0.1	0.712	0.674- 0.753
$F(\bar{\omega})$: Steady-state prob. of default	Beta	0.008	0.004	0.037	0.026- 0.047
μ_p: Monitoring cost	Beta	0.275	0.15	0.114	0.088- 0.147
σ_a: Capacity utilization	Normal	1	1	1.864	0.551- 2.72
S': Investment adjust. cost	Normal	5	3	15.893	13.642-17.921
ξ_p: Calvo prices	Beta	0.5	0.1	0.778	0.727- 0.821
α_π: Weight on inflation in Taylor rule	Normal	1.5	0.25	2.05	1.916- 2.198
$\rho_{\tau^{oil}}$: Oil price shock	Beta	0.75	0.1	0.859	0.833- 0.872
ι_p: Weight on steady state inflation	Beta	0.5	0.15	0.838	0.786- 0.894
ι_w: Weight on steady state inflation	Beta	0.5	0.15	0.5	0.353- 0.735
ι_{mu}: Wage weight on persis. tech. growth	Beta	0.5	0.15	0.907	0.856- 0.95
$\rho_{signals}$: Correlation coefficient of signals	Beta	0.5	0.2	0.929	0.883- 0.988
$\rho_{\lambda_{f,t}}$: Price mark-up shock	Beta	0.5	0.2	0.922	0.901- 0.951
ρ_{μ_t}: Equity shock	Beta	0.5	0.2	0.962	0.942- 0.987
ρ_{g_t}: Government consumption shock	Beta	0.5	0.2	0.078	0.035- 0.134
$\rho_{\mu^*_z}$: Persistent. product. shock	Beta	0.5	0.2	0.883	0.832- 0.922
ρ_{ϵ_t}: Transitory product. shock	Beta	0.5	0.2	0.834	0.795- 0.862
ρ_{π}: Idiosyn. inflat. innov.	Beta	0.5	0.2	0.928	0.901- 0.952
ρ_{ζ_c}: Demand shock	Beta	0.5	0.2	0.969	0.924- 0.989
ρ_{ζ_i}: Margin. effic. of invest. shock	invg2	0.001	0.001	0.134	0.121- 0.155
$\sigma_{\sigma,\pi}$: Std. dev., anticipated risk shock	invg2	0.002	0.003	0.003	0.002- 0.003
$\sigma_{\sigma,0}$: Std. dev., unanticipated risk shock	invg2	0.002	0.003	0.022	0.019- 0.024
$\sigma_{\lambda_{f,t}}$: Price markup shock	invg2	0.002	0.003	0.008	0.006- 0.009
σ_{μ_t}: Equity shock	invg2	0.002	0.003	0.027	0.026- 0.029
σ_{g_t}: Government consumption shock	invg2	0.002	0.003	0.012	0.011- 0.013
$\sigma_{\mu^*_z}$: Persistent. product. shock	invg2	0.002	0.003	0.006	0.005- 0.007
σ_{γ_t}: Financial wealth shock	invg2	0.002	0.003	0.008	0.007- 0.008
$\sigma_{_t}$: Transitory product. shock	invg2	0.583	0.825	1.645	1.335- 1.891
σ_{ϵ_t}: Monetary policy shock	invg2	0.583	0.825	0.032	0.032- 0.034
σ_{π}: Std. dev. of idiosyn. inflat. innov.	invg2	0.002	0.003	0.049	0.044- 0.055
σ_{ζ_c}: Demand shock	invg2	0.002	0.003	0.02	0.015- 0.027
σ_{ζ_i}: Margin. effic. of invest. shock	invg2	0.002	0.003	0.005	0.003- 0.008
Meas. error, Real Net Worth Growth	Weibull	0.01	5	0.045	0.037- 0.053

The steady state properties of our model when parameters are set to their mean for Spain are provided in Table 3.3 as well as the corresponding historical values. As shown in this table, the model characterizes the long-run features in the data to same extent, but there are quantitative differences. We think that these differences are due to the extreme simple specification of the external finance and the banking sector. Our strategy for computing the posterior distribution of the model parameters does not make use of information in the data about the sort of ratios displayed in Table 3.3. Therefore, it is not surprising that when the model parameters are assigned their values at the posterior mode, the model's performance relative to these ratios in Table 3.3 deteriorates somewhat.

Table 3.3: Steady-state properties, Model at priors versus data

Variable	Model	Sample averages
$\frac{i}{y}$	0.268	0.246
$\frac{c}{y}$	0.528	0.561
$\frac{k}{y}$	8.104	
$\frac{n}{k-n}$	0.985	0.8-6.28
Transfer received by new entrepreneurs as percent of GDP	0.002	
Credit velocity	0.245	
Short-term risk free rate (APR)	4.668	

3.6.1 Estimation results

Figure 3.9 displays the year-over-year growth rate of GDP, the log-level of equity, the year-over-year growth rate of credit and the and credit spread. The solid lines are the observed data and the dotted lines are the results of our estimated model simulations. We can see that in Panel A and D the two lines are close to each other. This implies that the decline in GDP after the 2007 recession is well captured by our model. The off-diagonal panels (B and C) show that our model results in larger fluctuations of both the equity level and the growth rate of credit.

Figure 3.9: The role of risk shock in the observed variables

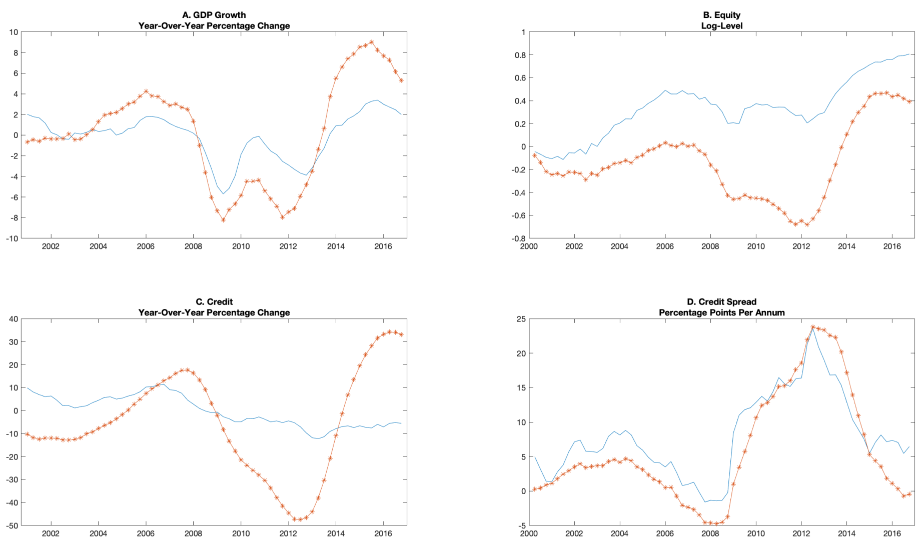


Table 3.4 displays the forecast error variance decomposition of observable variables at business cycle frequencies considering periodic components with cycles of 8-to-32 quarters,

obtained using the model spectrum. Table 3.5 reports the variance decomposition for long-term periodic components defined by cycles lasting 9-to-15 years. The statistics are derived using the mode of the posterior distributions of the shocks reported in Table 3.4.

We find three important results related to the explanatory power of the shocks over the business cycle. First, the anticipated risk shock dominates all other shocks. It explains 89% of the variation in GDP and more than three quarters of the variation in investment and credit at the business cycle frequencies. These proportions increase when we analyze its contribution at low frequency cycles, when the cointegration of financial variables and the real economy is stronger. Second, the anticipated risk shock affects the economy through the financial variables. This shock is able to explain 89% of the variations in GDP, 88% in investment, 83% in the net worth and 100% in the premium. However, it falls short to explain fluctuations in consumption and inflation. Third, these results suggest that the *unanticipated* risk shock has no explanatory power in our model. This result further highlights the importance of *anticipated* risk shocks during the financial crisis. Before the crisis began, Spain was immersed in a credit bubble created in the housing market. A few economic pundits started pointing out that the possibility of a housing bubble. Therefore, the crisis was somewhat anticipated due to deep imbalances in the real estate sector as well as the fears on a global financial recession hitting hardly the local banking sector.

The consumption demand shock, ζ_c, is able to explain half of the variations in consumption and it explains 9% of the changes in GDP. The markup shock, $\lambda_{f,t}$, helps explaining 14% of the variations in GDP and 21% in consumption. The monetary policy shock loses its standard explanatory power on the variations of macroeconomics variables. The inflation differential innovation seems to capture the changes on the interest rates and inflation. The inflation differential innovation is able to explain more than half of the variations of the EMU inflation and the real and nominal interest rates. The rest of the shocks do not show a high explanatory power. In particular, the efficiency of the investment shock, $\zeta_{I,t}$, has not explanatory power when compared with the results reported in Christiano et al. (2010) for the US.

In sum, our estimation results suggest that the anticipated risk shocks, $\sigma_{1,2,3,4,5,6,7,8}$, play a crucial role in explaining the fluctuations of the Spanish economy in both the short and the long run. In order to clarify these conclusions, we provide additional intuition based on an impulse-response analysis.

Table 3.4: Variance decomposition at business cycle frequencies (Percent)

Variables/Shock	Trans. Tech.	Exog.Spend.	Finan. Wealth	Markup	Persist. Tech.	MP	Demand	M.E.I	Idiosyn. inflat. innov.	Unanticipated Risk	Anticipated Risk
	$\epsilon_t, \mu_{z,t}$	g_t	γ_t	$\lambda_{f,t}$	$\mu_{z,*}$	ϵ_t	ζ_c	$\zeta_{I,t}$	π_{EA}	σ_t	$\sigma_{1,2,3,4,5,6,7,8}$
Consumption	8	0	0	21	6	0	51	0	11	0	1
Credit	2	0	2	4	0	0	1	0	1	0	89
GDP	4	3	0	14	7	0	9	0	11	0	52
Working hours	24	2	0	14	3	0	7	0	9	0	42
Inflation	18	0	0	42	0	1	12	0	21	0	8
EU Inflation	8	0	0	19	0	0	5	0	65	0	3
Investment	1	0	0	4	0	0	0	0	5	0	88
Net Worth	0	0	0	1	0	0	0	0	13	0	83
Price Invest.	0	0	0	0	0	0	0	0	0	0	0
Premium	0	0	0	0	0	0	0	0	0	0	100
Interest Rate	8	0	0	17	0	2	6	0	63	0	5
Real Interest	6	0	0	13	0	2	5	0	71	0	4
Wages	7	0	0	52	33	0	2	0	4	0	1

Table 3.5: Variance decomposition at low frequencies (Percent)

Variables/Shock	Trans. Tech.	Exog.Spend.	Finan. Wealth	Markup	Persist. Tech.	MP	Demand	M.E.I	Idiosyn. inflat. innov.	Unanticipated Risk	Anticipated Risk
	$\epsilon_t, \mu_{z,t}$	g_t	γ_t	$\lambda_{f,t}$	$\mu_{z,*}$	ϵ_t	ζ_c	$\zeta_{I,t}$	π_{EA}	σ_t	$\sigma_{1,2,3,4,5,6,7,8}$
Consumption	10	0	0	25	7	0	46	0	9	0	2
Credit	1	0	1	3	0	0	1	0	0	0	94
GDP	4	1	0	15	6	0	7	0	8	0	57
Working hours	14	1	0	20	2	0	7	0	9	0	45
Inflation	15	0	0	34	0	1	14	0	26	0	11
EU Inflation	10	0	0	23	0	1	10	0	49	0	8
Investment	1	0	0	4	0	0	0	0	4	0	90
Net Worth	0	0	0	2	0	0	0	0	10	0	87
Price Invest.	0	0	0	0	0	0	0	0	0	0	0
Premium	0	0	0	0	0	0	0	0	0	0	100
Interest Rate	10	0	0	21	0	2	11	0	48	0	9
Real Interest	5	0	0	11	0	2	6	0	72	0	5
Wages	8	0	0	62	23	0	2	0	3	0	1

3.6.2 The key role of risk signals

Figures 3.10 and 3.11 display the responses of macroeconomic variables to the unanticipated risk shock and anticipated risk signals to different horizons (σ where i=1,2,3,4,5,6,7,8), respectively. These two graphs allow us to assess the relative importance of anticipated versus unanticipated risk shocks.

Figure 3.10: Impulse Response Functions to an unanticipated risk shock, $\sigma_{0,t}$

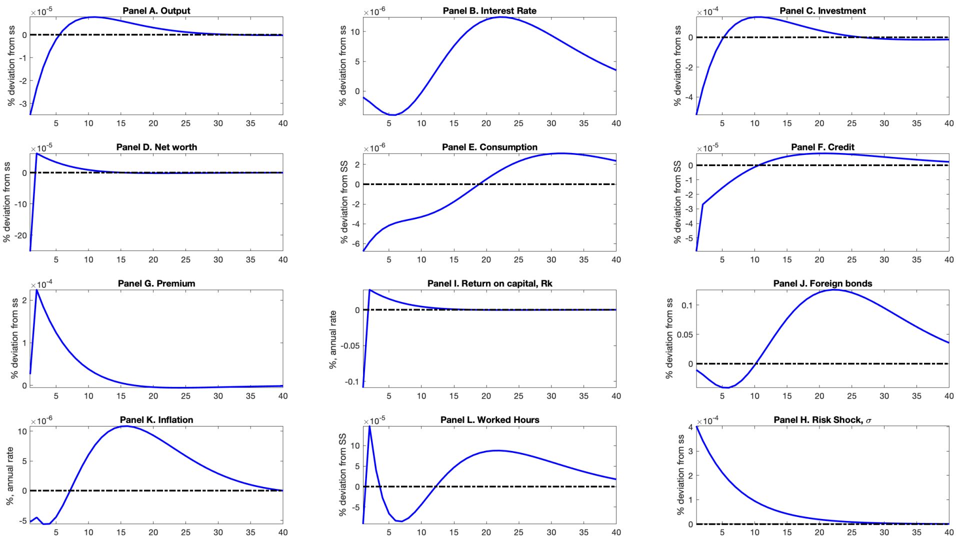
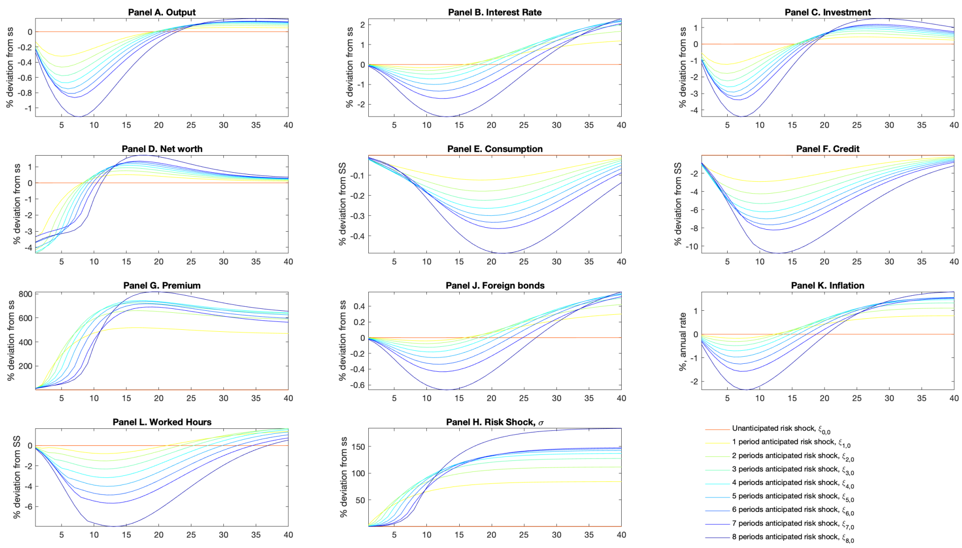


Figure 3.11: Impulse Response Functions to anticipated shocks, $\sigma_{1,2,3,4,5,6,7,8,t}$



Figures 3.10 and 3.11 allow us to assess the relative importance of anticipated versus unanticipated risk shocks. Clearly, the responses to an *unanticipated* risk shock are much smaller than those to the *anticipated* shocks. Moreover, we see that all the responses across *anticipated* signals share the same sign. However, the longer horizon signals, seem

to have a higher impact on macroeconomic variables than the short-term signals but the size of the responses varies across variables. This finding is in line with Fujiwara et al. (2011), where they conclude that news shocks with longer signal horizons have larger effects on nominal variables.

The unanticipated and anticipated risk shock responses are consistent with economic intuition. Thus, when the risk increases, the probability of a poor performance of entrepreneurs increases and the interest rate on loans increases. The increase in interest rates has two effects on entrepreneurs. First, it makes borrowing more expensive. Second, the "Fisher deflation" effect that refers to the decrease in the net worth that occur when an unexpected decrease in the price level increases the real value of their debt decreasing their net worth. As a consequence of these two effects, the entrepreneurs borrow less and purchase less capital. Therefore, the investment drops leading to a fall in output and consumption. The fall in investment decreases the price of capital, which magnifies the effect of the "Fisher deflation effect", and further reduces the net worth of entrepreneurs. The economy enters in a recession phase. However, we have included German foreign bonds in our model. Thus, the economy recover from the national slow-down relaying on the purchase of risk-free foreign bonds. Therefore, holding risk-free bonds helps off-set the effects of the propagation of systemic risk in the national economy (i.e. Spain).

Figure F.1 displays the period-to-period contribution of each shock to the GDP growth. Clearly the anticipated risk shocks, displayed as blue, dominate all other shocks in explaining the fluctuations of GDP. Moreover, the *anticipated* risk signals are able to explain almost all the variations in the premium as shown in Figure F.2.

Figure 3.12: Impulse Response Functions to an idiosyncratic inflation innovation, π_{SP}

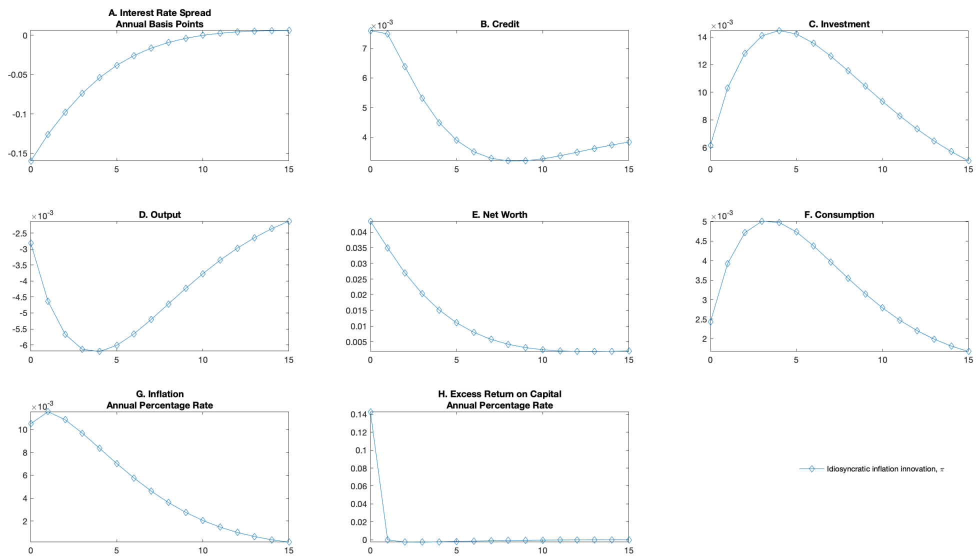


Figure 3.12 shows the impulse-response functions to an idiosyncratic inflation innovation. As we have seen before, the inflation differential is able to explain 11% of the variations in GDP and more than 60% of the variation on interest rates. An increase in the inflation differential means that inflation in Spain increases relative to EMU's inflation. As a consequence, the real value of the entrepreneurial net worth increases and the interest rate decreases which allows the entrepreneurs to borrow more. Thus, credit

and investment increase. However, the increase in the investment sector is not able to offset the increase of the level of prices in the Spanish economy. As a consequence of the decrease in the interest rates on credits to entrepreneurs, banks start buying more foreign bonds. Thus, the national output decreases creating a slow-down of the small economy (i.e. Spain).

We have used the impulse response to support our claim that the *anticipated* risk shock and the idiosyncratic inflation innovation in our empirical analysis are key in explaining the Spanish business cycle. We have seen that the anticipated risk shocks result in larger responses on the macroeconomic variables than those associated with an *unanticipated* risk shock. Next, we will analyze the transmission mechanism behind more standard shocks, such as the monetary policy shock, the transitory technology shock, and others.

Figure 3.13: Impulse Response Functions to a three shock: ξ_0, ζ_i, σ

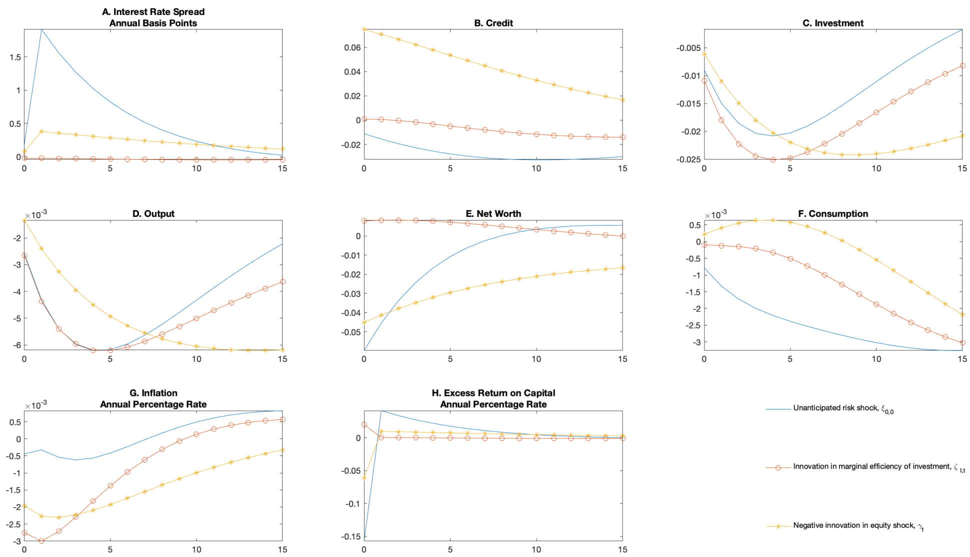
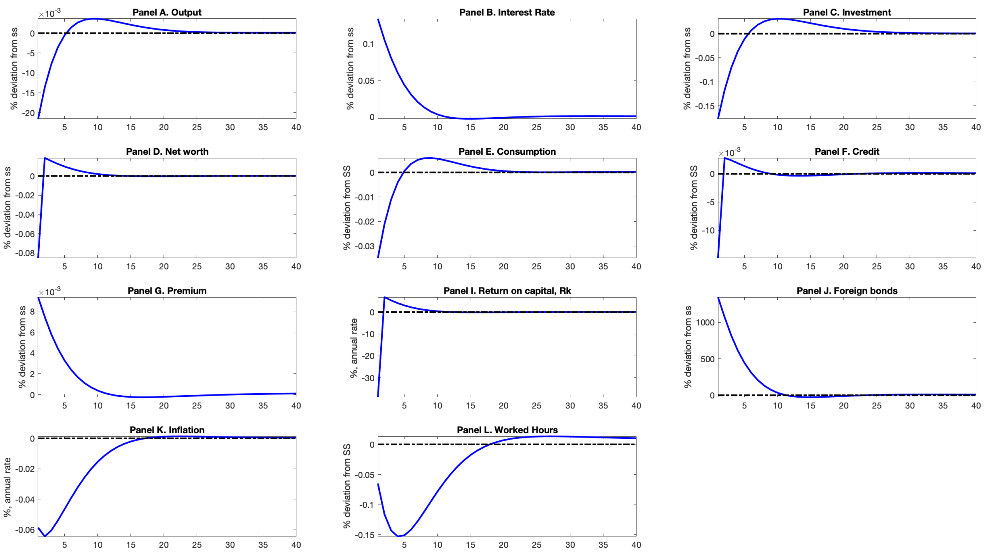


Figure 3.13 displays the responses to three shocks: the unanticipated risk shock, the innovation in the marginal efficiency of investment (MEI) and a negative innovation in equity shock. Our computed impulse response functions resemble those obtained by Christiano et al. (2014) for the US. The explanatory power of the unanticipated risk shock, the MEI shock and the negative equity shock is in all cases small. Even if the unanticipated risk shock does not have any explanatory power in our model the signs of the impulse responses are intuitively correct as we have seen for the anticipated risk shocks. Counterintuitively, and in line with the results obtained by Christiano et al. (2010), an innovation in the marginal efficiency of investment decreases investment leading to a fall in output.The responses to a negative innovation in the equity shock resemble the simulated responses to a risk shock. A negative equity shock decreases the net worth of the entrepreneurs, making their debt burden higher and decreasing the value of their assets. As a result, the economy enters into a recession. However, due to the propagation of risk into the economy, the households decide to increase their consumption. This generates, an increase in the value of capital and a higher need of entrepreneurs to finance their capital purchases. The increase in foreign bond purchases creates a higher decrease in investment and output.

The impulse response functions to a standard monetary shock are shown in Figure 3.14. The propagation mechanism behind this shock is similar to the one exhibited by the risk shocks. The monetary policy shock increases the interest rate. Thus, borrowing becomes more expensive for entrepreneurs. At the same time, the real value of the entrepreneurial net worth decreases. As a consequence, investment and consumption fall. This economic decline induces a general loss in the small economy's confidence, which leads to an increase of the purchase of foreign-bonds. However, notice that the responses of the aggregate macroeconomic variables are much smaller when a monetary policy shock takes place than when the economy receives risk signals in advance.

Figure 3.14: Impulse Response Functions to a monetary policy shock, ϵ



3.7 Conclusion

This paper studies the role of the risk signals as a trigger and propagator of the financial crisis of the recession starting around 2008 in Spain. We use Bayesian techniques to estimate a variant of Christiano et al. (2010, 2014) model that allows banks from the small economy (e.g. Spain) to buy foreign bonds. Our model variant also includes the inflation differential between Spain and the EMU in order to assess the efficiency of the single monetary policy in the Spanish business cycle.

We estimate the model for Spain over the period 2000Q1-2017Q4. We use quarterly observations of ten macroeconomic series that are standardly used in the estimation of DSGE models and three additional financial time series: credit to non financial corporations, the risk premium of sovereign bonds and entrepreneurial net worth considered in Christiano et al. (2010, 2014).

Our empirical results show that *anticipated* risk shocks account for a sizeable 52% of fluctuations in the GDP, 89% in credit and 100% in the risk premium. The idiosyncratic innovation of inflation also appears to be an important driving force of the business cycle fluctuations in Spain. This innovation accounts for a 11% of the variations in GDP and 13% in the net worth of entrepreneurs. Moreover, these shocks largely explain the episode of credit crunch and the contraction of investment and output. Such a sequence has been observed during the recent recession (2009-2013) in Spain which was likely anticipated by economic pundits. Our results show that anticipated risk shocks dominate all other shocks. Further research on the identification of news or "risk signals" is warranted in order to understand better the causes and consequences of the last recession in Spain.

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Data appendix

We provide the sources for the twelve observed variables used in the estimation.

Population series are used to normalize quantity variables.

- **GDP:** Gross domestic product at market price, Chain linked volumes, reference year 2010, Quarterly, Working day and seasonally adjusted, (ECB series).
- **Consumption:** Final consumption of households and NPISH's, Chain linked volumes, reference year 2010, Quarterly, Working day and seasonally adjusted, (OECD database).
- **Investment:** Gross fixed capital formation, Chain linked volumes, reference year 2010, Quarterly, Working day and seasonally adjusted, EA 17 fixed composition, (ECB series).
- **Inflation:** Deflator of Gross domestic product at market price, Quarterly, Working day and seasonally adjusted, (FRED series), logarithmic first difference.
- **EU Inflation:** Deflator of Gross domestic product at market price, Quarterly, Working day and seasonally adjusted, EA 17 fixed composition (database), logarithmic first difference.
- **Price of investment:** Deflator of Gross fixed capital formation, Quarterly, Working day and seasonally adjusted, (OECD database).
- **Hours worked:** Hours of All Employees, Quarterly, Working day and seasonally adjusted, (ECB series).
- **Wage:** Compensation of Employees, received by Households and NPISH's, Quarterly, Seasonally adjusted, (OECD database).
- **Short-term risk-free rates:** Nominal Short-Term Interest Rate (AWM: STN) and Euribor 3-month, Historical close, Quarterly, average observation through period, (ECB series).
- **Credit:** Loans to Non-financial corporations, Closing balance sheet, Quarterly, Neither seasonally nor working day adjusted, (ECB series).
- **Entrepreneurial net worth:** IBEX35 Index, Historical close, Quarterly, average observation through period, (BOLSA DE MADRID database).
- **Population:** Working Age Population: Aged 15-64: All Persons for the Euro Area, Persons, Quarterly, Seasonally Adjusted , (FRED series).

List of equations of the model

This section displays all the equilibrium conditions of the model.

$$s_t = \left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} \frac{1}{\epsilon_t z_t^{1-\alpha}} \left[\tilde{r}^k\right]^{\alpha} \left[\frac{w_t}{p_t}\right]^{1-\alpha}, \tag{B1}$$

$$s_t = \frac{\left[\tilde{r}^k\right]}{\alpha \epsilon_t \left(\frac{z_t l_{j,t}}{k_{j,t}}\right)^{1-\alpha}}, \tag{B2}$$

$$r_t^k = \frac{\alpha \epsilon_t}{(1+\Psi_{k,t} R_t)} \left(\frac{\Upsilon \mu_{z,t}^* L_t (w_t^*)^{\frac{\lambda_w}{\lambda_w - 1}}}{u_t k_t}\right)^{1-\alpha} s_t \tag{B3}$$

$$E_t \left[\lambda_{z,t} Y_{z,t} + \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}}\right)^{\frac{1}{1-\lambda_{f,t+1}}} \beta \xi_p F_{p,t+1} - F_{p,t}\right] = 0, \tag{B4}$$

$$E_t \left[\lambda_{f,t} \lambda_{z,t} Y_{z,t} s_t + \beta \xi_p \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}}\right)^{\frac{-\lambda_{f,t+1}}{\lambda_{f,t+1}-1}} K_{p,t+1} - K_{p,t}\right] = 0, \tag{B5}$$

$$P_t^* = \left((1-\xi_p) \left(\frac{1 - \xi_p \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}}\right)^{\frac{1}{1-\lambda_{f,t+1}}}}{1-\xi_p} \right)^{1-\lambda_{f,t}} + \xi_p \left(\frac{\tilde{\pi}_t}{\pi_t} p_{t-1}^*\right)^{\frac{\lambda_{f,t}}{1-\lambda_{f,t}}} \right)^{\frac{1-\lambda_{f,t}}{\lambda_{f,t}}}, \tag{B6}$$

$$E_t \left\{ [1 - \Gamma_t(\bar{\omega}_{t+1})] \left(\frac{1+R_{t+1}^k}{1+R_{t+1}^e}\right) + \frac{\Gamma'(\bar{\omega}_{t+1})}{\Gamma'(\bar{\omega}_{t+1}) - \mu G'(\bar{\omega}_{t+1})} \left[\left(\frac{1+R_{t+1}^k}{1+R_{t+1}^e}\right) (\Gamma'(\bar{\omega}_{t+1}) - \mu G'(\bar{\omega}_{t+1})) \right] \right\} = 0, \tag{B7}$$

$$(1+R_{t+1}^k) \left[\Gamma(\bar{\omega}_{t+1}) - \mu G(\bar{\omega}_{t+1})\right] = (1+R_{t+1}^e) B_{t+1}, \tag{B8}$$

$$\lambda_{zt} = E_t \{ \frac{\beta}{\pi_{t+1} \mu_{z,t+1}^*} \lambda_{zt+1} \left(1 + R_{t+1}^{BO}\right) \} \tag{B9}$$

$$E_t[(1+\tau^C) \zeta_{c,t} \lambda_{z,t} - \frac{\mu_{z,t}^* \zeta_{c,t}}{c_t \mu_{z,t}^* - b c_{t-1}} + b\beta \frac{\zeta_{c,t+1}}{c_{t+1} \mu_{z,t+1}^* - b c_t}] = 0 \tag{B10}$$

where the continue here

$$E_t \{ -\zeta_{c,t} \lambda_{zt} + \frac{\beta}{\pi_{t+1} \mu_{z,t+1}^*} \zeta_{c,t+1} \lambda_{zt+1} \left(1 + R_{t+1}^k\right) \} = 0 \tag{B11}$$

$$E_t\left\{\varsigma_{c,t}(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}} l_t \frac{(1-\tau^l)\lambda_{z,t}}{\lambda_w} + \beta\xi_w(\mu_z^*)^{\frac{1-\vartheta}{1-\lambda_w}}(\mu_{z,t+1}^*)^{\frac{\vartheta}{1-\lambda_w}-1}\left(\frac{1}{\pi_{w,t+1}}\right)^{\frac{\lambda_w}{1-\lambda_w}} \frac{\tilde{\pi}_{w,t+1}^{\frac{1}{1-\lambda_w}}}{\pi_{t+1}} F_{w,t+1} - F_{w,t}\right\} = 0, \tag{B12}$$

$$E_t\left\{\left[(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}} l_t\right]^{1+\sigma_L} \varsigma_{c,t}\varsigma_t + \beta\xi_w\left(\frac{\tilde{\pi}_{w,t+1}}{\pi_{w,t+1}}(\mu_z^*)^{1-\vartheta}(\mu_{z,t+1}^*)^{\vartheta}\right)^{\frac{\lambda_w}{1-\lambda_w}(1+\sigma_L)} K_{w,t+1} - K_{w,t}\right\} = 0, \tag{B13}$$

$$w_t^* = \left[(1-\xi_w)\left(\frac{1-\xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_z^*)^{1-\vartheta}(\mu_{z,t+1}^*)^{\vartheta}\right)}{1-\xi_w}\right)^{\lambda_w} + \xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_z^*)^{1-\vartheta}(\mu_{z,t+1}^*)^{\vartheta} w_{t-1}^*\right)^{\frac{\lambda_w}{1-\lambda_w}}\right]^{\frac{1-\lambda_w}{\lambda_w}}, \tag{B14}$$

$$\bar{k}_{t+1} = (1-\delta)\bar{k}_t + F(I_t, I_{t-1}, \varsigma_{i,t}) = (1-\delta)\bar{k}_t + (1-S(I_t, I_{t-1}, \varsigma_{i,t}))I_t. \tag{B15}$$

$$E_t\left[\lambda_t Q_{\bar{k},t}F_{1,t} - \lambda_t\frac{P_t}{\Upsilon^t\mu_{\Upsilon,t}} + \beta\lambda_{t+1}Q_{\bar{k},t+1}F_{2,t+1}\right] = 0, \tag{B16}$$

$$\frac{\left[u_{t+1}\tilde{r}_{t+1}^k - \Upsilon^{-(t+1)}\tau_{t+1}^{oil}a(u_{t+1})\right]p_{t+1} + (1-\delta)Q_{\bar{k}_{t+1}}}{Q_{\bar{k},t}} + \tau^k\delta = 1 + R_{t+1}^k \tag{B17}$$

$$\bar{n}_{t+1} = \gamma_t((1+R_{t+1}^k)Q_{\bar{k}_{t-1}}\bar{k}_t - \left[1 + R_t^e + \mu\int_0^{\bar{\omega}}\frac{\omega dF_t(1+R_t^k)Q_{\bar{k},t-1}\bar{k}_t}{Q_{\bar{k},t-1}\bar{k}_t - \bar{n}_t}\right]\left(Q_{\bar{k},t-1}\bar{k}_t - \bar{n}_t\right)) + w^e, \tag{B18}$$

$$d_t = \frac{\mu G(\omega_t)(1+R_t^k)q_{t-1}k_t}{\pi_t\mu_{z,t}^*} \tag{B19}$$

$$\begin{aligned} Y_t = \mu\int_0^{\bar{\omega}_t}\omega dF(\omega)(1+R_t^k)\frac{Q_{k,t-1}\bar{k}_t}{p_t} + \frac{\tau^{oil}a(u_t)}{\Upsilon^t}\bar{k}_t + \frac{\Theta(1-\gamma_t)}{p_t}V_t + g_t + c_t \\ + \left(\frac{i_t}{\Upsilon^t\mu_{\Upsilon,t}}\right)i_t + BO_{t+1} - (1+R_t^b)BO_t, \end{aligned} \tag{B20}$$

$$R_{t+1}^b = R^b + \psi_2\left(e^{BO_t - BO} - 1\right). \tag{B21}$$

$$\pi_t - \pi = \left(\pi_t^{EA} - \pi^{EA*}\right) + \epsilon_t^{\pi} \tag{B22}$$

$$R_t - R = \rho_p\left(R_{t-1} - R\right) + (1-\rho_p)\left[\alpha_\pi\left(\pi_t^{EA} - \pi^{EA*}\right)\right] + \frac{1}{400}\epsilon_t^p - (1-\rho_p)\alpha_\pi\epsilon_t^{\pi} \tag{B23}$$

$$\sigma_t = \rho_\sigma\sigma_t - 1 + \underbrace{\xi_{0,t} + \xi_{1,t-1} + ... + \xi_{p,t-p}}_{=v_t} \tag{B*}$$

Endogenous variables

Table D.1: Variables in the model

c_t^*	Scaled aggregate consumption
ϵ_t	Transitory technology shock
g_t	Scaled government spending
γ_t	Equity shock
h_t	Working hours
i_t	Scaled investment
$\bar{k}_{t+1}$	Scaled entrepreneurial capital
$\lambda_{f,t}$	Intermediate goods stock
$\lambda_{z,t}$	Marginal utility of consumption
$\mu_{\Upsilon,t}$	Investment good technology shock
$\mu_{z^*,t}$	Growth rate of z^{star}
n_{t+1}	Entrepreneurial net worth
$\bar{\omega}_t$	The omega separating bankrupt and non-bankrupt entrepreneurs
π_t	Inflation
p_t^*	Useful variable in pricing equation
q_t	Scaled market price of capital
R_t^e	Nominal risk-free rate
r_t^k	Rental rate of capital
R_t^k	Return on capital
s_t	Marginal cost
σ_t	Risk shock
d_t	Equity
u_t	Utilization rate of capital
$\tilde{w}_t$	Scaled real wage
w_t^*	Useful variable in wage equation
$\zeta_{c,t}$	Preference shock on consumption
$\zeta_{I,t}$	Marginal efficiency of investment
R_t^b	Interest rate on bonds
BO_t	Scaled bonds
$y_{z,t}$	Scaled production
Auxiliar variables	
$F_{p,t}$	Convenience variable for price evolution
$F_{w,t}$	Convenience variable for wage evolution
ϕ	Fixed cost that ensures zero profits

Variables used to match the data	
c_t^{obs}	Observed aggregate consumption
$credit^{obs}$	Observed credit
GDP^{obs}	Observed GDP
$pinvest^{obs}$	Observed price of investment
$premium^{obs}$	Observed premium
w^{obs}	Observed wages
${R_e}^{obs}$	Observed nominal risk-free rate
${Rr_e}^{obs}$	Observed real risk-free rate
π_t	Observed inflation of Spain
π_t^{EU}	Observed inflation of the EMU
i^{obs}	Observed investment
h^{obs}	Observed working hours
n^{obs}	Observed net worth

Exogenous variables

Table E.1: Shocks in the model

$\sigma_{0,t}$: Unanticipated risk shock
$\sigma_{1,2,3,4,5,6,7,8,t}$: Anticipated risk shock
$\lambda_{f,t}$: Price markup shock
μ_t: Equity shock
g_t: Government consumption shock
μ_z^*: Persistent. product. shock
γ_t: Financial wealth shock
ϵ_t: Transitory product. shock
ϵ_t: Monetary policy shock
π_{SP}: Idiosyncratic inflation innovation
ζ_c: Consumption preference shock
ζ_i: Marginal efficiency of investment shock (M.E.I)

Shock decomposition

Figure F.1: Contribution to GDP growth

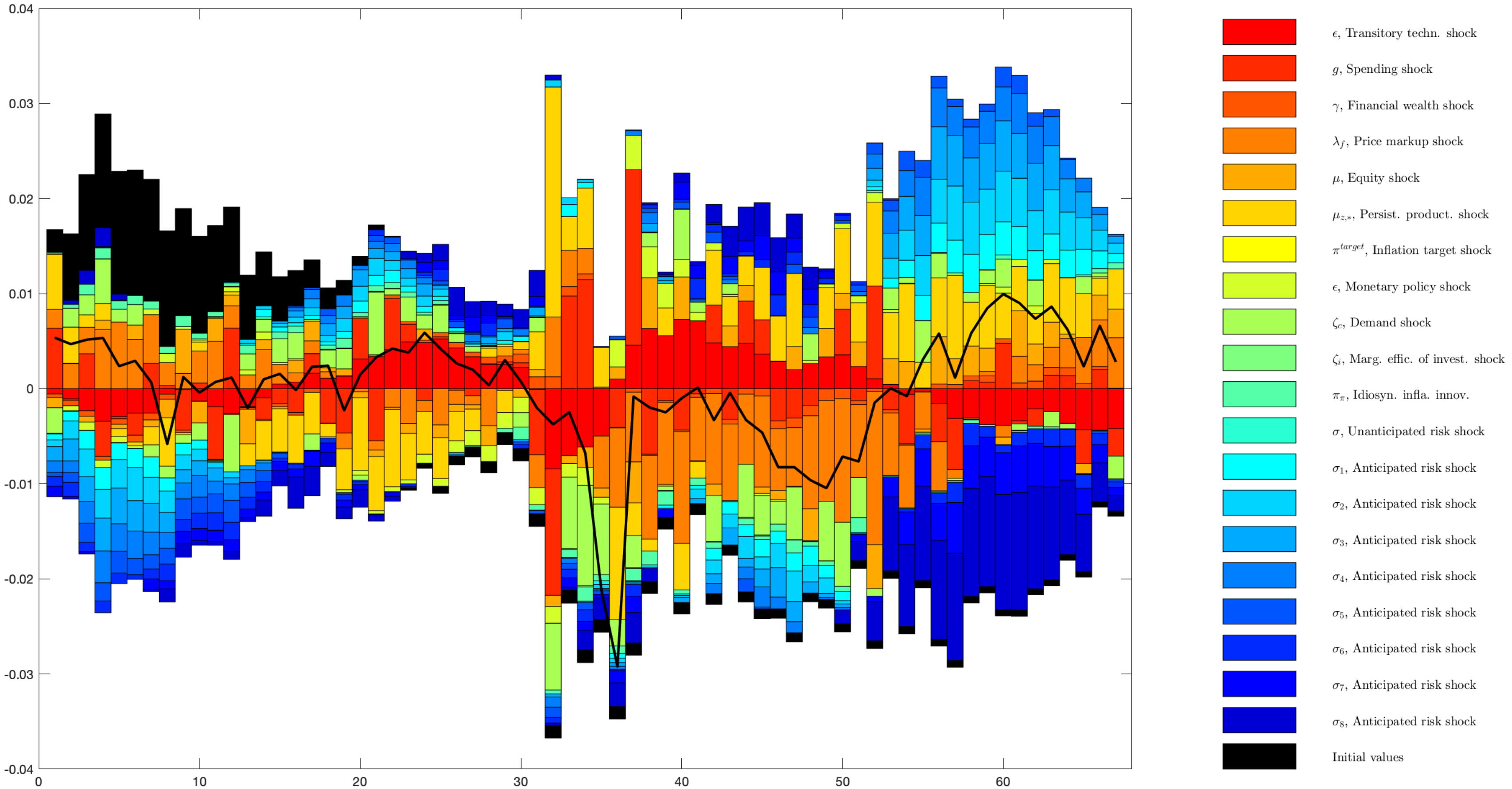


Figure F.2: Contribution to the Risk Premium

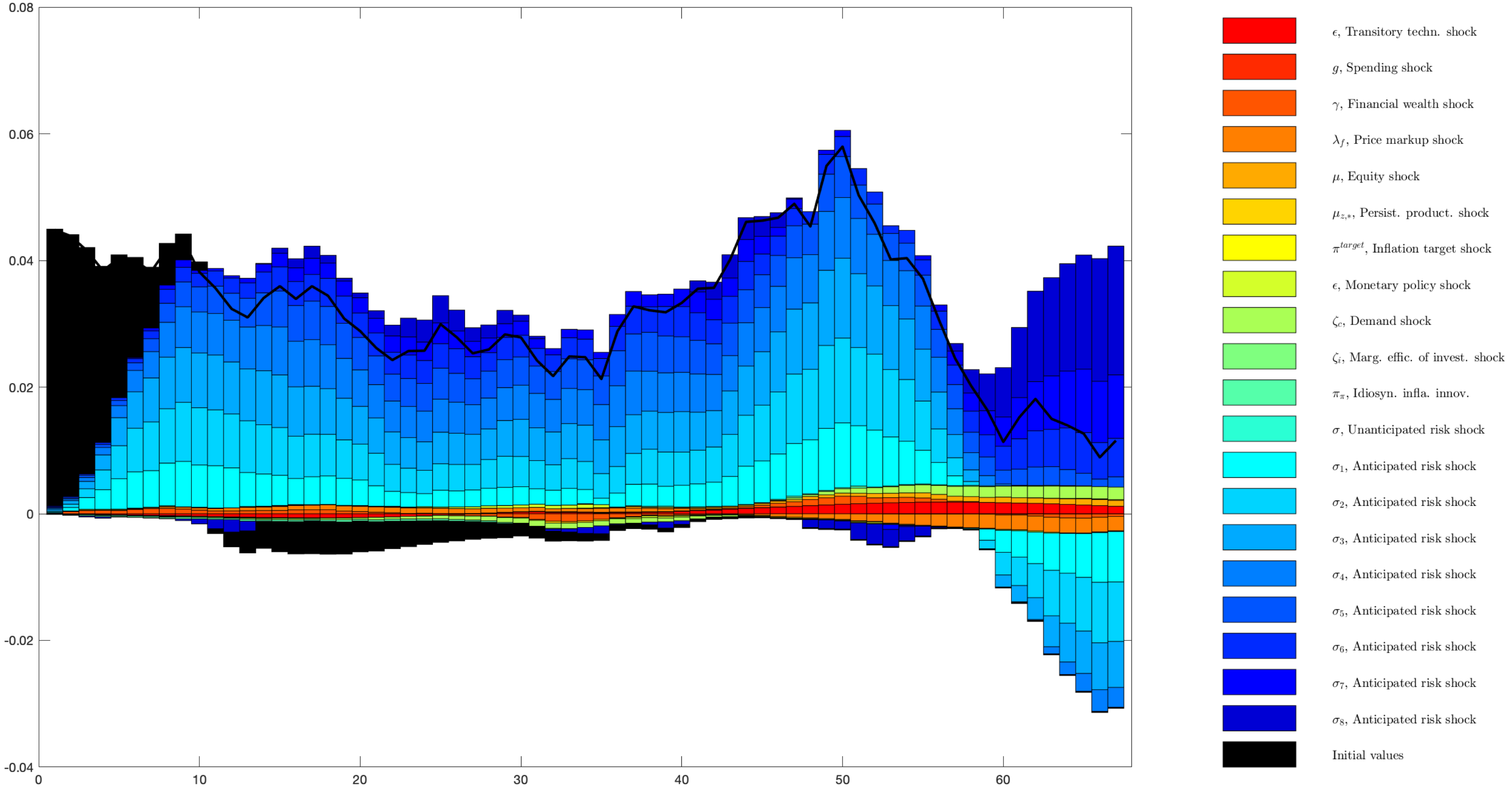


Figure F.3: Contribution to consumption growth

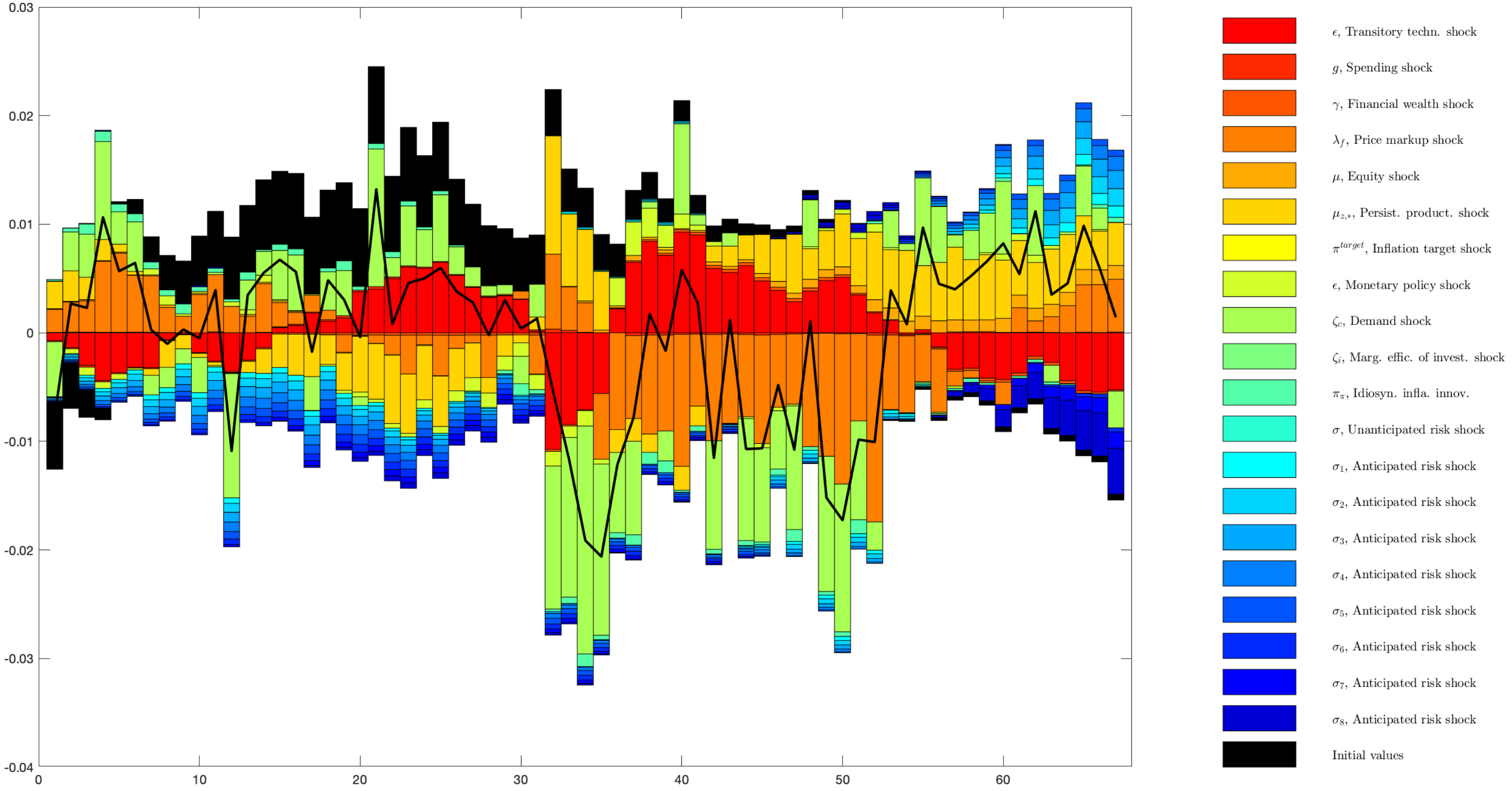


Figure F.4: Contribution to credit growth

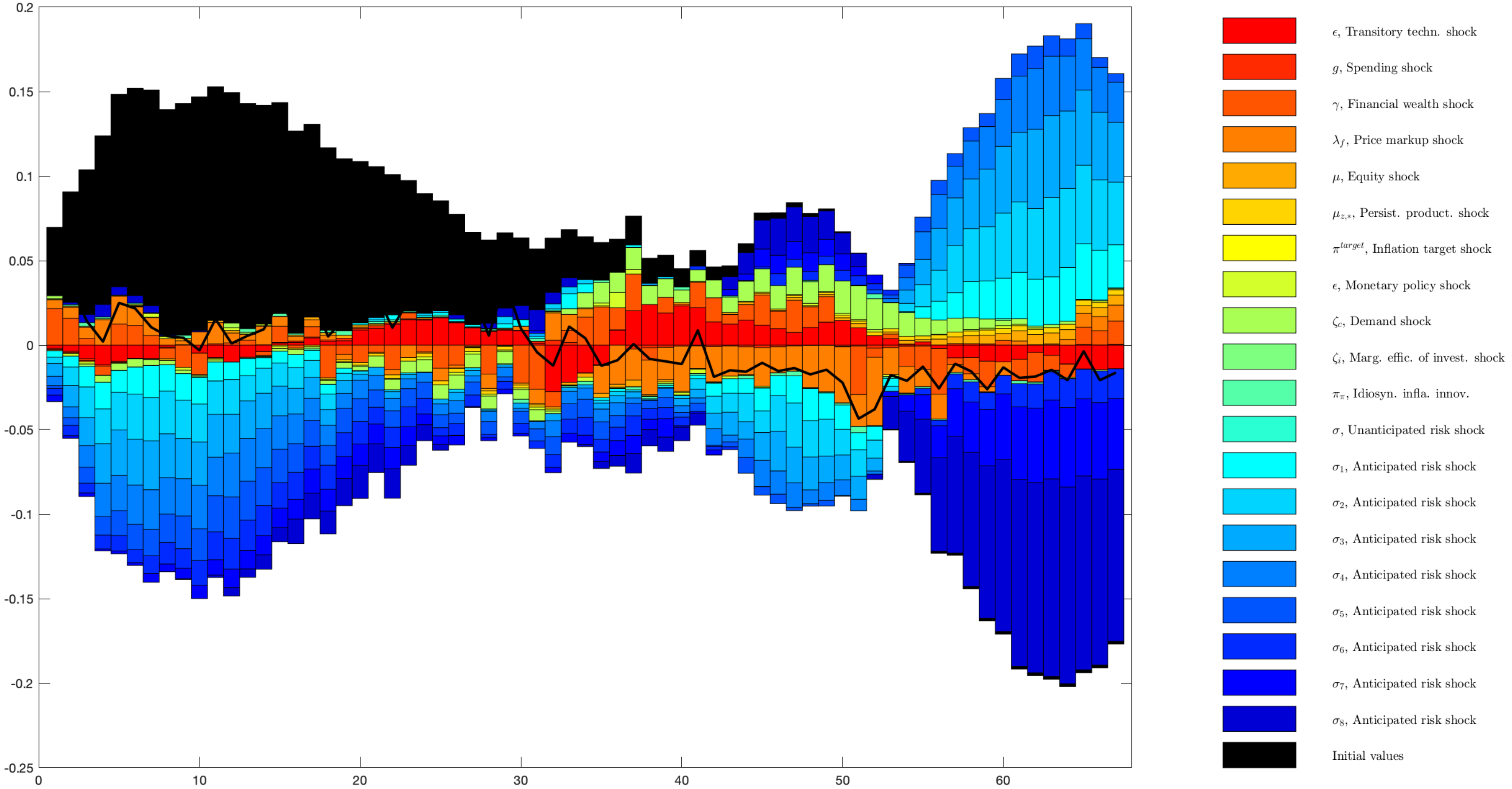


Figure F.5: Contribution to Net Worth growth

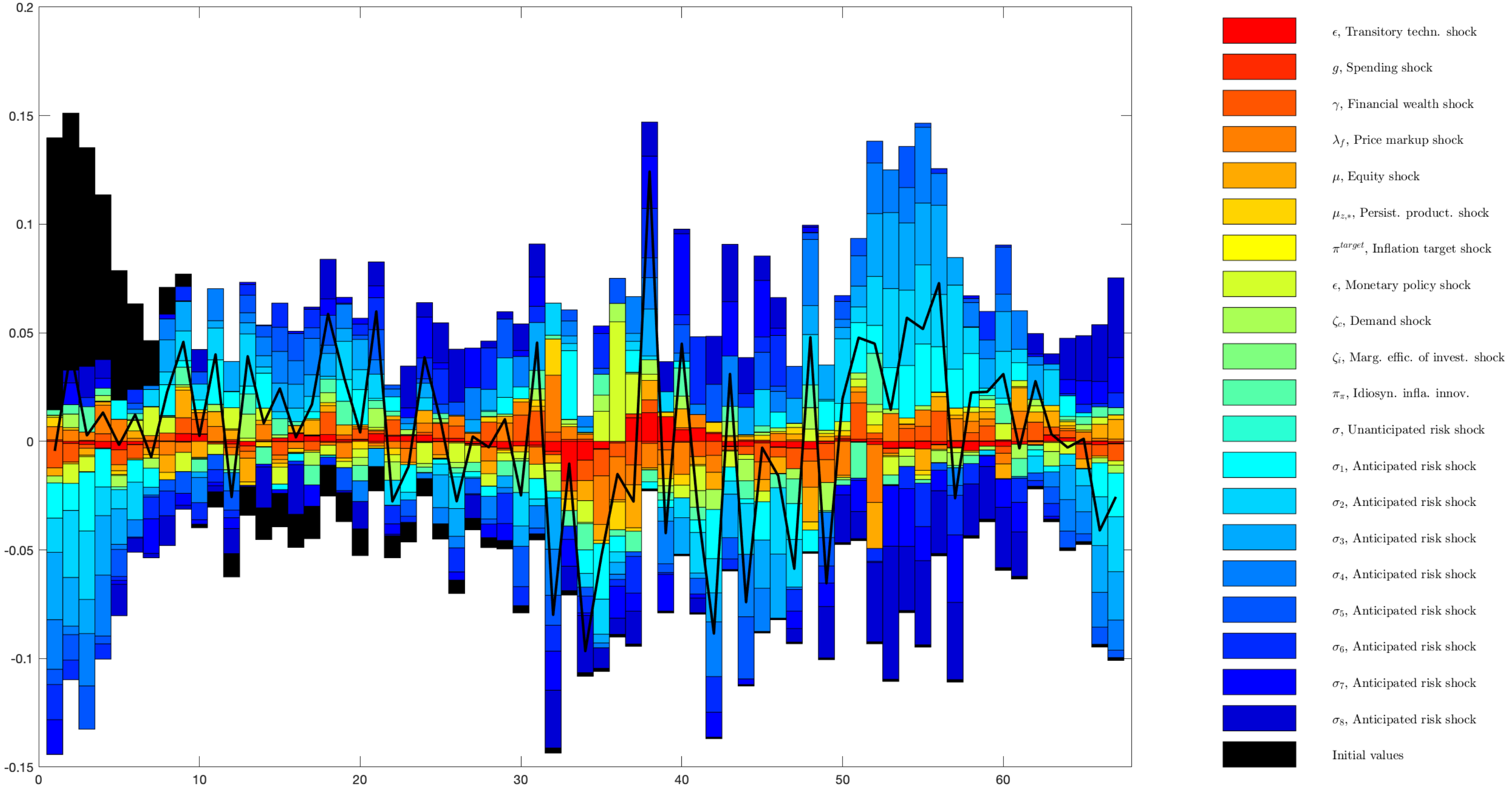


Figure F.6: Contribution to Investment growth

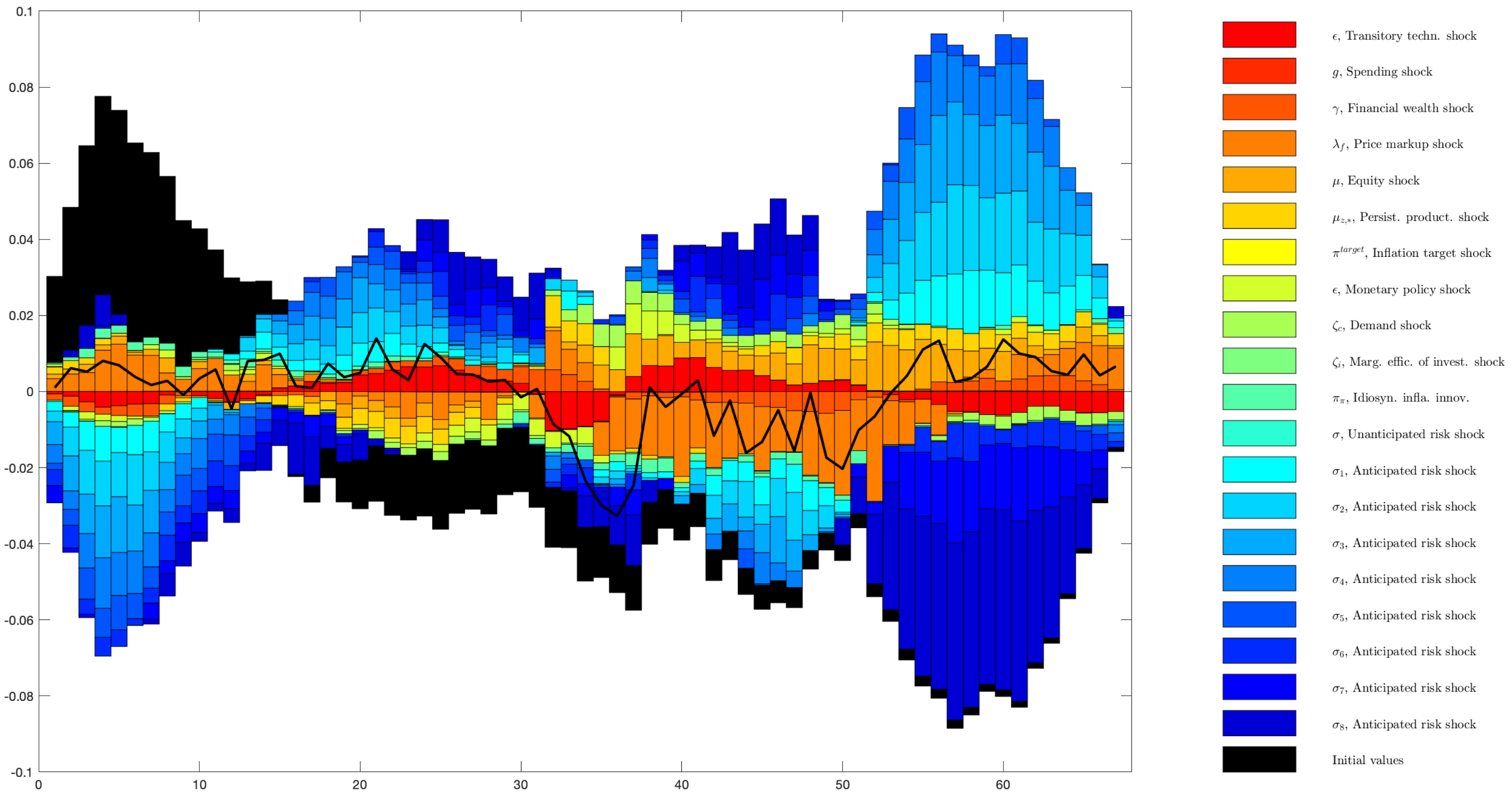


Figure F.7: Contribution to working hours growth

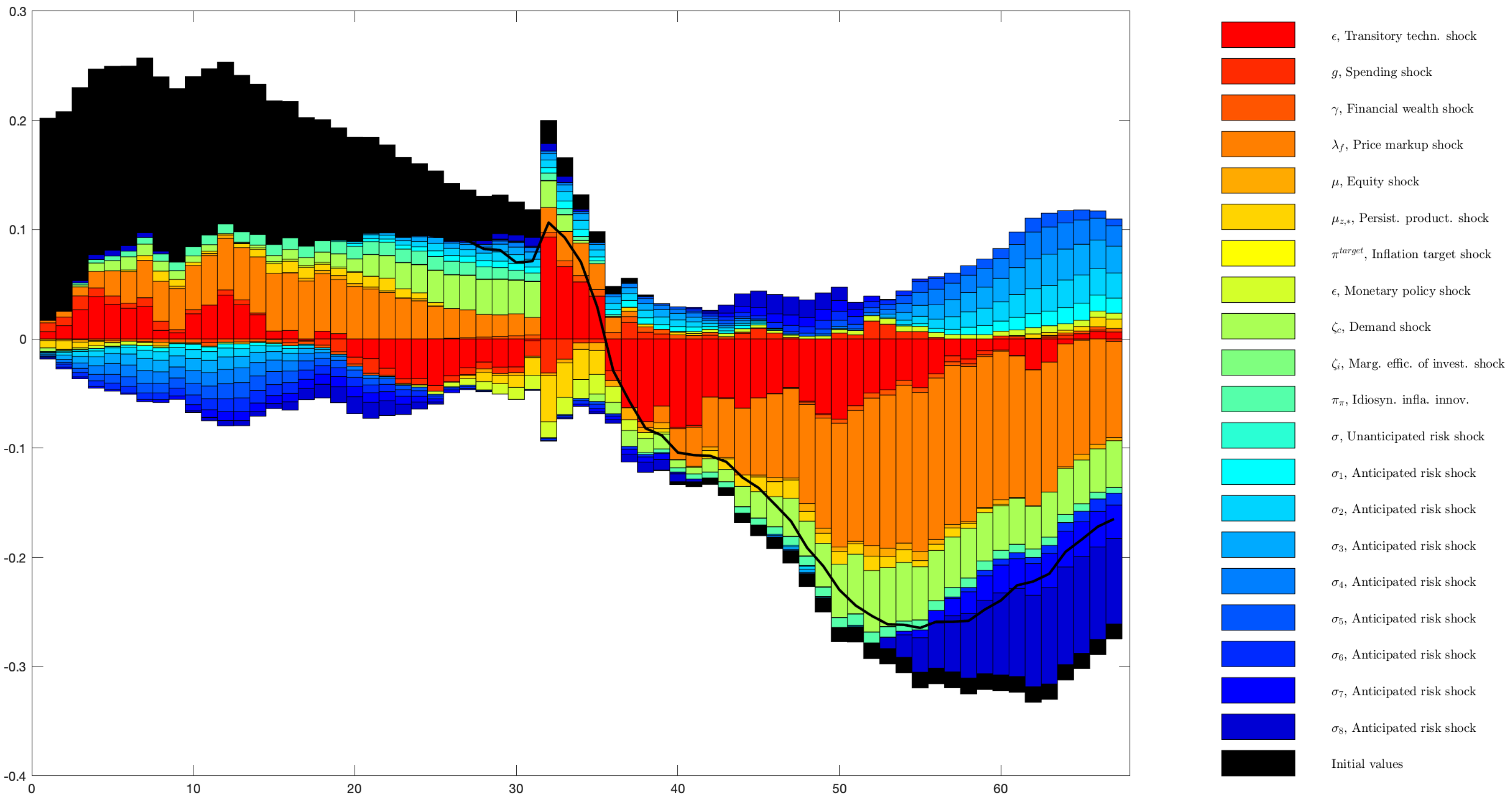
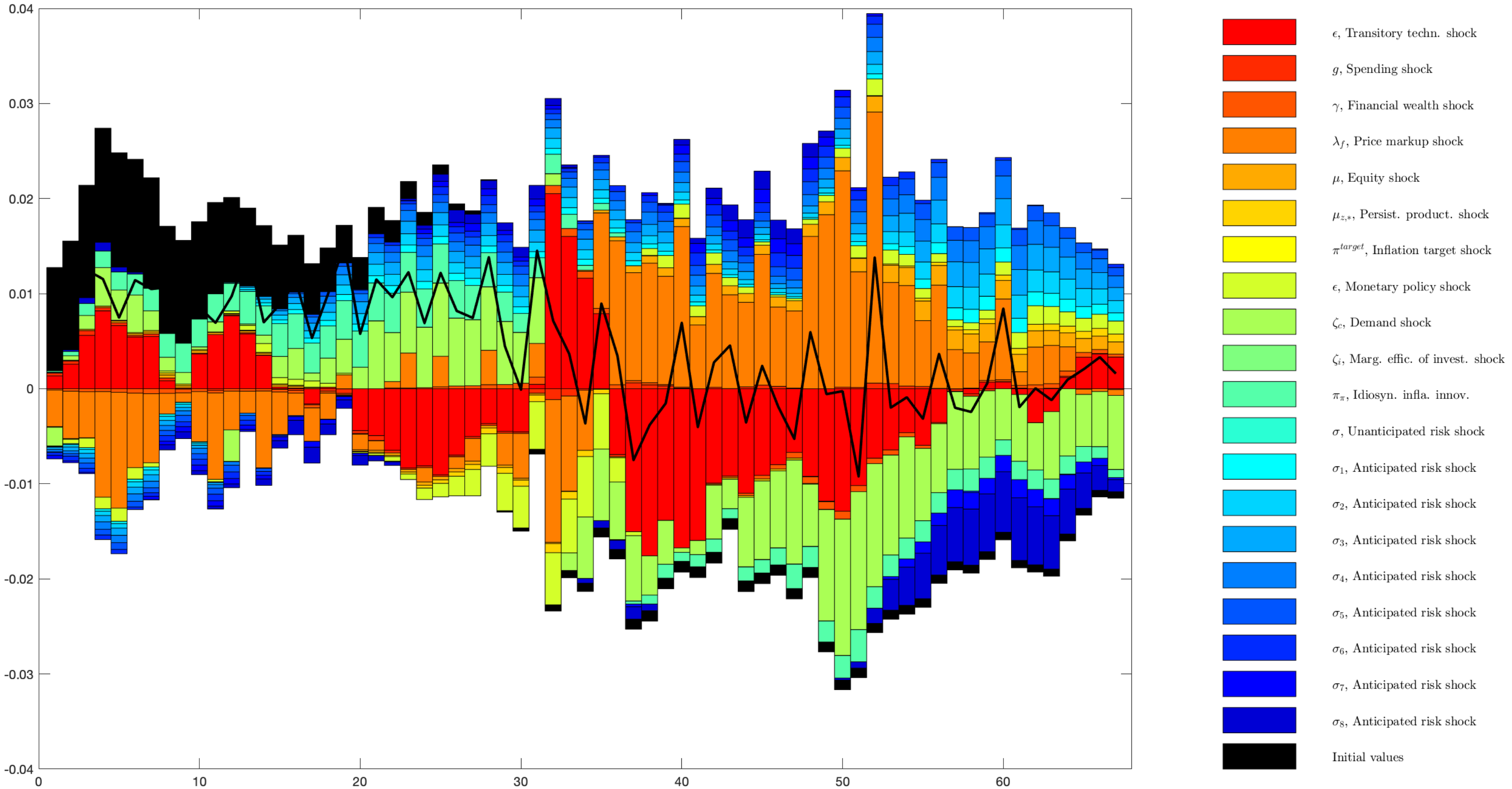


Figure F.8: Contribution to inflation



Learning, Parameter Variability, and Swings in the US Macroeconomic Dynamics

- Has the Lucas Critique become less relevant?

"My paper, "Econometric Policy Evaluation: A Critique" was written in the early 70s. Its main content was a criticism of specific econometric models—models that I had grown up with and had used in my own work. These models implied an operational way of extrapolating into the future to see what the "long run" would look like. (...)

Of course every economist, then as now, knows that expectations matter but in those days it wasn't clear how to embody this knowledge in operational models."

– *R.E. Lucas Jr.* Economic dynamics interviews Robert Lucas on modern macroeconomics, Econ. Dyn. Newsl. (2012)

4.1 Abstract

Recent studies show that the estimated parameters of models (obtained under the rational expectations hypothesis) are largely time varying. This paper shows that assuming adaptive learning (rather than rational expectations) reduces the estimated parameter variability of standard models strongly (by around 68%). Moreover, the reduction in parameter variability induced by adaptive learning is much stronger for the subsets of parameters that control nominal price and wage rigidity and the subset of policy rule parameters (at 91% and 100%, respectively). Furthermore, our estimation results suggest that adaptive learning helps to explain the recent swings in the comovements between real and nominal US macroeconomic variables, but the swing in the relative weight of supply and demand shocks seems to be the most important driving force.

4.2 Introduction

Recent literature shows evidence that the parameters in the DSGE models used to study aggregate fluctuations are in general time-varying (see, among others, Inoue and Rossi (2011), Canova and Ferroni (2012), Castelnuovo (2012*a*,*b*), Hurtado (2014), Casares and Vázquez (2018), Castelnuovo and Pellegrino (2018), Canova (2019)). These findings have important implications. On the one hand, the instability of structural parameters somewhat weakens the ability of DSGE models to assess policies reliably (Fernández-Villaverde et al. (2007)). On the other hand, parameter variability may be an important source for explaining the macroeconomic dynamic swings observed during the post-WWII era in the US.

This paper analyzes parameter variability by estimating the canonical medium-scale DSGE model suggested by Smets and Wouters (2007) under both RE and AL following Slobodyan and Wouters (2012*a*,*b*) approach to AL. Both versions of the model are estimated for the whole sample and then using a 20-year rolling-window approach. Our estimation results show that learning dynamics help to explain a large proportion of the parameter variability observed under the standard RE hypothesis typically assumed in macroeconomic modelling. The intuition is simple: Under RE, a time-invariant relationship links the endogenous variables to the (predetermined and exogenous) state variables of the economy whenever the structural parameters of the model are constant. Therefore, parameter variability becomes the only source of macroeconomic dynamic swings under RE other than that generated from the exogenous shocks of the model. By contrast, the relationship linking endogenous variables with state variables becomes time varying under AL even when the structural parameters are time invariant, which might result in much richer macroeconomic dynamics.

- A time-invariant parameter scenario characterized by the RE estimated model using the whole sample (1961:3-2016:2) where the dynamic swings are driven only by specific shock realizations.
- A time-invariant model-parameter scenario described by the model estimated under AL for the whole sample where the dynamic swings are the combined outcome of specific shock realizations and the resulting changes in learning dynamics.
- A time-varying parameter scenario characterized by the model estimated under RE using a rolling-window approach, where the dynamic swings are the result of both specific shock realizations and shifts in model parameters.
- Finally, a time-varying parameter scenario characterized by the model estimated under AL using a rolling-window approach, where the dynamic swings may be due to all three sources, i.e. specific shock realizations, parameter variability, and learning.

Our estimation results show that assuming AL reduces parameter variability by roughly 68%. The reduction in parameter variability induced by AL is much stronger for the subsets of parameters that control nominal price and wage rigidities and the policy rule parameters (at 91% and 100%, respectively). Moreover, the AL version provides a better model fit than the RE version. These findings certainly strengthen the potential of DSGE models under AL for implementing policy assessment, showing that AL helps to resolve the issue raised by Fernández-Villaverde et al. (2007). Moreover, our estimation results also show that the AL model estimated does a better job in reproducing the dramatic swings in the correlations between real and nominal variables observed in US data than the RE version. Those correlations are found to be moderately negative in the 1960's and 1970's but they become strongly positive more recently. Nonetheless, the fall in the importance of supply shocks relative to demand shocks (due to the fall in both persistence and the size of innovations of price- and wage-markup shocks as shown below) seems to be the most important driving force in explaining these dramatic swings in the comovement between real and nominal variables. In spite of the relative success of AL in explaining these comovements, AL still falls short in explaining the recent fall in inflation persistence.

The rest of the paper is structured as follows. Section 4.3 discusses the related literature. Section 4.4 briefly describes the main features of the model. Section 4.5 discussed the empirical results from both the whole sample and the rolling-window estimation approaches under RE and AL. The same section also quantifies the variability of the model parameters under the two expectations hypotheses. Section 4.6 analyzes the ability of the alternative model specifications to account for the recent US macroeconomic swings. Section 4.7 concludes.

4.3 Related literature

US macroeconomic dynamics feature large swings during the post-World War II period: From the stagnation of the 1970's and early 1980's (characterized by high macroeconomic volatility, accelerating inflation, and low output growth) to the Great Moderation period (featuring low volatility, decreasing inflation, and rather stable output growth) followed by the Great Recession (featuring a few sudden drops in output and near zero inflation levels).

Our paper relates to some strands of the literature that investigates these macroeconomic dynamic swings. In particular, there are two prominent hypotheses based on parameter variability explaining the large swings in US macroeconomic dynamics from the high-inflationary period of the 1970's and early 1980's to the Great Moderation period (1984-2007). The first states that parameter variability is mostly associated with changes in shock process parameters. Thus, the good-luck hypothesis put forward by Sims and Zha (2006), among others, explains the Great Moderation period as the result of favorable outcomes of shock processes.[1] Alternatively, the good-policy hypothesis suggested by Clarida et al. (2000) explains the Great Moderation as the result of a sound monetary policy featuring stable parameters that describe the reaction of the short-term nominal interest rate to deviations of inflation and economic activity from their respective targets, with a more agressive response of the policy rate to deviations of inflation from its target since the early 1980's (i.e. a Taylor (1993) rule).[2]

In recent empirical macroeconomics literature there are various approaches for analyzing parameter variability in DSGE models. Fernández-Villaverde et al. (2007) estimate a model assuming time-varying coefficients and stochastic volatilities. Another approach considers a Markov regime-switching process (Bianchi (2012), and Liu et al. (2011)). As pointed out by Castelnuovo (2012*b*), these approaches are admittedly extremely compelling, but they also constrain the researcher to focus on a rather small number of time-varying parameters due to their high computational costs. Cogley (2007) and Inoue and Rossi (2011) argue that these "one-at-the-time" approaches are problematic on econometric grounds because if the parameters considered as constant are actually time varying, the estimation results may attribute the time variation to the wrong source.

As an alternative with more affordable computational costs, we follow the rolling-window approach suggested by Canova and Ferroni (2012) to assess parameter variability in estimated models. More precisely, they analyze the relationship between monetary policy and inflation dynamics in the US by estimating a medium-scale DSGE model with money using Bayesian techniques. They show that policy shocks account for part of the

[1] Many papers (among others, Bernanke and Mihov (1998), Cogley and Sargent (2005), and Primiceri (2005)) find little evidence of a drastic change in the US monetary policy rule in the early 1980's.

[2] Lubik and Schorfheide (2004) and Boivin and Giannoni (2006) provide further evidence supporting this hypothesis.

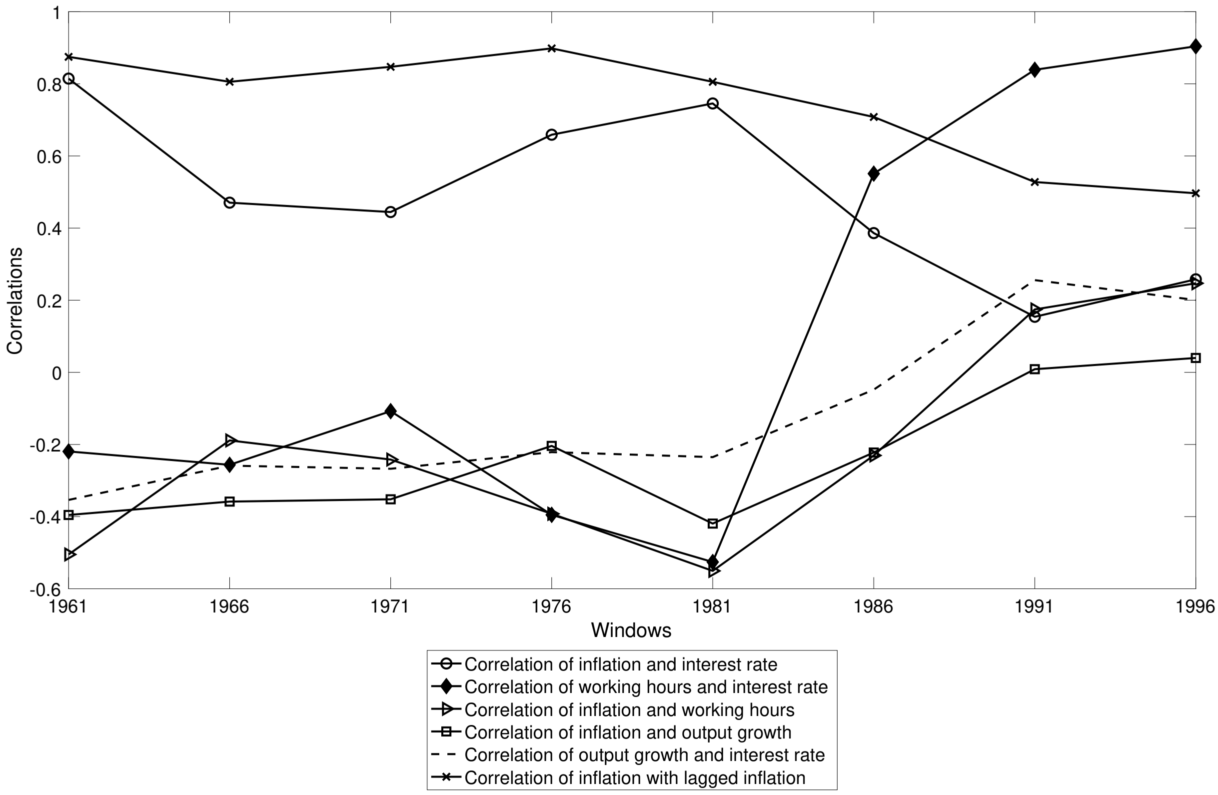
decline in inflation volatility. They also show that the variability of a few structural parameters contributes to this finding. Similarly, Castelnuovo (2012*a*) uses a rolling-window Bayesian estimation of a DSGE model with money. He finds that a specification with drifting parameters for money, consumption nonseparability and the Federal Reserve's reaction to nominal money growth fits the data better. In a similar vein, Hurtado (2014) estimates Smets and Wouters (2007) model using a rolling-window approach. He shows that most parameters, including those that were meant to be structural, exhibit major shifts. This applies specifically to those related to Calvo price stickiness and the elasticity of labor supply.

More recently, using a rolling-window approach as in Canova and Ferroni (2012) and Castelnuovo (2012*a*,*b*), Casares and Vázquez (2018) analyze the weakening in the correlation of inflation and the short-term nominal interest rate, known as the Gibson paradox. They show that a flatter New Keynesian Phillips Curve (higher price stickiness) and a lower persistence of markup shocks explain most of the Gibson paradox. In addition, a higher interest-rate elasticity of money demand, an increasing role played by demand side shocks, and less systematic behavior by the Fed's monetary policy also account for the recent patterns of US inflation dynamics.

The rolling-window approach also taken in this paper might have limitations because it may miss out the role that time-varying parameters play in shaping expectations. Put differently, it assumes that agents are unaware of parameter instability due to their neither having memory of the past windows nor using past evidence on expectation updates (Castelnuovo (2012*b*)). This caveat is overcome to some degree under AL because agents learn from actual data in each window.[3]

[3] Moreover, notice that from the second and subsequent windows we consider the estimated parameters from the previous window as initial values of the estimated parameters (including those characterizing agents' beliefs).

Figure 4.1: Comovements of real and nominal variables



Note: In all figures in this paper the year shown in the x-axis is the initial year of the corresponding 20-year window.

At a deeper level, large macroeconomic dynamic swings involve (dramatic) changes in the dynamic comovement between real and nominal variables, as illustrated in Figure 4.1. Figure 4.1 uses a 20-year rolling-window approach to show the time-varying evolution of the first-order autocorrelation of inflation and the contemporaneous correlation coefficients between the following pairs of variables: Inflation and the nominal interest rate, the nominal interest rate and hours worked, the nominal interest rate and output growth, inflation and hours worked, and inflation and output growth. The fall in both inflation persistence and the correlation between inflation and the nominal interest rate (i.e. the Gibson paradox) has received some attention in the literature (Cogley et al. (2012); and Casares and Vázquez (2018)), but the swings in the correlation between real and nominal variables have so far not been acknowledged. For instance, the contemporaneous correlation between the nominal interest rate and hours worked is moderately negative at around -0.4 until the early 1980's, but becomes strongly positive after the mid-1980's, reaching a peak of 0.9 in the last two decades.[4] An exception is the correlation between (the cyclical component of) real output and inflation, which has been widely studied (Fuhrer and Moore (1995); Den Haan (2000)). Recently, Cassou and Vázquez (2014) extend the methodology of Den Haan (2000) to compute correlations between output and inflation at different forecast horizons, and propose a small-scale New-Keynesian monetary model

[4]The swings in the other correlations between real and nominal variables are more modest, but they still imply switches from negative to positive correlations.

to explain the patterns observed.[5]

This paper also relates to a recent paper by Milani (2019) by considering AL à la Slobodyan and Wouters (2012*a*,*b*). He studies a small-scale New-Keynesian model to examine how the estimated variability of the Fed's inflation target can be determined by the expectation hypothesis assumed. Milani (2019) finds that the estimated inflation target exhibits large shifts over time (it is estimated at 2% in the early 1960's, increases to 8% in the 70's, and goes down to 4% in the 1980's and 2% in the 1990's) when RE is assumed. However, the estimated inflation target values are between 2% and 3% over the whole postwar sample when AL is assumed. By assuming a medium-scale DSGE model, we confirm Milani's (2019) finding; however we also extend his analysis on the implications of AL on the estimated variability of the Fed's inflation target to a much larger set of model parameters. Finally, regarding the potential of AL for explaining macroeconomic swings, our paper also relates to Bullard and Singh (2012). They study the reduction in volatility in the US during the Great Moderation period.[6] They show that including a learning mechanism accounts for about 30% of the volatility reduction observed in postwar US data.

4.4 The DSGE model

We consider the workhorse model estimated in Smets and Wouters (2007) (henceforth, SW) for the US economy, updated here with recent data covering the sample period 1961:3-2016:2.

The SW model contains both real and nominal frictions that affect decisions by households and firms. Thus, households maximize expected utility over an infinite horizon. Current consumption utility includes an external habit component characterized by lagged aggregate consumption. Households supply differentiated labor services and set nominal wages subject to a Calvo (1983) lottery mechanism. Moreover, households decide on how much capital to accumulate, given the investment adjustment cost function, and rent their capital to monopolistic firms. Depending on the rental rate, the capital stock is used more or less intensively.

Firms produce differentiated goods, decide on labor and capital inputs, and set the prices of the goods that they produce, again according to the Calvo-lottery model. Marginal costs of firms depend on wages, the rental rate of capital, and an exogenous productivity shock. The Calvo models considered for price- and wage-setting assume partial indexation to lagged inflation. Hence, inflation dynamics have both forward- and backward-looking components. Moreover, a more general aggregator, which allows for a time-varying de-

[5]Their model features a very high degree of internal habit persistence, which generates a rich structure on the demand side by introducing additional forward-looking terms into the dynamic IS curve that shows up in the 3-equation New-Keynesian model. Their model does a good job in replicating the dynamic correlation patterns at different horizons as long as the right balance between the effects of supply and demand shocks obtains through a calibration method that resembles the simulated method of moments (Lee and Ingram (1991), and Christiano et al. (2005)). However, they do not analyze the dynamic correlations between other nominal and real variables analyzed in this paper.

[6]After 1984, variance in US macroeconomic aggregates declined because boom and recession regimes moved closer together, keeping conditional variance unchanged. In their model, Bayesian households attempt to learn the latent state of the economy by including an unobserved regime-switching process. This process makes the signal extraction problem more difficult for Bayesian households, and they respond by moderating their behavior, which reinforces the effect of a less volatile stochastic technology during this period.

mand elasticity, replaces the standard Dixit-Stiglitz aggregator of both goods and labor markets used in small-scale versions of the New-Keynesian model.

Finally, a Taylor-type rule describes monetary policy. This policy rule includes an inertial component in addition to the policy reaction components associated with inflation, the output gap, and the growth rate of output gap. We follow Slobodyan and Wouters (2012*a*,*b*) by defining the output gap simply as the deviation of output from its underlying neutral productivity process and not as the natural output gap considered in the SW model. By doing this, we avoid the modeling of the flexible economy, which considerably reduces the number of forward-looking variables that need to be characterized under AL.

The Appendix describes the complete log-linearized version of the SW model and provides a brief explanation of how AL expectation formation works.

4.5 Data, estimation strategy, and empirical results

The data set used in the estimation exercises includes all the observable time series used in Smets and Wouters (2007). Thus, we consider the growth rates (i.e. the first-differences of the logarithms) of real GDP, real consumption, real investment, and real wage; and the time series of the inflation rate (obtained as the first-differences of the log of the GDP deflator), the federal funds rate, and the log of total hours worked. Moreover, per-capita variables are computed using the civilian non-institutional population (16 years and over). The sample period is 1961:3-2016:2.

In order to investigate potential parameter instability, the model was estimated under both RE and AL, for a rolling-window sequence for eight consecutive periods separated by a span of 5 years. This rolling-window estimation strategy results in the following eight overlapping 20-year quarterly subsamples: (i) 1961:3-1981:2; (ii) 1966:3-1986:2; (iii) 1971:3-1991:2; (iv) 1976:3-1996:2; (v) 1981:3-2001:2; (vi) 1986:3-2006:2; (vii) 1991:3-2011:2; and (viii) 1996:3-2016:2.

The estimation follows a two-step Bayesian procedure for each version of the model (i.e. the RE and AL versions) and each of the (sub-) samples defined above. In terms of priors, we select the same set of distributions as in Smets and Wouters (2007), which are shown in Table 4.1. The priors are identical across all (sub-) samples studied. This is a rather conservative strategy in the present context because we do not want different estimation results across our subsamples be an outcome of the use of different priors.

Table 4.1 further shows the posterior mean, and the $5\% - 95\%$ confidence intervals for the RE and AL versions of the model using the whole sample period. The log-likelihood indicates that the AL version provides a better model fit than the RE version. Thus, the marginal likelihood of the AL model is larger (-1248.71) than that associated with the RE model (-1262.81). The estimated parameter coefficients show different estimated values as already shown in Slobodyan and Wouters (2012*a*) for a slightly shorter sample that does not include the Great Recession period. There are a few striking differences: The estimate of the investment adjustment cost parameter is 5.50 under RE but is much lower at 3.55 under AL. Similarly, the estimates of the wage indexation and steady-state inflation (i.e. the Fed's inflation target) parameters are much lower under AL (0.29 versus 0.65 and 0.58 versus 0.90, respectively). The lower estimate of the annual inflation target under AL ($2.32\% = (0.58 \times 4) \times 100$) is in line with the estimate found by Milani (2019). By contrast, the estimates of the risk aversion parameter and the inertial coefficient of the policy rule are higher under AL than under RE. Regarding price and wage markup shock persistence, AL implies almost i.i.d. shocks (the autoregressive and the moving-average

Table 4.1: Estimated Posteriors of the Structural Parameters

	RE		AL	
Log-likelihood	-1262.81		-1248.71	
	Mean	5%-95%	Mean	5%-95%
φ: cost of adjusting capital	5.509	(3.510,7.585)	3.549	(2.996,3.996)
λ: consumption habit formation	0.707	(0.570,0.847)	0.697	(0.662,0.733)
σ_c: risk aversion	1.159	(0.934,1.355)	1.597	(1.479,1.740)
σ_l: Frisch elasticity	1.333	(0.370,2.216)	1.053	(0.266,1.757)
ξ_p: price Calvo probability	0.749	(0.676,0.816)	0.844	(0.807,0.877)
ξ_w: wage Calvo probability	0.801	(0.707,0.937)	0.869	(0.834,0.896)
ι_p: price indexation	0.266	(0.128,0.395)	0.376	(0.198,0.587)
ι_w: wage indexation	0.648	(0.454,0.854)	0.286	(0.160,0.396)
ψ: capital utilization adjusting cost	0.636	(0.441,0.816)	0.678	(0.472,0.875)
Φ: steady-state price markup	1.535	(1.411,1.662)	1.501	(1.422,1.577)
ρ: inertia (policy rule)	0.837	(0.802,0.872)	0.935	(0.919,0.952)
r_π: inflation (policy rule)	1.756	(1.440,2.055)	1.571	(1.379,1.784)
r_y: output gap (policy rule)	0.018	(0.000,0.037)	0.032	(0.004,0.062)
$r_{\Delta y}$: output gap growth (policy rule)	0.177	(0.147,0.209)	0.097	(0.073,0.118)
π^{SS}: quarterly steady-state inflation	0.901	(0.673,1.114)	0.58	(0.494,0.674)
$100(\beta^{-1}-1)$: quarterly discount rate	0.158	(0.068,0.250)	0.159	(0.128,0.192)
$\bar{l}$: steady-state hours	1.397	(-1.497,4.400)	2.806	(1.703,3.926)
δ: steady-state growth rate	0.382	(0.344,0.418)	0.402	(0.383,0.424)
α: capital share	0.195	(0.162,0.225)	0.16	(0.138,0.181)
ρ_o: learning parameter	-	-	0.962	(0.954,0.970)
σ_a: Std. of productivity innovation	0.467	(0.423,0.509)	0.461	(0.430,0.482)
σ_b: Std. of consumption innovation	0.163	(0.082,0.257)	0.12	(0.110,0.128)
σ_i: Std. of investment innovation	0.335	(0.274,0.390)	0.352	(0.324,0.381)
σ_g: Std. of spending innovation	0.471	(0.433,0.508)	0.461	(0.437,0.485)
σ_p: Std. of price markup innovation	0.13	(0.110,0.152)	0.134	(0.119,0.146)
σ_w: Std. of wage markup shock	0.36	(0.319,0.398)	0.348	(0.321,0.380)
σ_R: Std. of policy innovation	0.22	(0.201,0.240)	0.211	(0.199,0.226)
ρ_a: Persistence of productivity shock	0.975	(0.960,0.991)	0.984	(0.978,0.989)
ρ_b: Persistence of consumption shock	0.581	(0.244,0.875)	0.651	(0.554,0.749)
ρ_i: Persistence of investment shock	0.78	(0.675,0.892)	0.398	(0.320,0.476)
ρ_g: Persistence of spending shock	0.97	(0.956,0.985)	0.981	(0.970,0.994)
ρ_p: Persistence of price markup shock	0.959	(0.927,0.995)	0.236	(0.087,0.387)
ρ_w: Persistence of wage markup shock	0.952	(0.879,0.997)	0.392	(0.112,0.635)
ρ_r: Persistence of policy shock	0.119	(0.023,0.218)	0.242	(0.172,0.315)
ρ_o: Persistence of learning parameter	-	-	0.962	(0.954,0.970)
μ_p: moving-average of price shock	0.916	(0.845,0.979)	0.455	(0.179,0.646)
μ_w: moving-average of wage shock	0.851	(0.780,0.919)	0.516	(0.378,0.659)
ρ_{ga}: correlation of prod. and spend. shocks	0.537	(0.416,0.658)	0.498	(0.422,0.579)

coefficients are close to 0.5 for both markup shocks) in line with the findings of Slobodyan and Wouters (2012*b*), whereas these markup shocks are very persistent under RE.

Table 4.2 shows the log data densities of the estimated model for each version of the model (RE and AL) and each of the windows considered. Moreover, the fourth row of

Table 4.2: Model fit comparison across windows: log density

	Windows							
	61-81	66-86	71-91	76-96	81-01	86-06	91-11	96-16
AL	-487.2	-513.3	-481.9	-454.1	-342.0	-304.1	-342.5	-367.4
RE	-525.1	-535.2	-509.1	-473.5	-354.2	-316.4	-369.0	-377.7
Log difference	37.9	21.9	27.2	19.4	12.2	12.3	26.5	10.3

Table 4.2 shows rather large odds in favor of the AL across all windows.

To highlight the differences across the two alternative expectations hypotheses and the subsamples, Figure 4.2 shows a selection of the estimated parameters that show higher parameter instability. The lines with solid circles (squares) represent the subsample estimates under the RE (AL) hypothesis. Meanwhile, the shaded-lined areas between the dashed lines (the area between the plain lines) are the 5%-95% confidence bands around the RE (AL) estimates.[7]

At first sight, it is clear that the parameter estimates show less variability under AL than under RE. The first row of graphs in Figure 4.2 shows that the persistence associated with risk premium shocks, price- and wage-markup shocks, and monetary policy shocks show a sizeable time variation. Notice also that the persistence of price- and wage-markup shocks is lower in recent decades, which reduces the importance of supply shocks relative to demand shocks. Moreover, the estimated values are lower under AL than under RE. Similarly, the parameter estimates that measure the size (standard deviations) of innovations differ by more across the two expectations hypothesis and sub-samples. This is in contrast to the similarities found for these parameters under RE and AL when the model is estimated for the whole sample.

The Calvo wage probability estimates under the two expectations hypotheses behave rather differently for the sample window 1991:3-2001:2. The estimate under AL increases while the estimate under RE decreases. Moreover, the estimate of the parameter featuring price indexation to past inflation differs between the two expectations hypotheses in the initial subsamples of the analysis but becomes closer after the sample window that starts in 1976.

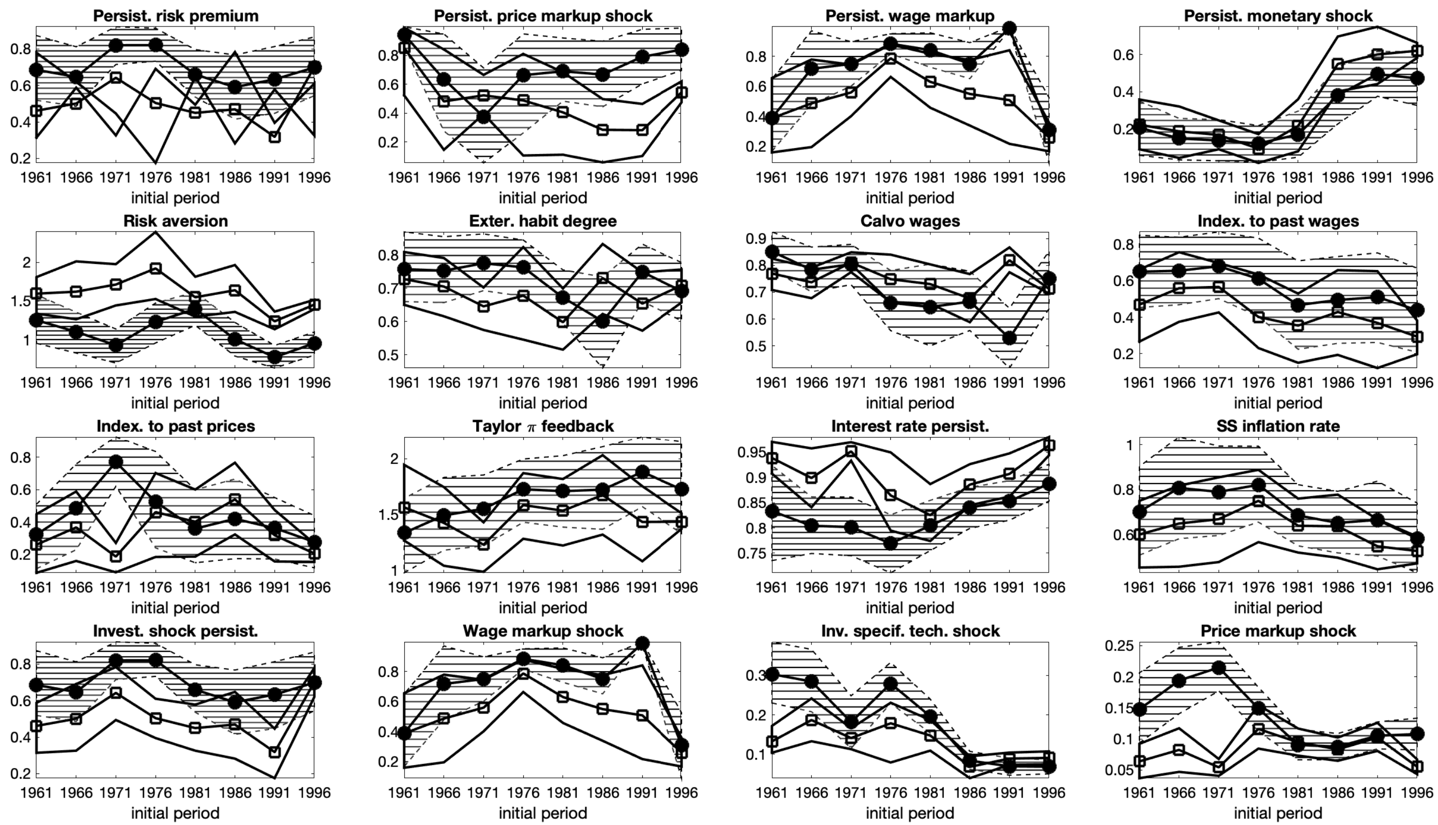
In line with the estimates for the whole sample discussed above, the posterior mean of interest rate persistence is higher for all subsamples under AL. The last graph in the third row displays the trend in the steady-state inflation estimate across subsamples. Interestingly, and in line with the findings in Milani (2019), the estimated value is always lower as pointed out above and also exhibits less variability under AL. These estimation results suggest that the large variability of the inflation target estimated under RE may to some extent be an artefact of the RE hypothesis that implicitly assumes that agents have perfect knowledge of the central bank inflation target. In contrast, when agents learn the inflation target, its estimate becomes much lower and rather stable

The last row of graphs in Figure 4.2 shows the high variation in the estimated persistence of the investment shock under the two alternative expectations hypotheses, although it is lower under AL. Next to the right, the estimated standard deviation of the wage markup innovation shows a smoother downtrend in the most recent subsamples under AL, which also contributes to the drop in the importance of supply shocks relative to

[7]The posterior means of all the estimated parameters under RE and AL for the eight sample windows studied are available from the authors upon request.

demand shocks. The next two figures to the right show the estimated standard deviations of the investment specific technology shock and the price markup shock. In general, the estimated standard deviation of all innovations under AL can be observed to be lower than those estimated under RE. This finding is rather intuitive: The variance of the shocks captures the degree of all sources of uncertainty under RE, but this is no longer so under AL because agents bear model uncertainty in addition to shock uncertainty.

Figure 4.2: Rolling-window selected parameter estimates



Note: The lines with solid circles represent the subsample estimates under the RE hypothesis. The lines with squares are the parameter estimates under AL. The shaded-lined areas between the dashed lines (the area between the solid lines without any additional symbol) are the 5%-95% confidence bands around the RE (AL) estimates.

Over and above the visual inspection of Figure 4.2, the variability of parameter estimates across windows can be summarized by a quadratic distance function defined by the following statistic J

$$J = \left[(1/n)\sum_{j=1}^{n}\left|\widehat{\theta}^{(j)} - \widehat{\theta}\right|\right]' \left[cov(\widehat{\theta})\right]^{-1} \left[(1/n)\sum_{j=1}^{n}\left|\widehat{\theta}^{(j)} - \widehat{\theta}\right|\right],$$

n $(= 8)$ denotes the number of windows, $\widehat{\theta}$ is the vector of estimated parameters obtained from the whole sample, $\widehat{\theta}^{(j)}$ is the vector of estimated parameters obtained from the subsample/window j, and $\left[cov(\widehat{\theta})\right]^{-1}$ is the inverse of the estimated covariance matrix of $\widehat{\theta}$.

This quadratic distance measure summarizes in a single statistic the variability of a given set of parameters relative to the estimated parameter values obtained from the whole sample under a particular expectation hypothesis.[8] Moreover, this variability measure can be computed for each individual parameter as well as for alternative subsets of model parameters. Hence, it can help to assess which subsets of parameters are more time (in)variant than others. This is important because the related literature emphasizes time variation in different sets of parameters. Thus, according to the good-luck hypothesis (e.g. Sims and Zha (2006)), the lower estimated parameter values characterizing the shock process parameters are the main factor driving the Great Moderation. Alternatively, the good-policy hypothesis (e.g. Clarida et al. (2000)) puts the emphasis on the stronger responses of monetary policy to deviations of inflation from its target as the main factor driving price stability and the Great Moderation.

Although the variability of monetary policy rule parameters and the shock process parameters are likely to be strong candidates to explain the recent swings in the US macroeconomic dynamics, it is also important to analyze the variability of the remaining structural parameters for several reasons. In particular, stability of structural-deep parameters is a much needed feature when using the model as a tool to assess the outcomes of alternative monetary policies. Thus, we compute the parameter variability measure J for structural parameters and shock process parameters. In addition, focusing on structural parameters, we also compute J for three selected groups of parameters: (i) the four Calvo parameters featuring nominal rigidities (price and wage Calvo stickiness parameters, and price and wage indexation parameters); (ii) the estimates of the policy rule parameters; and (iii) the estimates of the remaining structural parameters. Finally, we also compute J for the estimates of the two subsets of parameters that characterize exogenous shock persistence, and the standard deviation of shock innovations.

Table 4.3 shows the value of J for the whole set of model parameters for both the RE and AL versions of the model, for alternative subsets of parameters, for the eight windows, and for the first five subsample windows (figures in parentheses), i.e. up to subsample 1981:3-2001:2, which does not include the latest two recessions (i.e. the 2001-recession and the Great recession starting around 2008) or their aftermath.

We start by focusing on the parameter variability measure when using the eight subsamples. We observe that AL reduces our measure of parameter variability by roughly

[8]Notice that this measure resembles the quadratic loss function used in the simulated method of moments estimator suggested by Lee and Ingram (1991), where the distance is weighted through $\left[cov(\widehat{\theta})\right]^{-1}$ (roughly speaking, the parameters estimated with less precision—i.e. with higher variance— receive a smaller weight in the distance function).

Table 4.3: Comparative measure J

		RE	AL	Relative measure
All parameters		0.167 (0.230)	0.054 (0.050)	-67.67 (-78.26)
Structural		0.153 (0.207)	0.051 (0.050)	-66.67 (-75.85)
	Calvo parameters	0.035 (0.127)	0.003 (0.032)	-91.43 (-74.80)
	MP rule parameters	0.005 (0.060)	0.000 (0.004)	-100.00 (-93.33)
	Other structural parameters	0.104 (0.011)	0.034 (0.001)	-67.31 (-90.91)
Shocks		0.178 (0.015)	0.261 (0.005)	46.63 (-66.67)
	Persistence parameters	0.012 (0.001)	0.008 (0.000)	-33.33 (-100.00)
	Variances	0.174 (0.014)	0.251 (0.005)	44.25 (-64.29)

67.7% (from 0.167 under RE to 0.054 under AL) as shown in the last column, which implies that AL absorbs a large proportion of the total parameter variability obtained under RE. A similar finding holds when the focus is only on the subset of structural parameters. Interestingly, the reduction in the variability measure implied by AL with respect to RE is stronger for the Calvo model and policy rule parameters (at 91.4% and 100%, respectively). This last finding is in line with Sargent et al. (2006) and shows major interaction between the beliefs of economic agents and shocks.[9] In line with these results, the parameter variability measure associated with the shock process parameters increases substantially with AL (46.6%), due to the large increase in variability associated with the estimates of the standard deviation of innovations under AL.

These findings are mostly qualitatively robust to those obtained by focusing only on the first five subsample windows. However, the reduction in parameter variability across the alternative sample windows implied by AL is stronger in this case than that obtained for the whole set of windows, and carries over to all parameter subsets.

4.6 Macroeconomic dynamic swings

The comovement between nominal variables (the nominal interest rate, inflation) and real variables (real output growth and hours worked) present large swings in the post-World War II era. Thus, the correlation coefficients between real and nominal variables were negative until the early 1980's, but became positive in the two recent decades as shown in Figure 4.1.

Figure 4.3-4.6 display the correlations between pairs of nominal and real variables. In each figure, the thick solid line denotes the actual correlation. The solid line with asterisk and the closely spaced dot line show the correlations for each window implied by the model estimated for the whole sample under RE and under AL, respectively. Meanwhile, the solid line with circles and the dashed lines show the rolling-window correlation estimates under RE and AL, respectively.[10]

The time-varying correlation between inflation and hours worked is shown in Figure 4.3. All models do a reasonable job in reproducing the dynamic swings in this correlation statistic. Regarding the correlation between the nominal interest rate and hours

[9]A major difference between the two papers is that Sargent et al. (2006) emphasizes the role of central bankers' beliefs, whereas in our model the emphasis is on the role of the beliefs of private agents (households and firms).

[10]This description also applies for Figure 4.7 and 4.8 discussed below.

worked, all models reproduce well the strong dynamic swing since the early 1980's as depicted in Figure 4.4, but AL appears to perform slightly better than RE in fitting this striking comovement pattern. Similarly, Figure 4.5 and 4.6 show that the estimated correlations for the whole sample under AL are able to approximate the actual correlations between inflation and output growth and between the nominal interest rate and output growth better than the other specifications.

An analysis of the comovement between real and nominal variables suggests that the negative correlation observed from the 1960's to the early 1980's was the result of strong supply shocks (e.g. oil shocks). The intuition is simple, following arguments in Mankiw (2003) (pp. 66-67): Strong supply shocks help to identify aggregate demand, which describes a negative correlation between real and nominal variables at equilibrium. By contrast, supply shocks have been much less important than demand shocks since the mid 1980's, as discussed above, which helps to identify the aggregate supply curve: A positive correlation between real and nominal variables. In sum, changes in the relative importance of supply and demand shocks may be an important driving force behind the comovement swings observed in recent US data, as also stressed in Cassou and Vázquez (2014).

In contrast to the above correlations, Figure 4.7 shows that the SW model has trouble reproducing the large drop in correlation between inflation and the nominal interest rate in recent decades (i.e. the Gibson paradox). Even though all models fall short of closely replicating this comovement, it can be seen that the estimated correlations computed under AL seem to reproduce the Gibson paradox better in the 1990's. Moreover, the ability of the model with money stressed in Casares and Vázquez (2018) to reproduce the Gibson paradox indicates the importance of including money demand in the SW model to account for this dynamic swing. By contrast, Figure 4.8 shows that the model under AL (both for the whole sample and across subsamples) is unable to reproduce the strong fall in inflation persistence observed since the early 1980's. The model estimated for the whole sample under RE comes closer than the AL specification to quantitatively reproducing the declining trend of the inflation persistence, but it still falls short. The differences between AL and RE in reproducing the fall in inflation persistence may be due to the additional strong source of persistence induced by the AL mechanism.

Figure 4.3: Correlation of worked hours and inflation

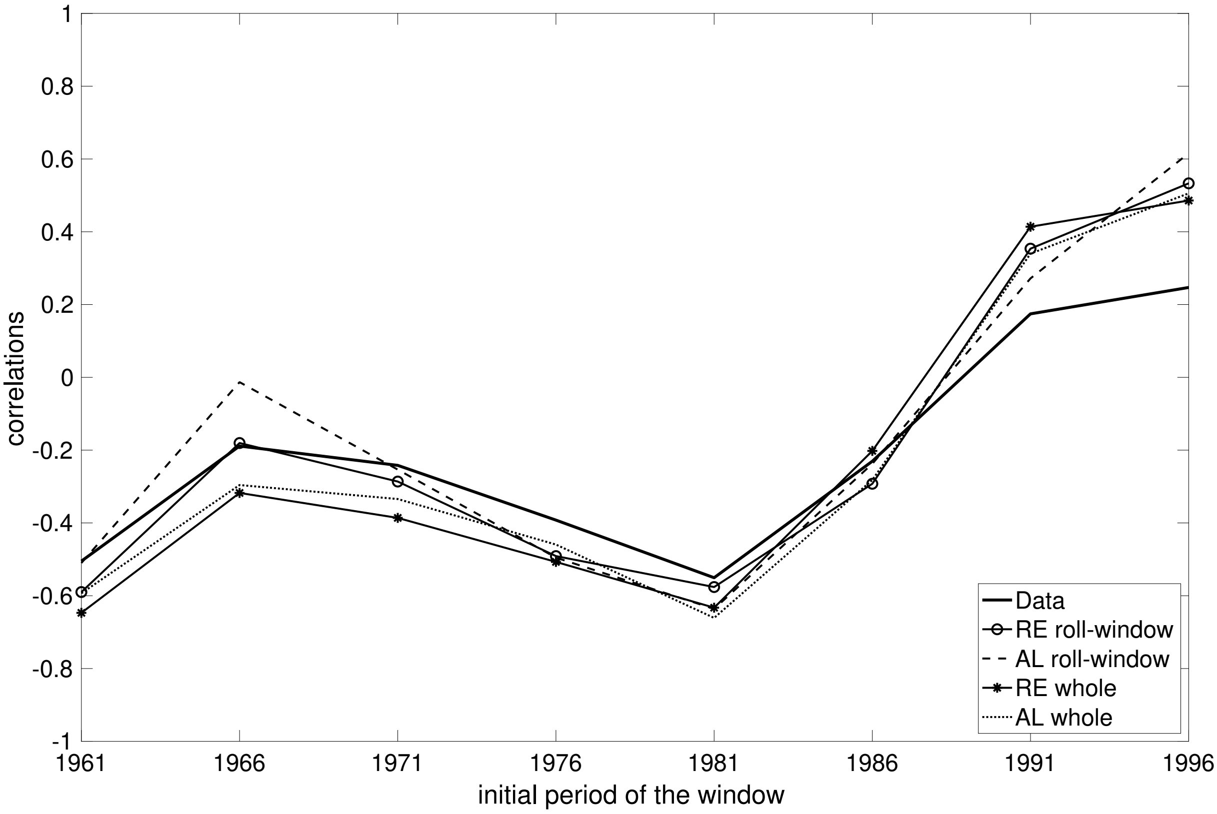


Figure 4.4: Correlation of worked hours and interest rate

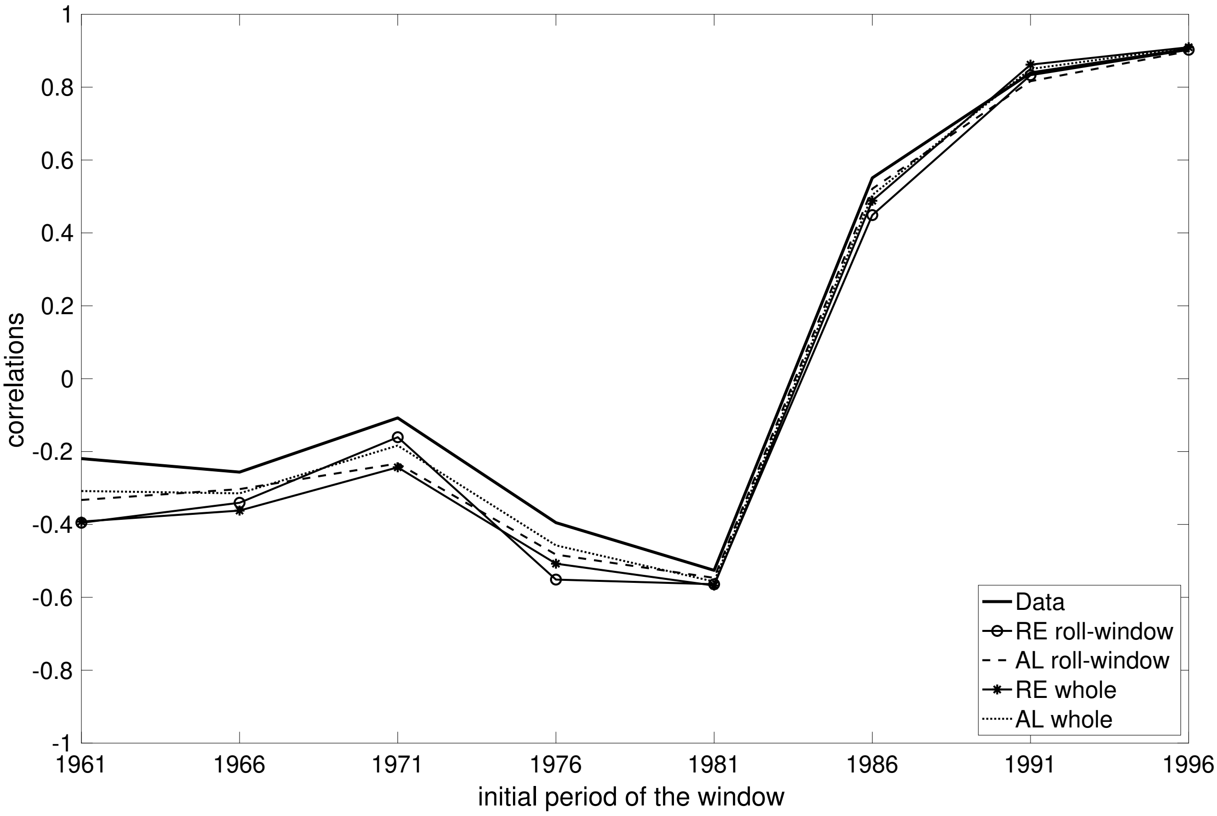


Figure 4.5: Correlation of output growth and inflation

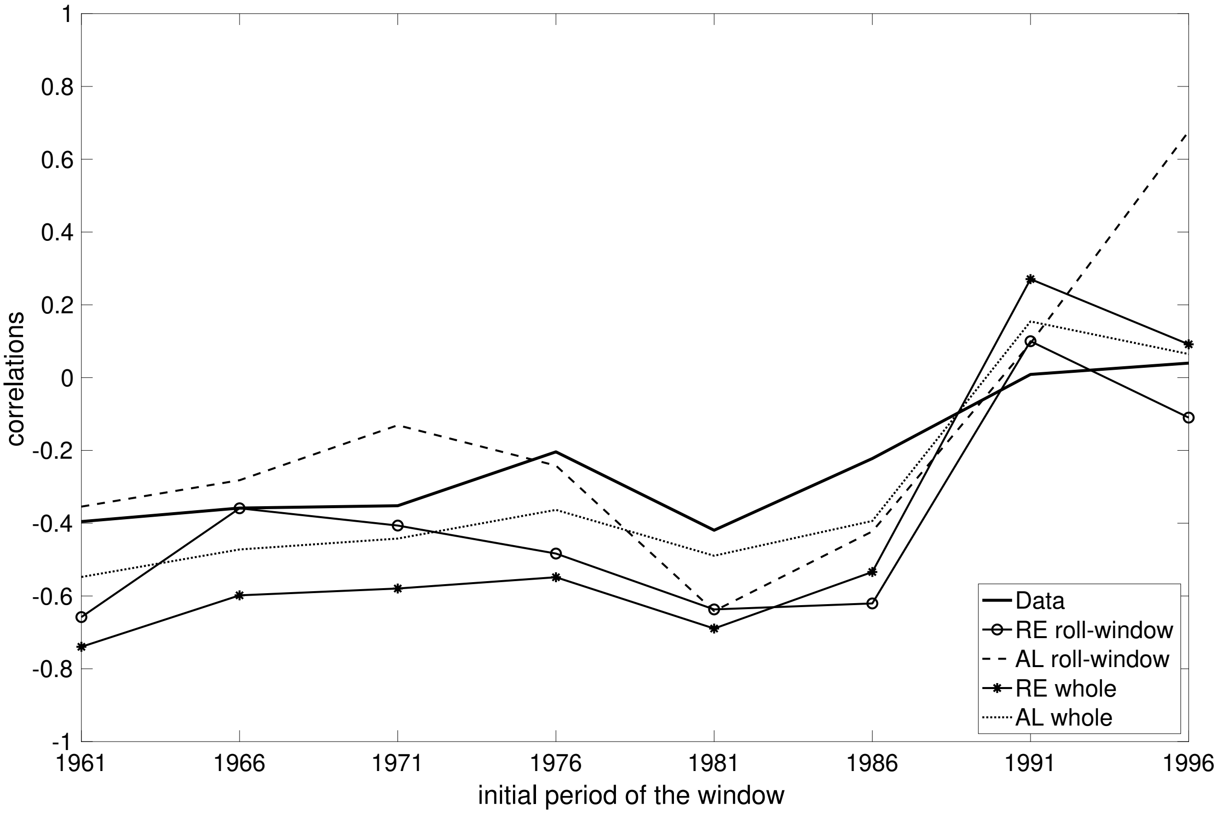


Figure 4.6: Correlation of output growth and interest rate

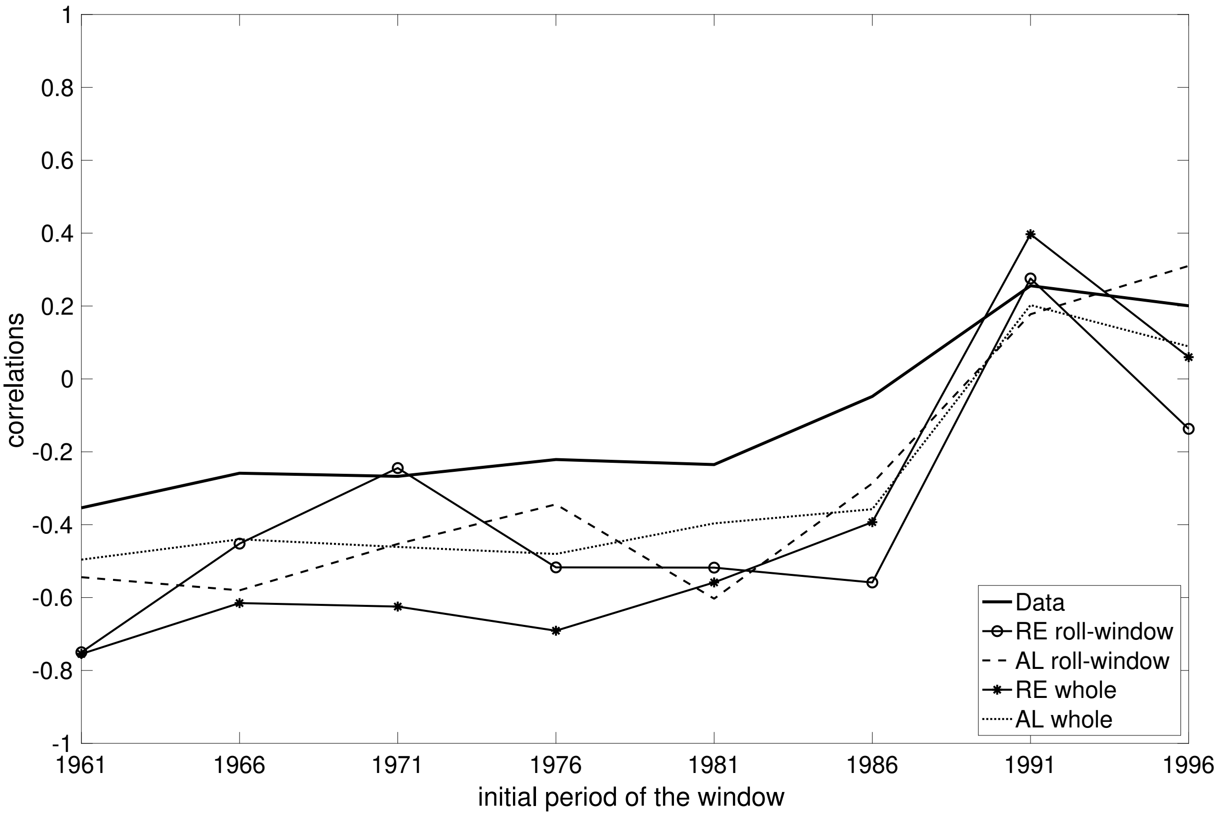


Figure 4.7: Correlation of interest rate and inflation

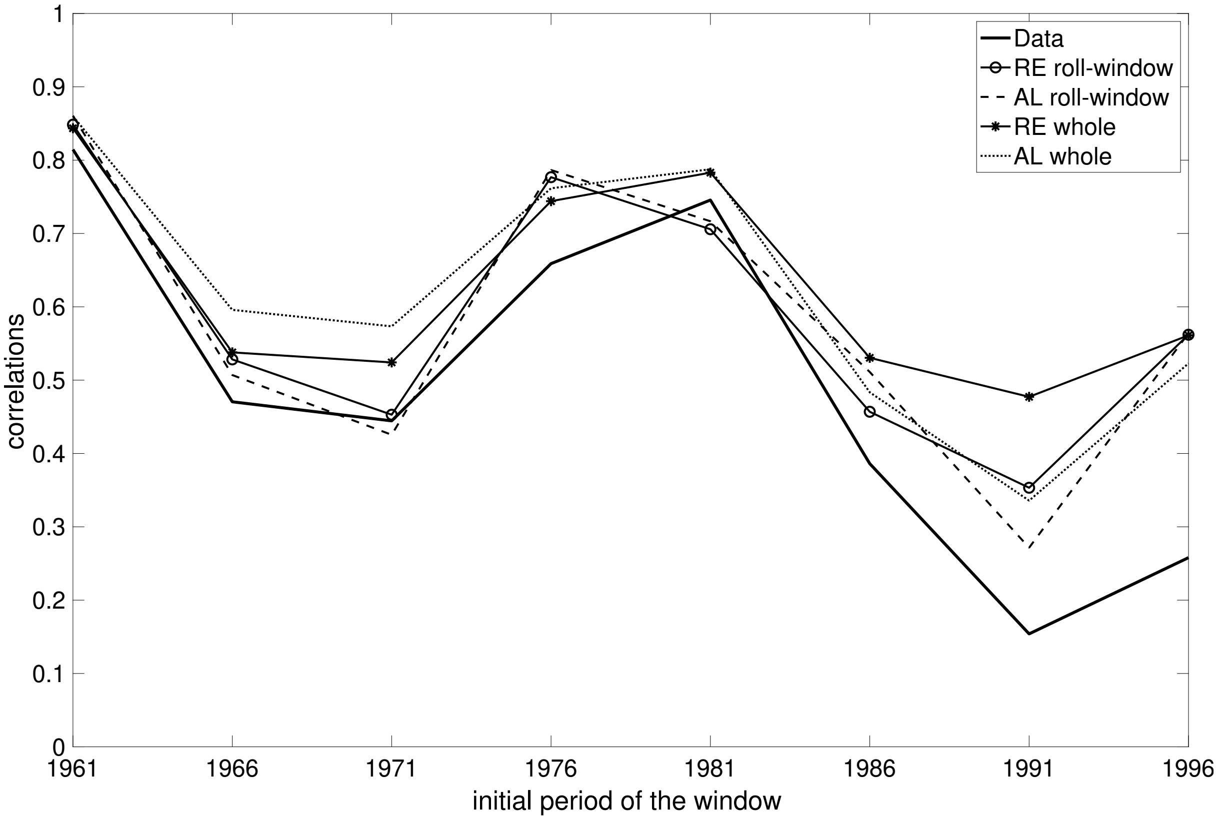
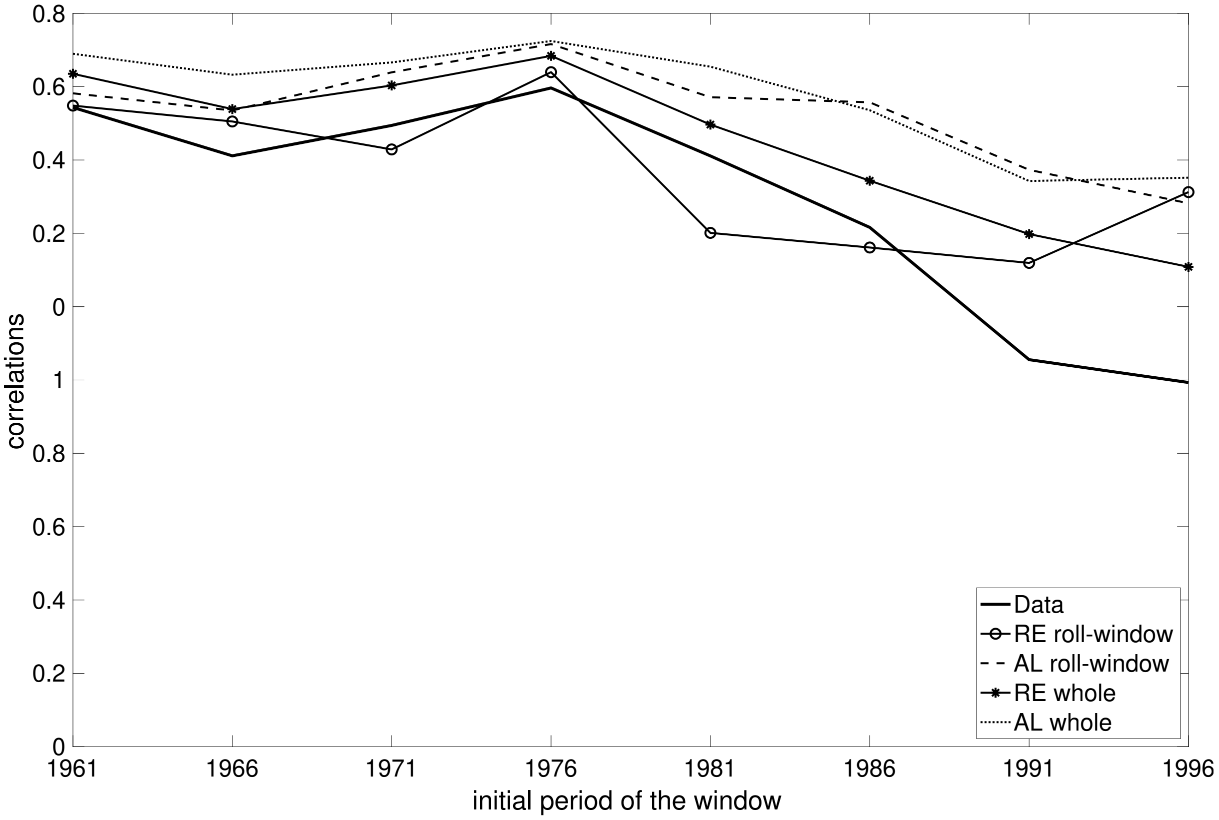


Figure 4.8: Inflation persistence



In order to discern the relative importance of AL expectations and parameter variability behind these correlation swings, we study two measures of fit for the estimated correlations under each expectations hypothesis. First, we compute the mean absolute deviations (MAD) of the estimated correlations for each model specification, $MAD(i, x, y)$, defined as follows

$$MAD(i, x, y) = \frac{1}{n} \sum_{j=1}^{n} \left| r_{x,y}^{i,j} - r_{x,y}^{actual,j} \right|,$$

where $n = 8$ indicates the number of windows, $r_{x,y}^{i,j}$ stands for the correlation coefficient between variables x and y for model specification i and for window j, and $r_{x,y}^{actual,j}$ denotes the actual correlation between variables x and y for window j.

Since the estimated correlations for a few specifications show rather erratic shifts across windows when compared to the actual correlations, we compute a second measure of fit defined by the ratio between the standard deviation of the estimated correlation across windows, for each model specification, and the standard deviation of the actual correlation across windows. Formally,

Since the estimated correlations for a few specifications show rather erratic shifts across windows when compared to the actual correlations, we compute a second measure of fit defined by the ratio between the standard deviation of the estimated correlation across windows, for each model specification, and the standard deviation of the actual correlation across windows. Formally,

$$RStDC(i, x, y) = \frac{\sigma(r_{x,y}^{i})}{\sigma(r_{x,y}^{actual})},$$

where $\sigma(r_{x,y}^{i})$ $(\sigma(r_{x,y}^{actual}))$ denotes the standard deviation of the estimated correlation $r_{x,y}$ for model specification i (actual data) across windows. Thus, a value of the statistic $RStDC(i, x, y)$ higher (lower) than one indicates that the estimated correlation between variables x and y for model i shows larger (smaller) swings than those displayed by the corresponding actual correlation.

Table 4.4 shows these two measures of fit for each correlation and model specification studied. More precisely, the first column of Table 4.4 shows the second-moment statistics (correlations) studied. The next four columns show the $MAD(i, x, y)$-statistic for each estimated correlation and model specification considered. Finally, the last four columns show the ratio of the standard deviations, $RStDC(i, x, y)$, for each estimated correlation and model specification analyzed.

For the $MAD(i, x, y)$-statistic, it can be observed that the estimated AL model, with both the whole sample period and the rolling-window approach, fits the actual correlation statistics between real and nominal variables better in general than the estimated RE model. The opposite occurs for inflation persistence.

In regard to the $RStDC(i, x, y)$ measure, Table 4.4 shows that the DSGE model under the two expectation (RE and AL) specifications results in larger swings for the correlations between real and nominal variables than the actual correlations. Nevertheless, the estimated correlations of the DSGE model under AL show a better fit according to this measure. Moreover, the rolling-window approach seems to result in too much variability in these correlations between real and nominal variables. By contrast, the estimated correlations between the two nominal variables and the inflation autocorrelation show smoother swings than the actual correlations as the low values of the $RStDC$ in the last two rows of Table 4.4 indicate—i.e. all of them are well below one. This result is consistent with the finding that the alternative specifications of the DSGE model fall short in quantitatively reproducing the drop in inflation persistence and the Gibson paradox observed in recent decades.

Table 4.4: Correlation Deviations

Correlations	MAD				RStDC			
	RE		AL		RE		AL	
	roll-window	whole	roll-window	whole	roll-window	whole	roll-window	whole
Hours worked, inflation	0.099	0.140	0.095	0.118	1.443	1.501	1.389	1.438
Hours worked, interest rate	0.077	0.082	0.057	0.047	1.067	1.088	1.044	1.047
Output growth, inflation	0.182	0.256	0.133	0.116	1.512	2.120	1.227	1.490
Output growth, interest rate	0.257	0.317	0.216	0.176	1.395	1.794	1.223	1.202
Inflation, interest rate	0.104	0.134	0.096	0.124	0.748	0.621	0.847	0.760
Inflation autocorrelation	0.078	0.080	0.122	0.142	0.628	0.689	0.441	0.485

4.7 Conclusions

This paper studies parameter instability by estimating a standard medium-scale DSGE model under both rational expectations and adaptive learning using a rolling-window approach. The estimated DSGE model under adaptive learning improves the model fit to the data compared to the rational expectations version. Estimation results further show that assuming adaptive learning (rather than rational expectations) reduces the estimated parameter variability by roughly two thirds. This reduction in the variability of parameter estimates is even stronger for the parameters that feature nominal rigidities and for the policy rule parameters. The improvement in the stability of structural parameter estimates certainly strengthens the ability of the adaptive learning version of the DSGE model to assess policies reliably.

The estimation results also show that the flexibility induced by the adaptive learning hypothesis helps to explain the recent swings in the comovements between nominal and real variables in the US. Nevertheless, our analysis also suggests that strong supply shocks were the force behind the negative comovement in the first half of the sample, up to the early 1980's. Since then, dominant demand shocks seem to have caused the dramatic swings in the correlations between the real and nominal variables.

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Brief overview of the SW model

Here we summarize the log-linear equations of the model. For a more detailed presentation, we refer to the discussion in Smets and Wouters (2007).

- Aggregate resource constraint:

$$y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g, \tag{A1}$$

where $c_y = \frac{C}{Y} = 1 - g_y - i_y$, $i_y = \frac{I}{Y} = (\gamma - 1 + \delta)\frac{K}{Y}$, and $z_y = r^k \frac{K}{Y}$ are steady-state ratios. As in Smets and Wouters (2007), the depreciation rate and the exogenous spending-GDP ratio are fixed in the estimation procedure at $\delta = 0.025$ and $g_y = 0.18$.

- Consumption equation:

$$c_t = c_1 c_{t-1,t}^r + (1 - c_1) E_t c_{t+1} + c_2 (l_t - E_t l_{t+1}) - c_3 (R_t - E_t \pi_{t+1}) + \varepsilon_t^b, \tag{A2}$$

where $c_1 = \frac{h/\gamma}{1+(h/\gamma)}$, $c_2 = \frac{(\sigma_c - 1) wL/(\phi_w C)}{\sigma_c(1+(h/\gamma))}$, and $c_3 = \frac{1-h/\gamma}{\sigma_c(1+(h/\gamma))}$.

- Investment equation:

$$i_t = i_1 i_{t-1} + (1 - i_1) E_t i_{t+1} + i_2 q_t + \varepsilon_t^i, \tag{A3}$$

where $i_1 = \frac{1}{1+\overline{\beta}}$, and $i_2 = \frac{1}{\left(1+\overline{\beta}\right)\gamma^2\varphi}$ with $\overline{\beta} = \beta\gamma^{(1-\sigma_c)}$.

- Arbitrage condition (value of capital, q_t):

$$q_t = q_1 E_t q_{t+1} + (1 - q_1) E_t r_{t+1}^k - (R_t - E_t \pi_{t+1}) + c_3^{-1} \varepsilon_t^b, \tag{A4}$$

where $q_1 = \overline{\beta}\gamma^{-1}(1 - \delta) = \frac{(1-\delta)}{\left(r^k + 1 - \delta\right)}$.

- Log-linearized aggregate production function:

$$y_t = \phi_p \left(\alpha k_t^s + (1 - \alpha) l_t + \varepsilon_t^a\right), \tag{A5}$$

where $\phi_p = 1 + \frac{\phi}{Y} = 1 + \frac{\text{Steady-state fixed cost}}{Y}$ and α is the capital-share in the production function.

- Effective capital:

$$k_t^s = k_{t-1} + z_t. \tag{A6}$$

- Capital utilization:
$$z_t = z_1 r_t^k, \tag{A7}$$
where $z_1 = \frac{1-\psi}{\psi}$.

- Capital accumulation equation:
$$k_t = k_1 k_{t-1} + (1-k_1) i_t + k_2 \varepsilon_t^i, \tag{A8}$$
where $k_1 = \frac{1-\delta}{\gamma}$ and $k_2 = \left(1 - \frac{1-\delta}{\gamma}\right)\left(1+\overline{\beta}\right)\gamma^2\varphi$.

- Price mark-up:
$$\mu_t^p = mpl_t - w_t = \alpha\left(k_t^s - l_t\right) + \varepsilon_t^a - w_t. \tag{A9}$$

- New-Keynesian Phillips curve:
$$\pi_t = \pi_1 \pi_{t-1,t}^r + \pi_2 E_t \pi_{t+1} - \pi_3 \mu_t^p + \pi_4 \varepsilon_t^p. \tag{A10}$$
where $\pi_1 = \frac{\iota_p}{1+\overline{\beta}\iota_p}$, $\pi_2 = \frac{\overline{\beta}}{1+\overline{\beta}\iota_p}$, $\pi_3 = \frac{A}{1+\overline{\beta}\iota_p}\left[\frac{\left(1-\overline{\beta}\xi_p\right)(1-\xi_p)}{\xi_p}\right]$, and $\pi_4 = \frac{1+\overline{\beta}\iota_p}{1+\overline{\beta}\iota_p}$. The coefficient of the curvature of the Kimball goods market aggregator, included in the definition of A, is fixed in the estimation procedure at $\varepsilon_p = 10$ as in Smets and Wouters (2007).

- Optimal demand for capital by firms:
$$-\left(k_t^s - l_t\right) + w_t = r_t^k. \tag{A11}$$

- Wage markup equation:
$$\mu_t^w = w_t - mrs_t = w_t - \left(\sigma_l l_t + \frac{1}{1-h/\gamma}\left(c_t - (h/\gamma)\, c_{t-1,t}^r\right)\right). \tag{A12}$$

- Real wage dynamic equation:
$$w_t = w_1 w_{t-1} + (1-w_1)\left(E_t w_{t+1} + E_t \pi_{t+1}\right) - w_2 \pi_t - w_3 \pi_{t-1} - w_4 \mu_t^w + \varepsilon_t^w. \tag{A13}$$
where $w_1 = \frac{1}{1+\overline{\beta}}$, $w_2 = \frac{1+\overline{\beta}\iota_w}{1+\overline{\beta}}$, $w_3 = \frac{\iota_w}{1+\overline{\beta}}$, and $w_4 = \frac{1}{1+\overline{\beta}}\left[\frac{\left(1-\overline{\beta}\xi_w\right)(1-\xi_w)}{\xi_w((\phi_w-1)\varepsilon_w+1)}\right]$ with the curvature of the Kimball labor aggregator fixed at $\varepsilon_w = 10.0$ and a steady-state wage mark-up fixed at $\phi_w = 1.5$ as in Smets and Wouters (2007).

- Monetary policy rule:
$$R_t = \rho R_{t-1} + (1-\rho)[r_\pi \pi_t + r_y \widetilde{y}_t)] + r_{\Delta y}\Delta\widetilde{y}_t + \varepsilon_t^R, \tag{A14}$$
where the output gap is defined as $\widetilde{y}_t = y_t - \phi_p \varepsilon_t^a$ (i.e. the output gap is defined as the deviation of output from its underlying neutral productivity process).

Equations-and-variables summary
- Set of equations:
Equations (A1)-(A14) determine solution paths for 14 endogenous variables.
- Set of variables:
Endogenous variables (14): y_t, c_t, i_t, z_t, l_t, R_t, π_t, q_t, r_t^k, k_t^s, k_t, μ_t^w, μ_t^p, and w_t
Predetermined variables (7): c_{t-1}, i_{t-1}, k_{t-1}, π_{t-1}, w_{t-1}, R_{t-1}, and y_{t-1}
Exogenous variables (7): AR(1) technology shock $\varepsilon_t^a = \rho_a \varepsilon_{t-1}^a + \eta_t^a$, AR(1) risk premium shock $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b$, AR(1) exogenous spending shock cross-correlated to technology innovations $\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga}\eta_t^a$, AR(1) investment shock $\varepsilon_t^i = \rho_i \varepsilon_{t-1}^i + \eta_t^i$, AR(1) monetary policy shock $\varepsilon_t^R = \rho_R \varepsilon_{t-1}^R + \eta_t^R$, ARMA(1,1) price mark-up shock $\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \eta_t^p - \mu_p \eta_{t-1}^p$, and ARMA(1,1) wage mark-up shock $\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \eta_t^w - \mu_w \eta_{t-1}^w$.

AL expectation formation

This part of the appendix provides a brief description of how AL works.[1] The model contains fourteen endogenous variables summarized by the vector y_t. In addition, the stochastic structure of the model is determined by seven exogenous shocks and their innovations. Neutral and investment-specific technological progress, risk premium, exogenous spending and non-systematic monetary policy shocks are represented by a first-order autoregressive process, whereas price and wage markup shocks are modelled as ARMA(1,1) processes. The vector w_t represents both the seven exogenous variables and the lagged innovations for the markup shocks. After linearization around the deterministic steady state, the model can be represented as follows:

$$A_0 \begin{bmatrix} y_{t-1} \\ w_{t-1} \end{bmatrix} + A_1 \begin{bmatrix} y_t \\ w_t \end{bmatrix} + A_2 E_t y_{t+1} + B_0 \epsilon_t = const. \tag{A15}$$

Under RE, the solution of the model is given by

$$\begin{bmatrix} y_t \\ w_t \end{bmatrix} = \mu + T \begin{bmatrix} y_{t-1} \\ w_{t-1} \end{bmatrix} + R\epsilon_t, \tag{A16}$$

where the matrices T and R are non-linear functions of the model, θ; and the intercept μ is a zero vector under RE. The vector y can be further decomposed into a vector y^s of state variables (those appearing with a lag), a vector y^f of forward-looking variables (showing up with a lead) and the so called static variables. More precise, agents have to form expectations on seven forward-looking variables in the SW model: consumption, investment, hours worked, wages, inflation, and the price and the return of existing capital.

Under AL, the expectations of the forward-looking variables, $E_t y_{t+1}$, are defined as linear functions of variables entering in the information set of agents, whose learning coefficients are updated as explained below. Once the expectations of the forward-looking variables, $E_t y_{t+1}$, are computed they are plugged into the matrix representation of the DSGE model to obtain a backward-looking representation of the model as follows

$$\begin{bmatrix} y_t \\ w_t \end{bmatrix} = \mu_t + T_t \begin{bmatrix} y_{t-1} \\ w_{t-1} \end{bmatrix} + R_t\epsilon_t, \tag{A17}$$

where the matrices μ_t, T_t and R_t are time-varying nonlinear functions of structural parameters (entering in matrices A_0, A_1, A_2, and B_0) together with learning coefficients discussed next.

The perceived law of motion process is generally defined as follows:

$$y_{t+1} = X_t \beta_{t-1} + u_{t+1},$$

[1]See Slobodyan and Wouters (2012*a*) for a detailed description.

where y is the vector containing the k forward-looking variables of the model, X is the matrix of the $k \times r$ regressors, β is the vector of the r updating learning coefficients, which includes an intercept, and u is a vector of errors. These errors are linear combinations of the true model innovations, ϵ. So, the variance-covariance matrix, $\Sigma = E[u_t u_t']$, is non-diagonal.

Agents are further assumed to behave as econometricians under AL. In particular, it is assumed that they use a linear projection method in which the parameters are updated to form their expectations for each forward-looking variable:

$$E_t y_{t+1} = X_t \beta_{t-1}.$$

Thus, agents update their learning coefficient estimates using data up to time $t-1$, but X_t contains contemporaneous values of the regressors. The updating parameter vector, β, is further assumed to follow an autoregressive process where agents' beliefs are updated through a Kalman filter. This updating process can be represented as in Slobodyan and Wouters (2012*a*) by the following equation:

$$\beta_t - \overline{\beta} = F\left(\beta_{t-1} - \overline{\beta}\right) + v_t,$$

where F is a diagonal matrix with the learning parameter $|\rho| \leq 1$ on the main diagonal and v_t are white noise errors with variance-covariance matrix V.

Following Slobodyan and Wouters (2012*a*), we assume that AL agents forecast the values of the forward-looking variables using an AR(2) process for each variable. Notice that this AL assumption deviates from RE in three important ways. First, the coefficients in the forecasting models are not restricted to be consistent with the decision rules of agents. Second, the information set that is used in the AR(2) forecasting models is much smaller than the state-variable vector that would be used under RE. Finally, the coefficients of the forecasting model are updated using a Kalman filter procedure briefly described next.

The Kalman filter updating and transition equations for the belief coefficients and the corresponding covariance matrix are given by

$$\beta_{t|t} = \beta_{t|t-1} + R_{t|t-1} X_{t-1} \left[\Sigma + X_{t-1}' R_{t|t-1}^{-1} X_{t-1}\right]^{-1} \left(y_t - X_{t-1}\beta_{t|t-1}\right),$$

together with $\beta_{t+1|t} - \overline{\beta} = F\left(\beta_{t|t} - \overline{\beta}\right)$. $\beta_{t|t-1}$ is the estimate of β using the information up to time $t-1$, and $R_{t|t-1}$ is the mean squared error associated with $\beta_{t|t-1}$. Therefore, the updated learning vector $\beta_{t|t}$ is equal to the previous one, $\beta_{t|t-1}$, plus a correction term that depends on the forecast error, $\left(y_t - X_{t-1}\beta_{t|t-1}\right)$. In addition, the mean squared error, $R_{t|t}$, associated with this updated estimate, $\beta_{t|t}$, is given by

$$R_{t|t} = R_{t|t-1} - R_{t|t-1} X_{t-1} \left[\Sigma + X_{t-1}' R_{t|t-1}^{-1} X_{t-1}\right]^{-1} X_{t-1}' R_{t|t-1}^{-1},$$

with $R_{t+1|t} = F R_{t|t} F' + V$.

Estimated posteriors for all subsamples

Table I.1: Priors and Estimated Posteriors of the Structural Parameters under RE

Parameters	Distribution	Mean	SD	61	66	71	76	81	86	91	96	measure
Log Likelihood				-525.1	-535.17	-509.13	-473.52	-354.23	-316.41	-368.98	-377.71	
φ: Investment adjustment cost	Normal	4	1.5	4.17	4.64	4.69	4.5	6.01	5.55	5.64	5.99	1.8503e-05
σ_c: Risk aversion	Normal	1.50	0.375	1.26	1.11	0.93	1.23	1.4	1.01	0.78	0.96	8.6676e-05
λ: External habit degree	Beta	0.7	0.1	0.76	0.75	0.78	0.76	0.67	0.6	0.75	0.69	0.0001357
ξ_w: Calvo parameter wages	Beta	0.5	0.1	0.85	0.78	0.8	0.66	0.64	0.66	0.53	0.75	3.7893e-06
σ_l: Frisch elasticity	Normal	2	0.5	1.33	1.45	1.62	1.6	1.55	1.49	1.93	1.16	2.3333e-06
ξ_p: Calvo parameter prices	Beta	0.5	0.10	0.58	0.57	0.66	0.68	0.76	0.84	0.79	0.81	8.8983e-06
ι_w: Indexation to past wages	Beta	0.5	0.15	0.65	0.66	0.68	0.61	0.47	0.49	0.51	0.44	1.6796e-06
ι_p: Indexation to past prices	Beta	0.5	0.15	0.32	0.48	0.77	0.52	0.36	0.42	0.36	0.28	0.054502
ψ: Capacity utilization cost	Beta	0.5	0.15	0.18	0.41	0.38	0.41	0.63	0.63	0.69	0.8	0.00020419
ϕ_p: Fixed cost share	Normal	1.25	0.125	1.49	1.47	1.44	1.53	1.5	1.42	1.34	1.36	1.7554e-05
r_π: Taylor rule inflation feedback	Normal	1.5	0.25	1.34	1.49	1.55	1.73	1.71	1.72	1.88	1.73	2.3455e-05
ρ: Interest rate persistence	Beta	0.75	0.10	0.83	0.8	0.8	0.77	0.8	0.84	0.85	0.89	0.015599
r_y: Taylor rule output level feedback	Normal	0.125	0.05	0.14	0.16	0.15	0.03	0.08	0.18	0.02	0.1	2.4518e-05
$r_{\Delta y}$: Taylor rule output growth feedback	Normal	0.125	0.05	0.18	0.17	0.17	0.13	0.12	0.09	0.08	0.08	0.0013113
$\bar{\pi}$: Steady state inflation rate	Gamma	0.625	0.1	0.7	0.81	0.79	0.82	0.69	0.65	0.67	0.58	0.00054463
$100(\beta^{-1}-1)$: Time preference rate	Gamma	0.25	0.1	0.21	0.29	0.26	0.34	0.19	0.17	0.21	0.15	0.0036708
$\bar{l}$: Steady state hours	Normal	0.0	2.0	6.17	6.17	5.85	7.05	8.27	9.03	0.58	5.17	0.010026
$\bar{\delta}$: Net growth rate in percent	Normal	0.4	0.10	0.43	0.35	0.36	0.39	0.48	0.48	0.36	0.34	0.00041995
ρ_{ga}: correlation of prod. and spend. shocks	Normal	0.5	0.25	0.58	0.58	0.57	0.47	0.47	0.51	0.41	0.52	1.4251e-05
α: Capital share	Normal	0.3	0.05	0.2	0.22	0.2	0.22	0.25	0.2	0.15	0.15	6.3689e-07

Table I.2: Priors and Estimated Posteriors of the Shocks Processes under RE

Parameters	Distribution	Mean	SD	61	66	71	76	81	86	91	96	measure
ρ_a: Persistence productivity shock	Beta	0.5	0.20	0.96	0.86	0.85	0.83	0.91	0.91	0.95	0.95	3.3038e-05
ρ_b: Persistence consumption innov. shock	Beta	0.5	0.20	0.32	0.4	0.7	0.19	0.25	0.83	0.84	0.89	3.3818e-05
ρ_g: Persistence spending shock	Beta	0.5	0.20	0.89	0.96	0.88	0.83	0.96	0.97	0.92	0.9	2.7399e-05
ρ_i: Persistence investment shock	Beta	0.5	0.20	0.69	0.65	0.82	0.82	0.66	0.59	0.63	0.7	2.4951e-05
ρ_r: Persistence monetary policy shock	Beta	0.5	0.20	0.21	0.15	0.14	0.12	0.17	0.38	0.49	0.47	1.5778e-05
ρ_p: Persistence price markup shock	Beta	0.5	0.20	0.94	0.64	0.38	0.66	0.69	0.67	0.79	0.84	9.2664e-06
ρ_w: Persistence wage markup shock	Beta	0.5	0.20	0.39	0.72	0.75	0.89	0.84	0.75	0.99	0.31	7.2879e-05
μ_w: Coefficient on Ma term wage markup	Beta	0.5	0.2	0.78	0.51	0.82	0.55	0.5	0.53	0.66	0.68	8.1919e-06
μ_p: Coefficient on MA term price markup	Beta	0.5	0.2	0.35	0.6	0.43	0.5	0.56	0.52	0.79	0.52	0.00034818
σ^a: Productivity shock	Invgamma	0.1	2	0.54	0.52	0.44	0.38	0.35	0.38	0.48	0.48	0.0587
σ^b: Investment specific technology shock	Invgamma	0.1	2	0.3	0.28	0.18	0.28	0.2	0.08	0.07	0.07	0.0869
σ^g: Spending shock	Invgamma	0.1	2	0.53	0.57	0.55	0.48	0.43	0.4	0.37	0.35	0.073
σ^i: Investment specific technology shock	Invgamma	0.1	2	0.46	0.5	0.34	0.39	0.37	0.35	0.32	0.31	0.0536
σ^m: Monetary policy shock	Invgamma	0.1	2	0.28	0.32	0.3	0.27	0.14	0.09	0.1	0.09	0.0963
σ^p: Price markup shock	Invgamma	0.1	2	0.15	0.19	0.21	0.15	0.09	0.09	0.11	0.11	0.0393
σ^w: Wage markup shock	Invgamma	0.1	2	0.23	0.21	0.14	0.2	0.27	0.3	0.49	0.63	0.1525

Table I.3: Priors and Estimated Posteriors of the Structural Parameters under AL

Parameters	Distribution	Mean	SD	61	66	71	76	81	86	91	96	measure
Log Likelihood				-487.21	-513.27	-481.85	-454.05	-342.08	-304.11	-342.54	-358.13	
φ: Investment adjustment cost	Normal	4	1.5	3.52	4.14	2.77	5.13	4.14	5.09	3.68	7.28	4.7153e-05
σ_c: Risk aversion	Normal	1.50	0.375	1.6	1.62	1.71	1.92	1.55	1.64	1.24	1.36	0.00028292
λ: External habit degree	Beta	0.7	0.1	0.73	0.71	0.65	0.68	0.6	0.73	0.65	0.82	0.00016988
ξ_w: Calvo parameter wages	Beta	0.5	0.1	0.77	0.74	0.81	0.75	0.73	0.68	0.82	0.67	0.0005118
σ_l: Frisch elasticity	Normal	2	0.5	1.27	1.83	1.68	1.56	1.71	1.58	1.71	1.74	0.0013297
ξ_p: Calvo parameter prices	Beta	0.5	0.10	0.65	0.61	0.64	0.66	0.7	0.78	0.86	0.83	0.00039395
ι_w: Indexation to past wages	Beta	0.5	0.15	0.47	0.56	0.57	0.4	0.35	0.43	0.37	0.42	0.00027372
ι_p: Indexation to past prices	Beta	0.5	0.15	0.26	0.37	0.19	0.46	0.4	0.54	0.32	0.48	0.0053825
ψ: Capacity utilization cost	Beta	0.5	0.15	0.44	0.41	0.38	0.41	0.67	0.67	0.83	0.74	0.00013178
ϕ_p: Fixed cost share	Normal	1.25	0.125	1.49	1.47	1.39	1.53	1.5	1.48	1.47	1.39	1.9435e-06
r_π: Taylor rule inflation feedback	Normal	1.5	0.25	1.56	1.43	1.23	1.59	1.54	1.68	1.43	1.68	2.3925e-05
ρ: Interest rate persistence	Beta	0.75	0.10	0.94	0.9	0.95	0.86	0.83	0.89	0.91	0.91	0.0093352
r_y: Taylor rule output level feedback	Normal	0.125	0.05	0.11	0.1	0.06	0.05	0.11	0.12	0	0.05	1.7835e-05
$r_{\Delta y}$: Taylor rule output growth feedback	Normal	0.125	0.05	0.18	0.16	0.21	0.15	0.1	0.06	0.06	0.06	0.00060662
$\bar{\pi}$: Steady state inflation rate	Gamma	0.625	0.1	0.6	0.65	0.67	0.75	0.64	0.64	0.55	0.55	0.00053542
$100(\beta^{-1}-1)$: Time preference rate	Gamma	0.25	0.1	0.26	0.25	0.27	0.23	0.19	0.16	0.24	0.14	0.00036863
$\bar{l}$: Steady state hours	Normal	0.0	2.0	2.7	3.88	4.3	5.58	7.79	8.09	3.54	3.33	0.0025182
$\bar{\delta}$: Net growth rate in percent	Normal	0.4	0.10	0.42	0.36	0.35	0.39	0.47	0.42	0.42	0.3	0.00080955
ρ_{ga}: correlation of prod. and spend. shocks	Normal	0.5	0.25	0.54	0.6	0.65	0.44	0.48	0.54	0.44	0.56	5.6729e-06
α: Capital share	Normal	0.3	0.05	0.19	0.2	0.19	0.2	0.23	0.2	0.18	0.14	6.8685e-06
ρ_o: Learning persistence	Beta	0.5	0.288	0.91	0.91	0.94	0.93	0.98	0.93	0.96	0.33	1.2325e-05

Table I.4: Priors and Estimated Posteriors of the Shocks Processes under AL

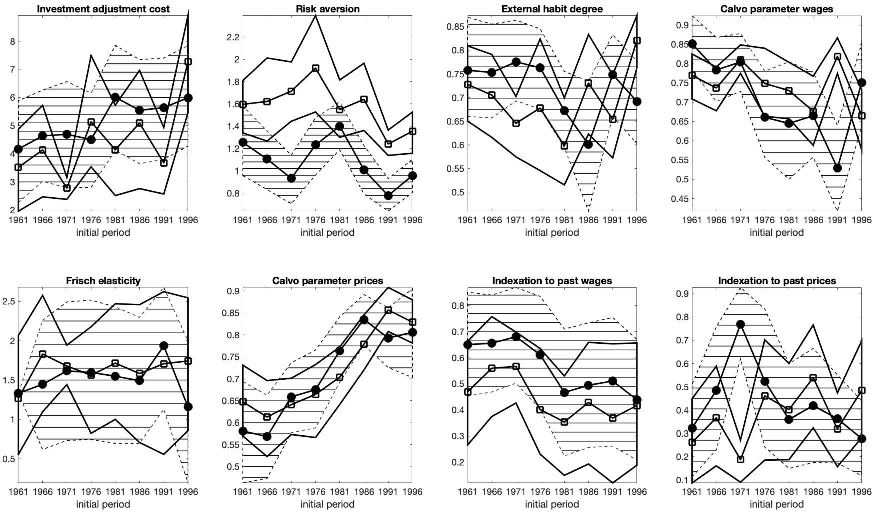
Parameters	Distribution	Mean	SD	61	66	71	76	81	86	91	96	measure
ρ_a: Persistence productivity shock	Beta	0.5	0.20	0.92	0.86	0.74	0.78	0.76	0.97	0.93	0.96	4.946e-05
ρ_b: Persistence consumption innov. premium shock	Beta	0.5	0.20	0.27	0.47	0.65	0.37	0.35	0.54	0.69	0.49	6.2716e-06
ρ_g: Persistence spending shock	Beta	0.5	0.20	0.87	0.94	0.86	0.77	0.94	0.96	0.94	0.9	3.8547e-05
ρ_i: Persistence investment shock	Beta	0.5	0.20	0.46	0.5	0.64	0.5	0.45	0.47	0.32	0.67	3.0676e-05
ρ_r: Persistence monetary policy shock	Beta	0.5	0.20	0.22	0.19	0.17	0.1	0.22	0.55	0.6	0.51	1.3189e-05
ρ_p: Persistence price markup shock	Beta	0.5	0.20	0.85	0.48	0.52	0.49	0.41	0.28	0.28	0.34	1.6762e-05
ρ_w: Persistence wage markup shock	Beta	0.5	0.20	0.39	0.49	0.56	0.79	0.63	0.55	0.51	0.29	6.1847e-05
μ_w: Coefficient on Ma term wage markup	Beta	0.5	0.2	0.73	0.5	0.42	0.65	0.52	0.54	0.43	0.56	4.7997e-07
μ_p: Coefficient on MA term price markup	Beta	0.5	0.2	0.57	0.48	0.36	0.45	0.44	0.39	0.5	0.66	3.7875e-05
σ^a: Productivity shock	Invgamma	0.1	2	0.52	0.51	0.42	0.37	0.35	0.37	0.42	0.48	0.0625
σ^b: Investment specific technology shock	Invgamma	0.1	2	0.13	0.19	0.14	0.18	0.15	0.07	0.09	0.07	0.0403
σ^g: Spending shock	Invgamma	0.1	2	0.52	0.55	0.55	0.48	0.42	0.39	0.36	0.34	0.0748
σ^i: Investment specific technology shock	Invgamma	0.1	2	0.36	0.45	0.38	0.45	0.41	0.33	0.23	0.25	0.0666
σ^m: Monetary policy shock	Invgamma	0.1	2	0.29	0.32	0.32	0.27	0.14	0.08	0.09	0.08	0.1008
σ^p: Price markup shock	Invgamma	0.1	2	0.06	0.08	0.05	0.12	0.09	0.08	0.1	0.11	0.0457
σ^w: Wage markup shock	Invgamma	0.1	2	0.18	0.17	0.13	0.21	0.27	0.3	0.38	0.49	0.1239

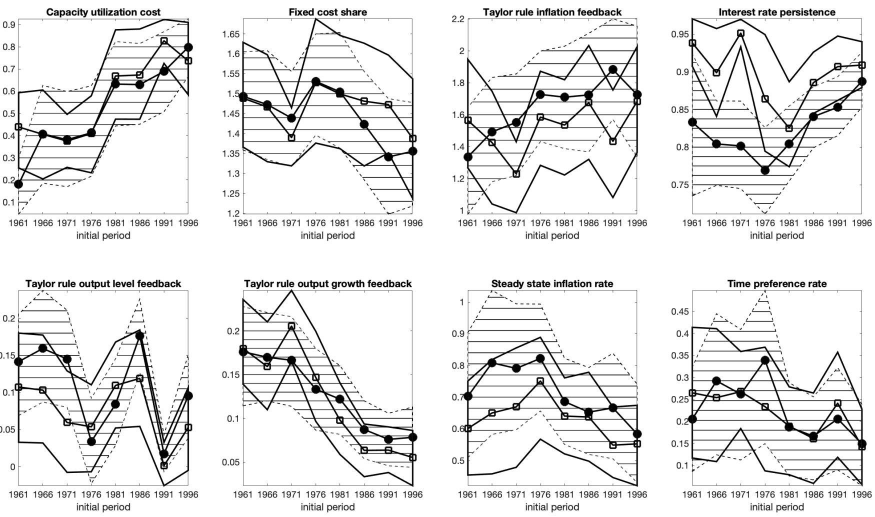
Estimated posteriors for the whole sample period

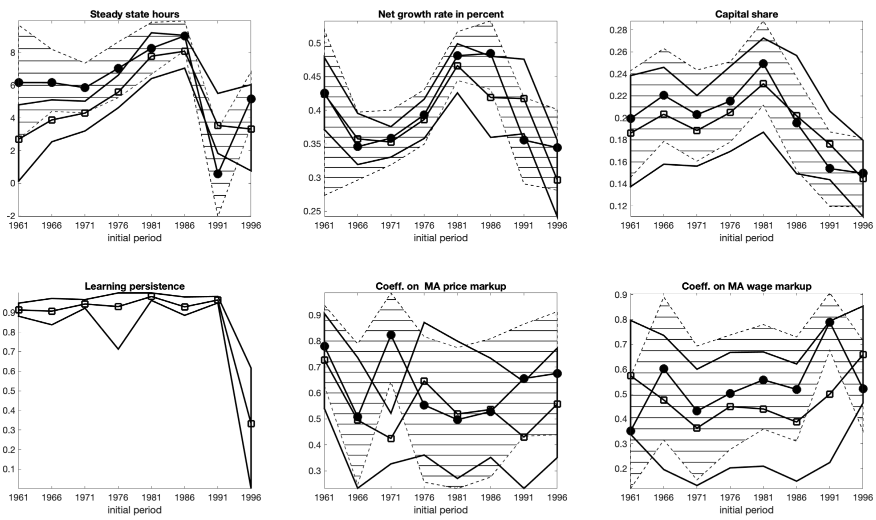
Table J.1: Priors and Estimated Posteriors of the Structural Parameters

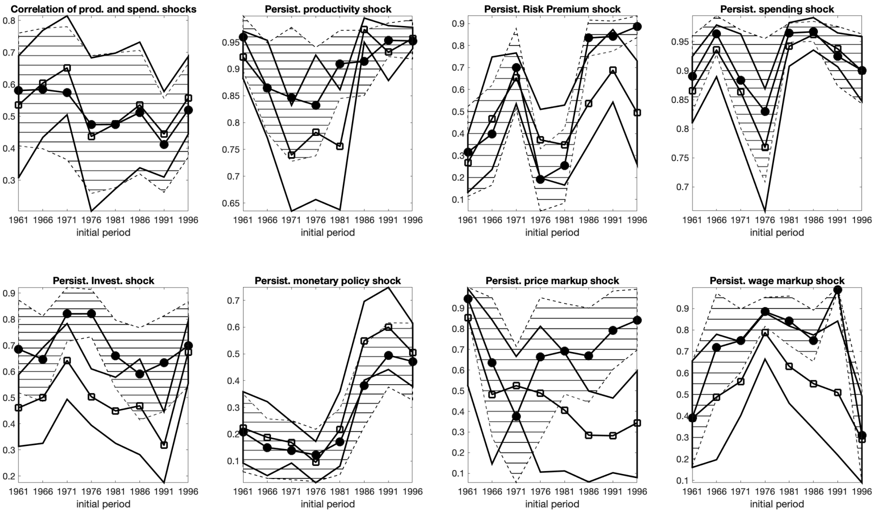
				RE		AL	
Parameters	Distribution	Mean	SD	Mean	Conf. Interv.	Mean	Conf. Interv.
φ: Investment adjustment cost	Normal	4	1.5	5.509	3.51-7.585	3.549	2.996-3.996
σ_c: Risk aversion	Normal	1.50	0.375	1.159	0.934-1.355	1.597	1.479-1.74
λ: External habit degree	Beta	0.7	0.1	0.707	0.57-0.847	0.697	0.662-0.733
ξ_w: Calvo parameter wages	Beta	0.5	0.1	0.801	0.707-0.937	0.869	0.834-0.896
σ_l: Frisch elasticity	Normal	2	0.5	1.333	0.37-2.216	1.053	0.266-1.757
ξ_p: Calvo parameter prices	Beta	0.5	0.10	0.749	0.676-0.816	0.844	0.807-0.877
ι_w: Indexation to past wages	Beta	0.5	0.15	0.648	0.454-0.854	0.286	0.16-0.396
ι_p: Indexation to past prices	Beta	0.5	0.15	0.266	0.128-0.395	0.376	0.198-0.587
ψ: Capacity utilization cost	Beta	0.5	0.15	0.636	0.441-0.816	0.678	0.472-0.875
ϕ_p: Fixed cost share	Normal	1.25	0.125	1.535	1.411-1.662	1.501	1.422-1.577
r_π: Taylor rule inflation feedback	Normal	1.5	0.25	1.756	1.44-2.055	1.571	1.379-1.784
ρ: Interest rate persistence	Beta	0.75	0.10	0.837	0.802-0.872	0.935	0.919-0.952
r_y: Taylor rule output level feedback	Normal	0.125	0.05	0.018	0-0.037	0.032	0.004-0.062
$r_{\Delta y}$: Taylor rule output growth feedback	Normal	0.125	0.05	0.177	0.147-0.209	0.097	0.073-0.118
$\bar{\pi}$: Steady state inflation rate	Gamma	0.625	0.1	0.901	0.673-1.114	0.58	0.494-0.674
$100(\beta^{-1}-1)$: Time preference rate	Gamma	0.25	0.1	0.158	0.068-0.25	0.159	0.128-0.192
$\bar{l}$: Steady state hours	Normal	0.0	2.0	1.397	-1.497-4.4	2.806	1.703-3.926
$\bar{\delta}$: Net growth rate in percent	Normal	0.4	0.10	0.382	0.344-0.418	0.402	0.383-0.424
ρ_{ga}: correlation of prod. and spend. shocks	Normal	0.5	0.25	0.537	0.416-0.658	0.498	0.422-0.579
α: Capital share	Normal	0.3	0.05	0.195	0.162-0.225	0.16	0.138-0.181
ρ_o: Learning persistence	Beta	0.5	0.288			0.962	0.954-0.97
ρ_a: Persistence productivity shock	Beta	0.5	0.20	0.975	0.96-0.991	0.984	0.978-0.989
ρ_b: Persistence consumption innov. premium shock	Beta	0.5	0.20	0.581	0.244-0.875	0.651	0.554-0.749
ρ_g: Persistence spending shock	Beta	0.5	0.20	0.97	0.956-0.985	0.981	0.97-0.994
ρ_i: Persistence investment shock	Beta	0.5	0.20	0.78	0.675-0.892	0.398	0.32-0.476
ρ_r: Persistence monetary policy shock	Beta	0.5	0.20	0.119	0.023-0.218	0.242	0.172-0.315
ρ_p: Persistence price markup shock	Beta	0.5	0.20	0.959	0.927-0.995	0.236	0.087-0.387
ρ_w: Persistence wage markup shock	Beta	0.5	0.20	0.952	0.879-0.997	0.392	0.112-0.635
μ_w: Coefficient on Ma term wage markup	Beta	0.5	0.2	0.851	0.78-0.919	0.516	0.378-0.659
μ_p: Coefficient on MA term price markup	Beta	0.5	0.2	0.916	0.845-0.979	0.455	0.179-0.646
σ^a: Productivity shock	Invgamma	0.1	2	0.467	0.423-0.509	0.461	0.43-0.482
σ^b: Investment specific technology shock	Invgamma	0.1	2	0.163	0.082-0.257	0.12	0.11-0.128
σ^g: Spending shock	Invgamma	0.1	2	0.471	0.433-0.508	0.461	0.437-0.485
σ^i: Investment specific technology shock	Invgamma	0.1	2	0.335	0.274-0.39	0.352	0.324-0.381
σ^m: Monetary policy shock	Invgamma	0.1	2	0.22	0.201-0.24	0.211	0.199-0.226
σ^p: Price markup shock	Invgamma	0.1	2	0.13	0.11-0.152	0.134	0.119-0.146
σ^w: Wage markup shock	Invgamma	0.1	2	0.36	0.319-0.398	0.348	0.321-0.38

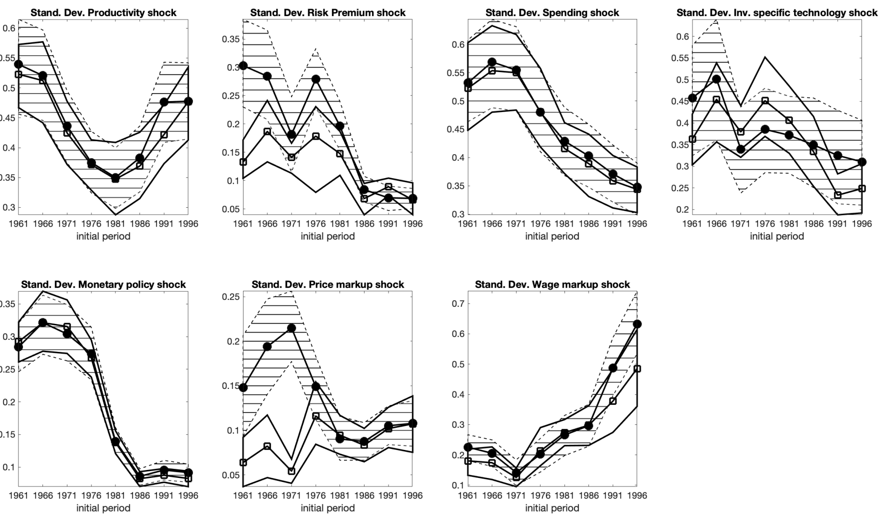
Comparison of estimates under RE and AL


Investment adjustment cost
Risk aversion
External habit degree
Calvo parameter wages
Frisch elasticity
Calvo parameter prices
Indexation to past wages
Indexation to past prices
initial period


Capacity utilization cost
Fixed cost share
Taylor rule inflation feedback
Interest rate persistence
Taylor rule output level feedback
Taylor rule output growth feedback
Steady state inflation rate
Time preference rate
initial period


Steady state hours
Net growth rate in percent
Capital share
Learning persistence
Coeff. on MA price markup
Coeff. on MA wage markup
initial period


Correlation of prod. and spend. shocks
Persist. productivity shock
Persist. Risk Premium shock
Persist. spending shock
Persist. Invest. shock
Persist. monetary policy shock
Persist. price markup shock
Persist. wage markup shock
initial period


Stand. Dev. Productivity shock
Stand. Dev. Risk Premium shock
Stand. Dev. Spending shock
Stand. Dev. Inv. specific technology shock
Stand. Dev. Monetary policy shock
Stand. Dev. Price markup shock
Stand. Dev. Wage markup shock
initial period

Correlations

Table L.1: Correlations

Inflation autocor.	61	66	71	76	81	86	91	96	All period
Data	0.87167	0.80567	0.84713	0.89823	0.80554	0.70807	0.52772	0.49657	0.88821
RE	0.87417	0.85253	0.8144	0.91977	0.70061	0.68065	0.65965	0.75622	0.92939
AL	0.89092	0.86754	0.91954	0.95806	0.88561	0.87866	0.78659	0.74889	0.95482
RE-whole	0.91756	0.86942	0.90166	0.942	0.84829	0.77173	0.69898	0.65429	0.92939
AL-whole	0.94483	0.91627	0.93302	0.96224	0.92727	0.86782	0.77132	0.77586	0.95482
Corr infla-interest									
Data	0.81451	0.47049	0.44451	0.65888	0.74558	0.38614	0.15402	0.25796	0.69576
RE	0.8484	0.52827	0.45288	0.77675	0.70576	0.4569	0.35326	0.56195	0.77802
AL	0.86058	0.50696	0.42549	0.78651	0.71665	0.51115	0.27155	0.52374	0.77778
RE-whole	0.8435	0.53787	0.52417	0.74406	0.78297	0.53046	0.47725	0.56107	0.77802
AL-whole	0.85991	0.59584	0.57339	0.76162	0.78753	0.48343	0.33575	0.52283	0.77778
Corr hours-interest									
Data	-0.21931	-0.25635	-0.10762	-0.39508	-0.52592	0.55099	0.83896	0.90406	0.25642
RE	-0.39537	-0.34045	-0.16057	-0.55129	-0.56402	0.44893	0.83281	0.90252	0.18922
AL	-0.33278	-0.30305	-0.23266	-0.48265	-0.54657	0.52118	0.81631	0.89546	0.22361
RE-whole	-0.39216	-0.36194	-0.24317	-0.5076	-0.56775	0.4883	0.86175	0.90954	0.18922
AL-whole	-0.30828	-0.31463	-0.18346	-0.45741	-0.55681	0.5041	0.84985	0.90921	0.22361
Corr hours-infla.									
Data	-0.50491	-0.18873	-0.2418	-0.39219	-0.5505	-0.23044	0.17447	0.24696	-0.045209
RE	-0.58988	-0.18041	-0.28627	-0.49108	-0.5761	-0.29235	0.35354	0.53306	-0.063665
AL	-0.50997	-0.013146	-0.25341	-0.49529	-0.63609	-0.23745	0.27189	0.52112	-0.049456
RE-whole	-0.64699	-0.31755	-0.38612	-0.50704	-0.63281	-0.20205	0.41387	0.48586	-0.063665
AL-whole	-0.59322	-0.29584	-0.33427	-0.4594	-0.66092	-0.28187	0.33992	0.50555	-0.049456
Corr output growth-infla.									
Data	-0.39546	-0.35835	-0.35197	-0.20393	-0.4193	-0.22228	0.0087894	0.039892	-0.21117
RE	-0.6579	-0.35902	-0.40643	-0.48336	-0.63684	-0.6204	0.099992	-0.10985	-0.53422
AL	-0.35439	-0.28191	-0.13077	-0.24168	-0.6413	-0.42255	0.094536	-0.1386	-0.35497
RE-whole	-0.73958	-0.59816	-0.5794	-0.54841	-0.68936	-0.53396	0.2707	0.091484	-0.53422
AL-whole	-0.54767	-0.47215	-0.44215	-0.36337	-0.48936	-0.3938	0.15436	0.06477	-0.35497
Corr output growth-interest									
Data	-0.35372	-0.25871	-0.26733	-0.2212	-0.23506	-0.047992	0.25568	0.20064	-0.094075
RE	-0.75004	-0.45201	-0.2446	-0.51716	-0.51785	-0.55856	0.27569	-0.13699	-0.4816
AL	-0.54409	-0.58015	-0.45283	-0.34419	-0.60307	-0.28658	0.17748	-0.025384	-0.29184
RE-whole	-0.7547	-0.6151	-0.62469	-0.69097	-0.55844	-0.39304	0.39709	0.059819	-0.4816
AL-whole	-0.49591	-0.44007	-0.46099	-0.48034	-0.3964	-0.35751	0.20264	0.089205	-0.29184

Conclusion

The present thesis aims to study the importance of real-time data inclusion, financial frictions, asymmetric information and the variability of structural parameters from a macroeconomic perspective with a focus on the interaction between the monetary policies and the real economy. This dissertation consists of three chapters, all of them are self-contained works.

The first chapter of the thesis clearly shows that both the Federal Reserve and the Bank of England take into account real–time inflation forecasts when implementing monetary policy, which induces an important new inflation bias source in both countries, although they do so in quite different ways. The Federal Reserve focuses on monitoring revised inflation during low unemployment periods, but it weights real-time inflation heavily in its decision making during high unemployment episodes. These results are in line with those found in Cassou et al. (2016). In contrast, the Bank of England uses a roughly equally-weighted average of real-time and revised inflation in its decision making which is fairly robust over the business cycle. Moreover, as in Ruge-Murcia (2003a, 2004) and Cassou et al. (2012) we find that the Ruge-Murcia asymmetric preference bias remains significant. In particular, the preferences of the two central banks are asymmetric, with stronger action taken when unemployment (output) is above (below) its natural rate (potential level) than when it is below (above).

As noted above, this new source of inflation bias can be a consequence of the degree of central bank independence that can differ from country to country. In order to compare the different degrees of real-time targeting we extend our analysis to other countries. Specifically, we include two European countries with independent monetary policies and three countries outside the European Union. Our results show that real-time inflation is an important new inflation bias source for all the countries. Specifically, the central banks of Australia and New Zealand follow closely the targeting policy of the Fed. This is in contrast to the central banks of Canada and Denmark that seem to be more close to the targeting policy of the Bank of England but they weight less heavily revised data during bad economic times. However, the central bank of Sweden seems not to take into account real-time data in their policy decision making at all.

Our analysis also tentatively suggests a relationship between the quality of the initial announcements of inflation as a predictor of final revised inflation and the weight given to real-time inflation in the policy function. Thus, US, Australia and New Zealand seem to focus only on real-time inflation during bad economic times. However, the Central Bank of Sweden seems to focus only on revised inflation whether the economy is doing well or not. The empirical evidence for UK and Denmark was not clear-cut. However, after taking into account the threshold that characterises the revision process into our estimation, the empirical evidence supports this hypothesis.

The second chapter presents and evaluates a model that helps study the role of the financial sector in the Spanish liquidity trap. We find that the financial frictions are able to explain the fluctuations of the macroeconomic variables in Spain. Our model is a variant of Christiano et al. (2014), we integrate a foreign sector that supplies government bonds to the Spanish banks of the type studied by Moreno et al. (2014).

We estimate the model for Spain over the period 2000Q1-2017Q4. We use quarterly observations of ten macroeconomic time series that are standardly used in the estimation of DSGE models and three financial series: credit to non financial corporations, entrepreneurial net worth and the risk premium of sovereign bonds. Estimation results show that 52% of the variability of output and 89% of the variability of credit in the business cycle are explained by anticipated risk shocks in the economy. These shocks account for the episode of the credit crunch during the Spanish recession and the contraction of investment and output. Such a sequence has been observed during the last recession starting around 2008 in Spain.

In the third chapter we estimate a medium-scale DSGE model both under rational expectations and adaptive learning using a rolling window approach to try to answer to the "Lucas Critique".

The results show that the inclusion of AL absorbs a large proportion of the total parameter variability obtained under RE. At the same time, the inclusion of AL has increased the fit of the model and has shown that it is able to correct the high estimated values of persistence and stickiness that we obtain under the rational expectations assumption. Overall, our estimation results reinforce those found by Bullard and Singh (2012) using a learning mechanism.

Moreover, the estimation based on the whole example under AL (i.e. assuming invariant parameters) is able to reproduce better the actual changes in the comovements between real and nominal variables. Our analysis also suggests that the strong supply shocks were the forces behind the negative comovement between nominal and real variables during the first part of the sample period analysed (i.e. the subsample period 1961-1981). Afterwards, dominant demand shocks could have caused the dramatic swings in the correlations between the real and nominal variables. Needless to say that this relationship is suggestive and further research is warranted.

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