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Financial Factors in Canadian Business Cycle

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RÉSUMÉ

L'ampleur de la récession mondiale suite à la crise financière américaine de 2008 a ravivé la popularité des modèles macroéconomiques qui intègrent des facteurs financiers pour étudier les cycles économiques. Depuis la Grande Récession aux États-Unis, ce pan de la recherche académique s'est principalement concentré sur l'étude de la dynamique de l'économie américaine. Toutefois, très peu d'études se sont penchées sur le cas canadien. Pourtant, le Canada a essuyé une grave récession en 2009 qui s'est accompagnée d'une dégringolade de ses marchés financiers et d'un resserrement de l'accessibilité au crédit. Ce mémoire a pour objectif de quantifier l'importance des chocs financiers pour les cycles économiques du Canada depuis 1991. Nous estimons le complexe modèle d'équilibre général dynamique et stochastique (DSGE) de Christiano et al. (2014) à l'aide de données canadiennes et de l'approche bayésienne, afin d'identifier les facteurs provoquant les fluctuations économiques et financières. À cette fin, nous utilisons des méthodes statistiques telles que la décomposition de la variance (deuxième moment) et la décomposition historique (premier moment) des séries chronologiques des variables observables. Plusieurs modèles alternatifs sont également estimés afin d'évaluer l'exactitude et la fiabilité des résultats obtenus préalablement. Enfin, nous transformons une variable correspondant à un choc financier en variable endogène. En somme, nous concluons que les chocs financiers représentent la cause principale des cycles économiques canadiens. Ces chocs expliquent jusqu'à 60% de la volatilité de la production et jusqu'à 74% de la volatilité des investissements. Leur contribution est significativement supérieure à celle des chocs technologiques. Selon nos résultats, des chocs financiers négatifs sont également responsables de la récente récession au Canada.

Mots clés : Modèle DSGE, Chocs financiers, Frictions financières, Estimation bayésienne, Décomposition de la variance, Décomposition historique.

ABSTRACT

The severe recession in many countries that followed the 2008 global financial crisis suggest that macroeconomic models designed to explain the causes of the business cycles have to incorporate financial factors. Following these events, the literature that investigate the American business cycles with financial factors has flourished. However, very few academic works similarly look at the dynamics of the Canadian economy. Yet, the recession of 2009 in Canada was accompanied with a harsh correction in the Canadian stock market and an important tightening of credit. In this thesis, we quantify the importance of financial factors for the Canadian business cycles since 1991. We estimate the large-scale Bayesian dynamic stochastic general equilibrium (DSGE) model of Christiano et al. (2014) with Canadian data and use several statistical tools to identify the key drivers of the macroeconomic and financial fluctuations. Among others, we compute the variance (second moment) decomposition and historical shock (first moment) decomposition of the relevant macroeconomic time series. Several alternative specifications of the baseline model are estimated to evaluate the robustness and the reliability of the results. Finally, we endogenize one financial shock by mapping it to actual data. Our results suggest that the financial shocks are the dominant factors behind the Canadian business cycles. They explain up to 60% of the volatility of output and up to 74% of volatility of investment. Their contribution to economic and financial fluctuations strongly dominate the technology shocks. Negative financial shocks are also found to be the main cause of the recent recession in Canada.

Keywords: DSGE model, Financial shocks, Financial frictions, Bayesian estimation, Variance decomposition, Historical decomposition.

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CHAPTER 1

INTRODUCTION

The popularity of macroeconomic models with financial frictions gained momentum after the recent financial crisis. Although it is not unanimous, the importance of financial factors (markets, frictions and shocks) in models that seek to understand business cycles is now well documented (Caldara et al., 2014, Christiano et al., 2014, Furlanetto et al., 2014, Gertler and Kiyotaki, 2010, Gilchrist et al., 2014, Jermann and Quadrini, 2012).

Williamson (1987) is the first to award a prime role for financial frictions in a regular real business cycle (RBC) model. His model replicates empirical evidences for several macroeconomic variables better than leading RBC models at the time such as Kydland and Prescott (1982) and Long and Plosser (1983).

More recently, Christiano, Motto, and Rostagno (2003, 2008, 2010, 2014), in a series of papers, undertake to model the economy of the United-States with complex dynamic stochastic general equilibrium (DSGE) models characterized with a critical role for financial factors. The main contributions of their work are the following: they show a significant role of financial and monetary markets for business cycles, they decompose the various shocks that drive the economy and their models fit macroeconomic time series data and co-movements with remarkable success. Their models are also able to explain the causes of the Great Depression, the 2001 recession, the Great Recession, as well as to describe the drivers of U.S. business cycles over the past two and a half decades.

One particularly relevant result for us is found in Christiano et al. (2014) (hereafter CMR). It suggests that the most important driver of American business cycles is a financial shock, labeled the risk shock [1]. It corresponds to a change in the cross sectional volatility in the firms investment outcomes. A growing body of evidence argues that this volatility is counter-cyclical, which indicates that the dispersion of investment outcomes

1. The risk shock successfully generates co-movement in several macroeconomic variables, a must for models aiming to explain business cycles.

increases during economic slowdown. CMR shows that the risk shock explains 60 percent of the American business cycle variance in output since 1985. More volatility is accompanied with an increase in the interest rate charged by banks and thus the credit spread widen, lowering credit, investment, consumption, output and employment.

While the last financial crisis has hit the Canadian economy less fiercely than its southern neighbor, the recession was nevertheless painful. Indeed, the non-energy export sector plunged by one third (and it has not yet entirely recovered) and the market for non-bank-sponsored asset-backed commercial paper (ABCP) collapsed. In July 2009, unemployment (in American standard) rose by 2.6 percentage points to 7.7% and the rate of job destruction was greater than in the 1990-91 recession. Although the labor market recovered relatively quickly the number of jobs lost during the recession, the number of involuntary part-time workers and the number of long-term unemployed have remained above pre-crisis levels. Moreover, wages have not yet start its usual upward trend.

In reaction, the Bank of Canada engaged in aggressive expansionary monetary policy. In the spring of 2009, it lowered interest rates to 0.25% and has even turned to unconventional monetary policies such as forward guidance - the Central Bank provides clear and credible information on how long the interest rates will remain low. However, the Bank for International Settlements (BIS) argues that the Canadian recovery was driven by increased debt levels (governments, businesses, consumers), thereby increasing the risk for another financial distress in the near future.

Building on the observed important role of the financial sector for recent Canadian business cycles, this thesis tries to generalize the empirical evidence on the importance of financial factors for the American economy in the Canadian context. We answer our research question through several empirical exercises. First, we estimate the model in CMR with Canadian data to understand what are the drivers of Canadian business cycle. We show the relative importance of the risk shock for Canadian output fluctuations through variance (second moment) decomposition and historical shock (first moment) decomposition of the macroeconomic time series. This allows us to understand the contribution of each possible driver to the fluctuation in relevant macroeconomic variables.

Second, we explore alternative specifications of the model to see how the results are impacted, including a model with flexible prices and wages, and with different characterization of the stochastic processes. Third, we enrich our dataset with a proxy for the risk shock. The risk shock thus becomes an observable variable. Since observable variables are used to estimate the parameters of the model, this exercise allows us to test how robust are the baseline results when an observed measures of uncertainty is including in the dataset. In the baseline case, the values of the risk shock are instead endogenously simulated from the solution of the model

We choose to work with the CMR model for two reasons. First, CMR develop a powerful and empirically plausible DSGE model for the U.S. economy. Indeed, CMR show that, among others, the out-of-sample forecasting properties of the model are good relative to a Bayesian vector autoregressive model or a simpler New Keynesian model without financial frictions. CMR also demonstrate that the data generated by their model for the risk shock are similar to other measures of uncertainty encounter in the recent literature.

Second, the CMR model grants a key role to the financial sector. Canadian DSGE models typically give a prime role for the technology, oil price and U.S. economy shocks. However, as pointed out earlier, the recent events suggest that the financial sector is very important for the Canadian economy. Obviously, a small-open economy model with a market for oil is desirable to model the Canadian economy, but the CMR model allows us to obtain one of the few empirical investigations of the role of financial factors for Canadian business cycle. To the best of our knowledge, there are only two empirical works (see section 2.2.1) that explicitly investigate the role of financial factors for Canadian business cycle, of which only one performs both variance and historical shock decompositions (none of them is published). In fact, there are very few Bayesian DSGE models with financial frictions and financial shocks at all that are estimated with Canadian data. An extension of the CMR model with a natural resource market and a foreign economy is left for future work.

The main contribution of this thesis is thus to quantify the role of financial factors for Canadian business cycle in a large-scale Bayesian DSGE model. We identify the shocks that are the main drivers of Canadian macroeconomic and financial fluctuations and we examine which shocks are responsible for the recent economic slowdown. Our results suggest that the financial shocks are the main driver of economic fluctuation in Canada, ahead of the technology shocks. The risk shock also appears to be the main factor causing the last recession in 2008-2009. Indeed, the risk shock is estimated to be highly cyclical. It had expansionary effect on output before the crisis and significant negative influence in 2008 and onwards. The impact of the risk shock on output fluctuations occurs through its impact on investment, mainly. In fact, the risk shock affects the credit spread, increases the cost of borrowing, limits the amount of credit available and reduces investment. Our analysis thus highlights the importance of modeling financial frictions for the Canadian economy. We find that nominal rigidities are crucial for our results to hold. We consider various alternative specification of the CMR model and find that the specification with the highest log marginal likelihood - the specification favored by the data - in the Canadian context is one that is not considered by CMR. We show that fiscal and monetary policies have been effective to prevent a deeper economic slowdown following the recent U.S. financial crisis. Finally, these results are relatively robust to the addition of observed measures of uncertainty as proxy for the risk shock in the dataset.

Chapter 2 contains the literature review. It describes the most important elements of the model that allow us to investigate the research questions. Chapter 3 presents the DSGE model of CMR. Chapter 4 introduces Bayesian econometrics. Chapter 5 presents the data used for the empirical work, the assumptions about the parameters and the methodology. Chapter 6 depicts the results. Finally, Chapter 7 concludes.

CHAPTER 2

LITERATURE REVIEW

The literature review covers three important topics of this thesis. First, we describe several elements that make up the financial markets in our model. Second, we motivate our research question with a review of the recent attempts to assess the role of financial factors in business cycles. Third, we review in details some of the most popular approaches to estimate DSGE models. Our preference for a Bayesian approach to estimate our model is justified in Chapter 4.

2.1 Modeling detailed financial markets

This section covers several elements that make up the financial markets in our model. They include the modelization of financial and monetary sectors, the incorporation of financial frictions and the characterization of financial shocks. With regard to the first element, an explicit banking sector is modeled that follows Chari et al. (1995). Households have demand-deposits in banks, which lend resources to entrepreneurs and intermediary firms.

Below, we provide details for the two other elements. The following subsections review the modelization of financial frictions, and of financial shocks.

2.1.1 Modeling financial frictions

There exist two classic attempt to theoretically model financial frictions. Our model adopts the Bernanke and Gertler (1989) (hereafter BG) financial accelerator mechanism. BG model financial frictions through endogenous market incompleteness derived from agency problems. Agency costs arise between lenders and borrowers because of asymmetry of information and default is costly due to monitoring cost. An external finance premium is thus charged to borrowers in order to compensate the losses from bankruptcies. BG assume that the agency costs between entrepreneurs and households are inversely proportional to entrepreneur's networth. Since networth is cyclical, these costs are high during recessions and low during booms. Therefore, investment in capital is counter-cyclical. Indeed, an initial negative shock to the economy causes a reduction in entrepreneur's networth, increases agency cost by assumption and decreases investment as a result. In sum, a financial accelerator emerges because this reduction in investment is added to the initial economic slowdown, further reducing the networth of entrepreneurs, and so on.

One criticism of the BG financial accelerator model is the absence of large amplification effect to productivity shock. An improvement is to add dynamism to the model. For instance, Kiyotaki and Moore (1997) (hereafter KM) propose an inter-temporal amplification mechanism in addition to the static mechanism. KM provide the second classic way to theoretically model financial frictions. Financial frictions are derived from limited enforcement and collateral constraint, instead of information asymmetry. Credit is constrained in the economy because borrowers cannot guarantee the repayment of their obligations and lenders cannot force them to repay. As a consequence, the amount of credit the borrowers have access to is limited by the collateral they can provide. KM proxy the value of aggregate collateral by asset prices, which is time-variant and cyclical. Indeed, credit expands in good times and shrinks during economic downturns. The interaction between credit and collateral introduces a new transmission mechanism by which a shock that hit the economy can display persistent effect. For example, a negative productivity shock reduces asset prices and decreases the value of aggregate collateral, thereby shrinking credits which further slowing down economic activity.

The main contribution of KM, however, is to propose an inter-temporal amplification mechanism in addition to this static mechanism, also present in BG. To do so, they assume that the price of assets mirror both present and future market conditions. They show that the effect of this mechanism dominates the static one.

While we use the BG approach to model financial frictions, we adopt a dynamic version of the financial accelerator model to obtain a similar inter-temporal mechanism to KM. Finally, financial frictions in our model lie with non-financial firms. It is so in most models that investigate the interaction between financial imperfections and business cycles. In contrast, Gertler and Karadi (2011) introduce financial intermediaries that transfer savings from household to non-financial firms. Firms thus do not borrow directly to household. Instead, households deposit their savings in financial intermediaries which lend funds to final good producers. This allows them to model financial frictions at the level of financial intermediaries. This idea is motivated by the recent evidence that suggests failure in the interbank system. This approach can also be found in Gertler and Kiyotaki (2010) and Kiyotaki and Moore (2012). The next subsection provide details on these two options in the modelization of financial frictions.

2.1.2 Modeling financial shock: equity shock

While the financial accelerator model of BG is confirmed by empirical studies (Bernanke et al., 1999, Carlstrom and Fuerst, 1997, Christensen and Dib, 2008), the amplitude of the amplification mechanism remains small and unsatisfying. Alternatively, empirical works now explore the effect of shocks that originate in the financial sector (i.e. financial shock) [1]. Hence, imperfect financial markets are considered a trigger of business cycles. They no longer simply propagate and amplify shocks originating in other markets such as productivity or monetary shocks (Quadrini, 2011).

Our model follows this recent literature and contains two financial shocks, in addition to an imperfect financial sector. The first is an equity shock. It affects directly the networth of entrepreneurs [2]. A similar equity shock can be found in Gertler and Karadi (2011) and Gertler and Kiyotaki (2010).

Gertler and Karadi (2011) includes three types of shocks to a model with financial intermediaries; the standard technology and monetary shocks, as well as a financial shock. The latter is defined as a change in the valuation of the assets held by financial intermediaries. Agency problems arise between household and financial intermediaries, which potentially limit the quantity of deposits that financial intermediaries draw from households. Hence, the amount of deposits is function of the intermediaries' networth.

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1. The term financial shock is defined broadly here and can refer to equity, risk, liquidity or credit shocks.

2. As stated in CMR, entrepreneurs are easily interpreted as non-financial firms, although they can also represent risky banks that hold a non-diversified portfolio.

The higher is the value of their assets, the more deposits they attract. This contrast with most of the literature, where entrepreneurs borrow directly to household in an imperfect market to produce final output.

The authors find a significant amplification effect of financial frictions to the two non-financial shocks due to the positive relationship between economic activity and networth of the financial intermediaries. They thus re-confirm the amplification mechanism of financial frictions highlighted in BG. More importantly, the financial shock has a significant and direct impact on credit, investment and output. Hence, the authors successfully model a financial shock that can be an explicit source of economic fluctuations.

Gertler and Kiyotaki (2010) investigate a very similar equity shock in an RBC model where financial intermediaries face limitation in their ability to attract funds from other intermediaries as well as deposits from households. The interest rate charged on loan is higher for financial intermediaries with fewer funds. A negative shock constrains their ability to obtain deposit and force them to sell assets, further decreasing their prices and, as a consequence, their values. Credit is thus tightened, dragging down GDP. Furthermore, the constraint on attracting deposit is magnified proportionally to the leverage ratio - the ratio of debt to capitalization. In sum, the decline in output is twice as large in the presence of financial frictions.

In contrast to our model, however, both of these models are in the tradition of flexible prices. We rather follow the recent popularity of models that include several nominal and real frictions along the lines of Christiano et al. (2005) and Smets and Wouters (2007). For instance, Del Negro et al. (2010) also investigate a shock similar to the financial shock in Gertler and Kiyotaki (2010) that hits the re-saleability of private assets. In fact, the shock corresponds to a change in the fraction of the illiquid asset that can be resold each period. They depart from the RBC literature by including several nominal and real frictions. They found that nominal wage and price rigidities are essential for the financial shock to have significant impact on macroeconomic outcomes.

The impact of a financial equity shock is also investigated in Del Negro et al. (2010). Their model incorporates financial frictions that lie with non-financial firms. Therefore, the financial shock affects the networth of those firms, instead of the valuation of the assets held by financial intermediaries (as in Del Negro et al. (2010) and Gertler and Kiyotaki (2010)). In fact, they do not explicitly model financial intermediaries. Similarly, Carlstrom et al. (2010) model financial shock as perturbations to the networth of non-financial intermediary firms. They integrate agency costs that lie with non-financial firms into a New-Keynesian model characterized with nominal frictions. In contrast to Del Negro et al. (2010), though, they model financial frictions as a constraint to the ability of firms to hire inputs, as in KM. The firms thus face a collateral constraint and the higher is the firm's networth, the more it can finance its input. The results of both Del Negro et al. (2010) and Carlstrom et al. (2010) suggest that financial shock has a quantitatively important effect on the economy. For instance, the analysis of the impulse response functions (IRF) shows that a negative shock to networth of firms increases credit distortion and marginal cost, pulling down investment and output.

2.1.3 Modeling financial shock: cross sectional time varying shock

The second financial shock in our model is labeled the risk shock and refers to uncertainty. It corresponds to an idiosyncratic shock that changes the cross sectional dispersion of returns on entrepreneurs investments. In fact, entrepreneurs purchase raw capital from households using their networth in combination with loans to produce effective capital. The idiosyncratic shock affects the transition from raw capital to effective capital. Entrepreneurs purchase K units of raw capital, which is converted into ω K units of effective capital, where $\omega = [0;1]$. The risk shock is the cross sectional standard deviation of the random variable ω. The dispersion of the returns across entrepreneurs in a given period can be high or low. When the dispersion of returns is low, entrepreneurs investments are less risky and when the dispersion of return is high, they are riskier. Therefore, a negative risk shock augments the dispersion of returns across entrepreneurs, some of them even defaults, which increases the interest rate and the credit spread. As a consequence, investment and output are contracted.

Early contribution such as Bernanke (1983) emphasizes the importance of uncertainty coupled with adjustment cost for economic activity. However, only very recently did Bloom (2009) build the first structural model, which stretches explicitly the role of uncertainty for business cycles. Bloom models uncertainty as time varying second-moment in total factor productivity (TFP). It is diffused into the economy through one of the two transmission mechanism. We explain them in turn in the following two subsections.

2.1.3.1 “ Wait and see ” transmission mechanism

The traditional transmission mechanism through which this uncertainty shock affects aggregate output is often called “ option value ” of investing or “ wait and see ”. One essential element of this mechanism is the presence of adjustment costs in the markets for input. Bloom assumes such imperfect markets for labor and capital inputs. The frictions, combined with a temporarily higher than usual level of uncertainty, push firms to “ wait and see ” until uncertainty subsides. Investment and hiring are thus pending. This cautious behavior depresses aggregate economic activity in the short term. Sooner or later, however, aggregate production promptly returns to normal once the demand for inputs entirely recovers. Bloom et al. (2012) quantify the impact of this uncertainty shocks on economic activity within a DSGE model characterized by heterogeneous firms and a mix of convex and non-convex adjustment costs. Their results confirm the “wait and see” hypothesis.

Although those papers constitute seminal contribution to the study of cross sectional time varying shocks, new empirical evidence shows that recessions can be more persistent (e.g. the Great Recession). However, the “ wait and see ” transmission mechanism can only explain short-lived economic downturns. This caveat can be overcome with the incorporation of a financial sector in these models. Indeed, the inclusion of imperfect financial markets results in a second transmission mechanism through which changes in uncertainty affect economic activity. Arellano et al. (2010) shows that this new mechanism allows uncertainty shocks to have persistent effects on output.

2.1.3.2 Financial transmission mechanism

Arellano et al. (2010) build a DSGE model where, in contrast to Bloom et al. (2012), firms do not face adjustment costs. The important feature of the model is instead the presence of financial frictions. While uncertainty shocks reduce significantly output in both models, the cause differs. Rather than generating a decline in productivity, as in Bloom et al. (2012), increased uncertainty creates a labor wedge. Moreover, financial imperfections generate an endogenous credit contraction, which makes the drop in output persistent. They argue that their model better match empirical facts than specifications with TFP shocks or with perfect financial market.

Our approach is closer to Arellano et al. (2010). Indeed, uncertainty is modeled as a time-varying second-moment financial shock, rather than a time varying second-moment TFP shock. Not only the later cannot reproduce persistent recessions, it is also not favored by recent empirical works.

For instance, Gilchrist et al. (2014) study the relative importance of the two transmission mechanisms on economic activity. With respect to the " wait and see " mechanism, the authors embed the capital accumulation process of firms with adjustment frictions in the form of fixed adjustment cost and partial ir-reversibility. The second mechanism is obtained with the inclusion of agency problems in the financial markets. Their results confirm the substantial effects of idiosyncratic uncertainty on investment and output. Furthermore, financial frictions produce a significant transmission mechanism. Indeed, uncertainty have real effects on macroeconomic outcomes mainly through the changes in credit spread, rather than through the traditional " wait and see " mechanism, although the latter is not insignificant. Also, exogenous credit spread shocks dominate uncertainty TFP shocks. These observations suggest that the impact of uncertainty occurs primarily through financial markets.

Bachmann et al. (2013) also provide evidences against the " wait and see " transmission mechanism. They construct measures of time-varying uncertainty from business surveys and explore their dynamic relationship with economic activity in Germany and the United States in a structural vector autoregressive model (SVAR). The two countries differ in particular in terms of adjustment frictions in labor and capital, a key component of the "wait and see" hypothesis. The United-States are assumed to be characterizes by smaller frictions than Germany.

They found that increased uncertainty in the United-States produce persistent economic slowdown. This result suggests that the “wait and see” channel is insufficient to explain the nexus between uncertainty and output in the absence of significant adjustment frictions. In addition, although the response of the German economy to an uncertainty shock is more consistent with the “wait and see” mechanism, the overall significance of this channel remains weak. The authors interpret these results as support for the presence of alternative channels through which uncertainty affects business cycles.

2.2 Assessing the role of financial factors in business cycles

While productivity shocks are traditionally found to explain most of economic fluctuations, recent empirical evidences favor instead the financial factors as the main driver. Here, we review the evolution of the importance of financial factors in empirical macroeconomics since the late 1980s.

Early evidences on the propagation and amplification role of financial imperfections are found in Carlstrom and Fuerst (1997) and Bernanke et al. (1999). They quantifies the contribution of financial frictions for business cycle by investigating the IRFs of several macroeconomic variables to standard shocks.

Carlstrom and Fuerst (1997) calibrate a model with agency problems to pursue two experiments. The first is a one-time shock to the distribution of wealth in the form of a transfer of capital from household to entrepreneurs. The second experiment is a standard productivity shock. The IRFs of output to the different shocks confirm the amplifying effect of financial frictions, although the effect is not large.

Bernanke et al. (1999) embed financial frictions at the level of the buyers of capital in a New-Keynesian dynamic model characterized by monopolistic competition, nominal price rigidity and a monetary market. They confirm as well the amplification effect of agency problems to wealth distribution and productivity shocks. They also find amplification effect to monetary and fiscal shocks. Credit constraints arise in the form of higher premium imposed to borrowers with lower networth, similarly to BG.

As mentioned earlier, the amplification and propagation effects of financial imperfections are not satisfactory and financial factors are now considered trigger of business cycles. Therefore, financial shocks are incorporated into DSGE models to investigate the full power of financial factors on business cycles. One possibility is then to study the IRF of GDP to a one standard deviation change in the financial shock. Such a strategy can be found in Kiyotaki and Moore (2012), Gertler and Kiyotaki (2010), Del Negro et al. (2010) and Gilchrist et al. (2014), for instance. More recently, the use of Bayesian econometrics brings a new standard approach to quantify the role of the financial factors in business cycles through Bayesian variance decomposition, shock decomposition, simulation and model comparison. This approach is used, among others, by Jermann and Quadrini (2012) and Christiano et al. (2010).

Jermann and Quadrini (2012) evaluate the importance of a financial shock for U.S. business cycles in a model that comprises 8 structural shocks. The financial shock corresponds to random changes in the enforcement constraint that limits the ability of firms to borrow. Financial frictions lie with intermediary good producers.

The authors go beyond testing the effects of financial shocks for the economy using IRF. They estimate a Bayesian DSGE model - a DSGE model estimated with Bayesian econometrics - that permits to evaluate the relative contribution of financial shocks for business cycles with Bayesian econometrics. The results indicate that financial shocks are more important than productivity shocks for fluctuations in several macroeconomic and financial variables. Indeed, the model's response to the constructed financial shocks closely match empirical data, while the responses to productivity shocks show clear divergence with actual data. Also, the financial shocks are significant contributors to the variance decomposition for the volatility of the growth rate of output, investment and labor. It is not for consumption though.

Christiano et al. (2010) estimate a DSGE model with US and Euro Area data also to quantify the relative importance of financial and TFP shocks for business cycles. The model includes 16 shocks in total, of which two are financial shocks and two are TFP shocks. The financial shocks are an equity shock and a risk shock, very similar to ours. They both hit the demand for capital. The authors find that financial shocks, in particular the risk shock, significantly outrun the TFP shocks as main driver of business cycles.

For instance, 47 and 35 percent of the variance in GDP is accounted by the risk shock in the US and the Euro Area, respectively.

In sum, financial shocks explains a major fraction of GDP fluctuations in the United States. They also outperform the alternative potential drivers of business cycles (the standard TFP shocks and the recent TFP uncertainty shocks). In addition, financial frictions represent a critical transmission mechanism for various shocks hitting the economy. With these developments in mind, we investigate the relationship between financial factors and Canadian output with a Bayesian DSGE model.

Hence, we seek to understand the causes of the Canadian business cycle over the last decades with state-of-the-art modeling and estimation strategies. Our results contribute to the literature that work toward a full understanding of the drivers of business cycles in Canada.

2.2.1 The case of Canada

To the best of our knowledge, only two papers quantify the role of financial factors for Canadian business cycle using a Bayesian DSGE model[3]. The first is Dib et al. (2008). Financial frictions such as in BGG are inserted into a small-open economy DSGE model. The model includes 11 aggregate shocks, of which two are financial shocks: shocks to the external financing cost in the domestic and foreign credit markets. Their results suggest that financial and, to a lesser extent, investment technology shocks are the main driver of macroeconomic fluctuations. The authors perform a variance decomposition exercise that shows financial shocks account for 35 and 55 percent of the volatility of tradable and non-tradable output, respectively. Their contributions to other variables such as investment, hours and consumption are significant as well. Also, the domestic financial shock is more important than the foreign financial shock. Dib et al. (2013) use this model to evaluate the benefits of a price level targeting (rather than an

3. There are actually very few Bayesian DSGE models estimated with Canadian data. Christensen et al. (2009) estimate a Bayesian DSGE model with financial frictions a la KM. However, they study the role of housing demand shock, and not financial shocks similar to the ones highlighted so far in the literature review. Justiniano and Preston (2010a) estimate a Bayesian DSGE model for the Canadian economy, but financial frictions and financial shocks are absent. Important Canadian DSGE model estimated via maximum likelihood includes Bouakez and Rebei (2008).

inflation target) in the presence of financial shocks. The authors show that the benefits from adopting a price level targeting rule are significantly greater in the presence of financial shocks. Indeed, these shocks account for 40% of the welfare gain.

The second article is Nishiyama (2011). It explicitly studies the linkage between financial activity and real economic activity, and measure how important are financial shocks for the Canadian business cycles. Financial frictions are modeled following BGG financial accelerator model. The model is subject to two financial shocks: a shock to the external finance premium and a shock to the networth of firms similar to the equity shock found in the literature. Both financial shocks are shown to have significant impact of the real side of the economy through IRF analysis. Also, Nishiyama (2011) performs both a variance decomposition and a historical shock decomposition exercises. The results suggest that financial shocks are at least as important for fluctuations in investment than are investment technology shocks in Canada. However, they account for a small portion of fluctuations in GDP. It is instead the technology shocks that explains most of its movements. However, when the financial shocks are dropped, the unconditional forecast error of GDP that is explained by the investment technology shock increases from 17% (baseline specification) to 49%. The author concludes that financial factors are proved important for Canadian business cycles.

Although the CMR model is a closed economy model, the financial sector is granted a key role. This allows us to provide one of the very few attempt to test the importance of financial factors for Canadian business cycles. We perform both variance and historical shock decompositions of the Canadian macroeconomic time series. We also investigate the consequence of the inclusion of anticipated components to various shocks and we endogenize the risk shock with proxies for uncertainty in Canada. Finally, our model has two financial shocks and it is estimated using 4 observable financial variables. Two of the financial variables (credit and networth) are not in the dataset of Nishiyama (2011). As we will see in Chapter 6, the inclusion of these two variables are crucial for the financial shocks to outperform the technology shocks as main driver of business cycles.

2.3 Traditional approaches to estimate DSGE models

This section describes some of the most important estimation techniques that are used when working with DSGE models. While Bayesian econometrics is becoming the dominant approach to estimate and evaluate DSGE models, the other approaches, labeled classical econometrics, are still widely used today. The presentation below is non-exhaustive, but describe three of the major classical estimation methods for DSGE models: Calibration, Generalized method of moments (GMM) and Maximum likelihood (ML) [4]. They are describe and compared with each others. Pioneered empirical applications are also briefly sketched. Note that the Bayesian approach and its advantages are presented in Chapter 4.

Before going further, it is useful to describe the standard methodology to estimate a DSGE model. The first step is to specify the nonlinear optimization problems of the various economic agents (households, firms, banks, government, monetary authority, and so on). Second, the optimization problems are calculated to obtain the Euler equations. To estimate the model via GMM, one does not need to go further in the resolution of the model. The GMM procedure is applied to Euler equations either one equation at the time or to the full system of equations. Third, the model is solved, often through log-linearization of the equilibrium relationships. The objective is to express the endogenous variables as functions of the exogenous and predetermined variables. A list of equations characterizing the solution of the model is obtained. Fourth, these equations are fitted in a state-space form. Fifth, the state-space form is estimated, so that inference and model evaluation can be performed. Calibration, ML and Bayesian inferences are all performed at this step.

2.3.1 Calibration

In 1976, Lucas initiated a famous shift in empirical macroeconomic with a critique, known as the Lucas critique, of the then popular system-of-equations analysis. In the

4. Other relatively important approaches include Simulated methods of moments (SMM) and Minimum distance estimator.

early 1980s, two main methodological approaches emerged as alternatives to the criticized systems-of-equations [5]. On the one hand, vector autoregressive (VAR) models are introduced by Sims (1980). VARs are statistical models typically estimated by ML or Bayesian methods. On the other hand, calibrated general equilibrium models are pioneered by Kydland and Prescott (1982). Calibration is not meant to estimate parameters and test various hypotheses, but rather to evaluate some quantitative experiments. Calibration does not require statistical techniques and probability theory to evaluate parameter estimates. Instead, one calibrates their values using economic knowledge (Kydland and Prescott, 1996).

A simple overview of the method is the following. First, recall that in order to investigate a research question by means of calibration, one needs to solve the model and express the endogenous variables in terms of the exogenous and predetermined variables. Then, fixed values for the parameters and the characterization of the shocks are selected (i.e., these values are not stochastic). In addition, instead of evaluating the fit of the model to the actual data, the outcomes of the calibrated model are compared to some stylized facts related to the initial empirical question. Such stylized facts are, for instance, empirical co-movements between aggregate economic variables, likelihood functions or impulse response functions (Canova, 2007). Sims (1980) also suggest to compare the calibration of the parameters of the model against the estimated parameters of unrestricted VARs.

The goal of this approach is typically not to replicate all features of the data, but simply a subset of features that relate to the research question. The model can thus fails in many regards, as long as it is useful in evaluating the main objective of the empirical work. The philosophical aspect of this methodology is that any model, be it a complex DSGE model or a simple VAR model, is at best a relatively " good " approximation of the true data generating process. Therefore, there is no point to use estimation procedures that assumes, under the null hypothesis, the model to be the true data generating process (Kydland and Prescott, 1996). Prescott clearly criticized the use of probabilistic theory

5. The critic of the system-of-equations was mainly about its lack of theoretical basis. Lucas shows that the estimated parameters are not robust to structural changes in the economy.

to perform quantitative experiments and thus challenged the mainstream econometrics at the time (DeJong and Dave, 2011, p. 257).

Canova (2007) highlights three main disadvantage of calibration versus traditional econometric. Calibration involves arbitrary choices, the selection of each parameter's value is done independently rather than from a coherent unified framework and the fit of the model on actual data cannot be tested. The later disadvantage is due to the absence of uncertainty in the estimation approach.

In practice, most empirical works, regardless of the estimation approach, use calibration for some parameters. Calibrating some parameters with existing knowledge has the advantage to improve the identification of the other parameters. However, this approach introduce a selectivity bias that arises when several different values can be found for one free parameter. Since the estimation of the non calibrated parameters rely on the assumption that the calibrated ones are set to their true value, the selectivity bias can result in inconsistent estimates. Sensitivity analysis is thus mandatory to explore the impact of choosing different values for the free parameters (Canova, 2007).

In our empirical analysis, we calibrate several parameters of the model, but not all. The remaining parameters are thus estimated. Calibration of the full model is not suited to discriminate among alternative models or specifications, one of our objective. In this regard, probabilistic theory and formal statistical inferences (like Bayesian) are needed. Moreover, Bayesian econometric can perform this task without the need to specify a null hypothesis. Instead, all specifications are considered as likely to be true, which represents a clear advantage over other probabilistic approaches (DeJong and Dave, 2011, p. 277-278)).

Example

Kydland and Prescott (1982) estimate a dynamic growth model to evaluate the importance of the "time to build" effective capital for business cycles. Their hypothesis is that productive capital takes more than one period to be built and that this delay is important for business cycles. They set this requirement to 4 periods. They argue that the model is valid if they can calibrate the parameters of the equilibrium relationships such that the model reproduces the co-movements of the cyclical components of several macroeconomic variables found in actual data. Specifically, the parameters are calibrated to reproduce the autocorrelation of output for 6 periods, the standard deviation of several variables such as consumption, investment and hours worked and their correlation with output, while making sure calibration does not depart too far from microeconomic evidences.

The optimal choice for the parameter is such that those stylized facts in the data are matched as precisely as possible. For instance, the optimal calibration for labor share, the depreciation rate and the risk aversion are 0.64, 0.10 and -0.5, respectively. Overall, the results are far from perfect, but they reproduce several features found in the dataset. Indeed, investment and consumption are more cyclical than output and the correlation between capital and output is negative. Moreover, their results are relatively nonsensitive to the selection of parameter values. Finally, the "time to build" requirement in the capital production explain the persistence in output fluctuations. On the basis of these results, Kydland and Prescott conclude that their calibrated model is valid.

2.3.2 Generalized method of moments

GMM estimates the parameters of the model by minimizing the distance between the empirical moments of the actual data and the theoretical moments of the model. The parameters are given a value such that the model replicate as closely as possible a predetermined set of targets, namely moments. In contrast to calibration, parametrization is executed using statistical procedures (DeJong and Dave, 2011).

GMM does not require the model to be solved. This is very important since the steps leading to the solution of the model and its state-space form can be burdensome (Ruge-Murcia, 2007). However, the model is claimed to be the true data-generating process under the null hypothesis. Recall that this requirement is strongly rejected by the advocates of calibration.

To use GMM, one needs orthogonality conditions of the form :

$$E[f(y_t, \theta)] = 0. \tag{2.1}$$

Where y_t is a vector of data observed in period t, θ is a vector of parameters to be estimated and f is a vector of functions (Canova, 2007). In practice, the GMM estimator of θ is such that the sample average of the orthogonality conditions above is minimize :

$$\frac{1}{T}\sum_{t=1}^{T} f(y_t, \theta). \tag{2.2}$$

The functions of interest f are typically variances, covariances, autocorrelations or other statistical moments. The functions can also correspond to conditions imposed by the model, instead of the econometrician. For example, Euler equation and inter-temporal conditions can substitute statistical moments (DeJong and Dave, 2011). The total number of conditions should be at least equal to the number of parameters to be estimated (Ruge-Murcia, 2007). When the former is greater than the later, every information in the orthogonality conditions is given a weight. In the opposite case, artificial orthogonality conditions are generated up to the number of estimated parameters. It is usually easy to find such orthogonality conditions in a DSGE set up, in particular from the optimality conditions and the constraints (Canova, 2007).

GMM can be used to estimate parts of a model like a single equation or to estimate an entire system of equations. GMM estimation of the full model is more efficient and less vulnerable to identification problems. However, even full model GMM estimation is based on limited aspect of the data. Therefore, GMM is less efficient than full-information approaches like ML, as long as there is no identification issues. However, in instances where identification does pose a serious problem, GMM might be superior to ML (Ruge-Murcia, 2007).

Although GMM is generally dominated by other estimation procedure such as ML in small samples, the later requires distributional assumptions about the errors and the properties of the distributions of the variables in the model. To find the distributions of endogenous variables and to apply ML can be computationally burdensome. GMM estimation does not require to define the distribution of the variables in the model or to find the solution of the model. Moreover, it can be applied to both linear and nonlinear models (Canova, 2007).

Example

Christiano and Eichenbaum (1992)[6] use existing standard RBC models to explore aggregate labor market dynamics. Their hypothesis is that standard RBC models fail to reproduce one stylized fact of labor market fluctuations, namely the weak correlation between hours worked and productivity of labor. The results confirm this claim. One reason might be the over reliance on the technology shocks to explain aggregate macroeconomic fluctuations. This shock primarily affects the marginal product of labor and thus overstate the correlation between hour worked and productivity. The authors then add a government expenditure shock to a standard RBC model. The new model is more consistent with actual data series.

The structural parameters of the model are estimated by GMM procedures, which contrast with the informal econometric strategies such as calibration often used in the traditional RBC literature. There are 8 structural parameters to estimate :

$$\Psi_1 = \{\delta, \theta, \gamma, \rho, \bar{g}, \sigma_\mu, \lambda, \sigma_\lambda\}. \tag{2.3}$$

The authors also consider various unconditional second moments :

$$\Psi_2 = \{\sigma_c^p/\sigma_y, \sigma_{dk}/\sigma_y, \sigma_n, \sigma_n/\sigma_{y/n}, \sigma_g/\sigma_y, corr(y/n,n)\}. \tag{2.4}$$

In sum, a total of $8+6=14$ unknowns shall be estimated. Those are stacked into $\Psi = [\Psi_1, \Psi_2]$. To calculate an estimate of Ψ, at least 14 unconditional moments need to be chosen. First, the authors choose eight unconditional first-moment restrictions that will be used to estimate the eight parameters in Ψ_1. For examples, a consistent estimate of the parameter δ^* is identified with :

$$E\{\theta^* - [1 - (dk_t/k_t) - (k_{t-1}/k_t)]\} = 0. \tag{2.5}$$

6. Pioneered works on GMM estimation of econometric models are Hansen (1982) and Hansen and Singleton (1982).

The parameter θ^* is identified with the first-moment restriction :

$$E\{\beta^{-1} - [\theta(y_{t+1}/k_{t+1}) + 1 - \delta]c_t/c_{t-1}\} = 0. \tag{2.6}$$

At least one such restriction is specified for each parameter in Ψ_1.

Second, the authors specify six unconditional first-moment restrictions that will be used to estimate the six elements in Ψ_2. Among them, the following first-moment conditions are used:

$$E[n_n^2 - \sigma_n^2] = 0 \tag{2.7}$$

$$E\{(y/n)_t^2(\sigma_n/\sigma_{y/n})^2 - n_t^2\} = 0. \tag{2.8}$$

The $8+6$ unconditional first-moment restrictions above are, respectively, defined by $H_{1,t}(\Psi_1)$ and $H_{2,t}(\Psi_2)$. Since these 14 unconditional moments are functions of the unknown parameters, we can represent them in matrix form $H_t = [H_{1,t}, H_{2,t}]$ corresponding to the 14 restrictions chosen to estimate the 14 unknowns. Actual data for the variables in the model are used to evaluate these moment restrictions. In particular, the true

$$EH_t(\Psi) = E[H_{1,t}(\Psi_1), H_{2,t}(\Psi_1)] = 0 \qquad \text{for all} \qquad t \geq 0. \tag{2.9}$$

Let its sample average be

$$g_T(\hat{\Psi}) = (1/T)\sum_{t=0}^{T} H_t(\hat{\Psi}). \tag{2.10}$$

The GMM estimator of Ψ is such that

$$g_T(\hat{\Psi}) = 0. \tag{2.11}$$

In sum, observed data are used to estimate the sample unconditional moments and the unknown parameters estimated values are such that these empirical moments are as close as possible to the theoretical moments.

2.3.3 Maximum likelihood

While GMM was predominant during the 80s and early 90s in academic works, there has been a shift to ML thereafter. In contrast to GMM and calibration, ML requires the characterization of the distributions of the stochastic innovations of the shocks. Also, ML inference is full-information. Therefore, it evaluates the entire set of implications of the model (DeJong and Dave, 2011).

The procedure is as follow. The first step to estimate DSGE models via ML is to solve the model and stack the solution into a state-space form. It is possible to express most log-linearized DSGE models in such a framework (Canova, 2007). However, DSGE models are highly non-linear, thus the solution is typically composed of nonlinear expectational difference equations. From there, algebraic manipulation are required to obtain the two relationships that characterize the state-space form, namely the measurement (or observation) equation and the transition (or state) equation :

$$y_t = Ax_t + Be_{1,t}, \tag{2.12}$$

$$x_t = Cx_{t-1} + De_{2,t}, \tag{2.13}$$

where y_t is a vector of endogenous (observable) control variables, x_t is a vector of endogenous (unobservable) state variables and $e_t = [e_{1,t}, e_{2,t}]$ is a vector of innovations. The innovations relates either to structural shocks or to measurement errors (Canova, 2007).

The second step is to compute the joint likelihood of the observable variables (y_t and x_t). From the state-space form, and assuming normality, the Kalman filter can be used to compute the entire joint likelihood function. ML is easily performed once the likelihood is computed. Recall that the presence of unobservables in the state-space model prevent the computation of the joint likelihood. If all variables were observable, this likelihood would be relatively easy to derive and then directly maximized to obtain ML estimates. However, unobservable variables are typically present in the solution of DSGE models. Fortunately, assuming the vector of innovations e_t is normal (i.e., $e_t \sim N(0,\Sigma)$), the

Kalman filter performs the evaluation of the joint likelihood of the state-space model in the presence of unobservables. The Kalman filter acts a little like a proxy for the unobservable variables. It is an iterative method that estimate the unobservable variables with the observable data. In fact, It starts with an initial estimate (often zero) and then update this estimate with the available data, one period at a time. The recursive updates of the likelihood permits the estimation of the model parameters and the computation of forecast for the dependent endogenous variable (Canova, 2007).

The third and final step is to maximize the likelihood of the model. Analytical solutions to the maximization problems are rare, therefore numerical methods are needed to obtain ML estimates. In particular, optimization algorithms such as simplex and derivative-based algorithms are required. Under the hypotheses that the state-space model define a covariance-stationary process and the true parameters do not lie on the boundary of the parameter space, ML provides consistent and asymptotically normal estimates. ML estimation of a DSGE model permits to compute impulse response functions, variance decomposition and forecasts (DeJong and Dave, 2011).

Several other challenges are encountered when DSGE models are estimated via ML. First, the model must not be singular. Indeed, singularity forces several linear combinations of the observable variables to hold perfectly and thus to be deterministic (Ruge-Murcia, 2007). This restriction is problematic because ML tells how likely it is that the model is able to fit the data. But when the model is singular, it fits the data with certainty, which makes ML irrelevant. A model is nonsingular as long as the number of exogenous shocks is at least equal to the the number of observable variables (DeJong and Dave, 2011). To address singularity, one can either drop observable variables, or add measurement errors (which act like shocks) until the number of exogenous shocks (at least) equals the number of observable variables [7]. The former solution, where a subset of the available data series is used to estimate the parameters of the model, can be preferable if one suspect that the extra observable variables would not provide significant information about the values of the parameters. A simple way to validate this claim is to estimate the model using different combinations of the available variables and to

7. One can also extend the model to include other structural shocks.

compare the estimates obtained (Canova, 2007).

Second, the ML estimates of the parameters require that the model reflects the true data generating process and thus should not be misspecified. It is therefore very important that the model behind the state-space form is credible. Moreover, although several model diagnostics are available to test for parameter stability and robustness, the strong assumption of normality must be assumed (DeJong and Dave, 2011). Third, DSGE models usually involve highly nonlinear relationships, thereby making identification of the parameters an important issue during estimation. For example, it is sometimes the case that the linearized equations characterizing the solution of the DSGE model contains many parameters, where some of them do not appear in enough equations to be identifiable (Canova, 2007).

Example

Lindé (2005) simulates data from a basic three-equations Keynesian model to shows that single equation estimation of the New Keynesian Phillips Curve (NKPC) produces bias estimates. The model is composed of the NKPC, an aggregate demand equation and a central bank's interest rate rule:

$$\pi_t = \omega E_t \pi_{t+1} + (1-\omega)\pi_{t-1} + \gamma y_t, \tag{2.14}$$

$$y_t = \beta_f E_t y_{t+1} + (1-\beta_f) y_{t-1} - \beta_r (R_t - E_t \pi_{t+1}) + \varepsilon_{y,t}, \tag{2.15}$$

$$R_t = (1-\rho)(\gamma_\pi \pi_t + \gamma_y y_t) + \rho R_{t-1} + \varepsilon_{R,t}. \tag{2.16}$$

The parameters are first calibrated to simulate data for the 3 variables that composed the model. Then, the initial calibration is dropped and the simulated data are used to estimate the single-equation NKPC parameters by GMM and, also, by non-linear least squares (NLE) procedures. The results suggest that the single-equation estimation by GMM or NLE both produce bias estimates. Then, the author estimates the entire model via full information ML (FIML) with the simulated data. This approach produces better estimates, even in the presence of severe measurement errors and model misspecification.

FIML procedure is then used to estimate the model with U.S. data. Recall that non-singularity condition requires that the number of shocks be at least equal to the number of variables in the model. The author thus adds a measurement error to the New-Keynesian hybrid Phillips Curve. The three-equations model estimated via FIML is:

$$\pi_t = \omega E_t \pi_{t+1} + (1-\omega)\pi_{t-1} + \gamma y_t + \varepsilon_{\pi,t}, \tag{2.17}$$

$$y_t = \beta_f E_t y_{t+1} + (1-\beta_f)\sum_{i=1}^{4}\beta_{y,i} y_{t-i} - \beta_r (R_t - E_t \pi_{t+1}) + \varepsilon_{y,t}, \tag{2.18}$$

$$R_t = (1 - \sum_{i=1}^{3}\rho_i)(\gamma_\pi \pi_t + \gamma_y y_t) + \sum_{i=1}^{3}\rho_i R_{t-i} + \varepsilon_{R,t}. \tag{2.19}$$

The results suggest that purely forward-looking NKPC is rejected. The right inflation dynamic contains both backward and forward looking components.

Recently, the popularity of ML has been challenged by the Bayesian approach. Bayesian DSGE models are indeed becoming the norm in empirical macroeconomic literature. In the next section, we present the model. We justify and elaborate on the econometric of Bayesian estimation in Chapter 4.

CHAPTER 3

MODEL

We borrow the large-scale DSGE model of CMR. Although we provide additional details and useful intuition, this section follows very closely the presentation in the CMR's article and technical appendix, both available online. The model is composed of a final good firm, intermediary good firms, a labor contractor, households, entrepreneurs, mutual funds, a monetary authority and a government. Below, the model is describe by market.

3.1 Goods market

The various final goods produced in the economy are simplified to a single, homogeneous good Y_t. It is produced by a representative firm that is assumed to operate in a competitive environment (i.e. although there is only one firm, it has no market power). The final good is produced using the now standard Dixit-Stiglitz technology :

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

where $Y_{j,t}$ is the intermediary good produced by the intermediate firm j at time t. The input in the production function of the final good producer is thus $Y_{j,t}$. The variable $\lambda(f,t)$ is a shock, defined as the markup shock. It affects the quantity of final good, Y_t, produced with a given amount of intermediate goods, $Y_{j,t}$. Hence, it impacts the profit markup of the final producer.

Intermediate good producers use the following technology in a monopolist environment :

$$Y_{j,t} = \begin{cases} \varepsilon_t K_{jt}^{\alpha} (z_t l_{jt})^{1-\alpha} - \Phi z_t^* & \text{if } \varepsilon_t K_j^{\alpha} t (z_t l_{jt})^{1-\alpha} > \Phi z_t^* \\ 0, & \text{otherwise} \end{cases}, \tag{3.2}$$

where $0 < \alpha < 1$. The inputs of the intermediate firms are K_{jt} and $z_t l_{jt}$. They correspond, respectively, to the services of effective capital and the quantity of homogeneous labor hired by the j^{th} firm at time t. The variable z_t^* refers to the steady state GDP. The fixed costs faced by the intermediate firm, Φ, are proportional to z_t^*. The variable Φ is endogenous and takes a value such that profits are zero. The variable ε_t is a covariance stationary technology shock, which shifts the production function for a given amount of capital and labor inputs. It resembles the standard temporary technology shock found in the RBC literature. In fact, the model has three technology shocks. The second is a shock to the growth rate of z_t^* in non-stochastic steady-state and it is labeled $\mu_{z^*,t}$. It corresponds to a persistent technology shock and affects the production of intermediate goods as well.

While the final producer operates in a competitive environment, intermediate producers set their prices, P_{jt}, subject to Calvo-style nominal frictions [1]. Each period, only a random fraction of firms, $1-\xi_p$, can re-optimize their prices. In comparison, when prices are perfectly flexible, all firms re-optimize in every period. The remaining non-optimizing firms set their price according to the following rule :

$$P_{jt} = \tilde{\pi} P_{j,t-1}, \tag{3.3}$$

where

$$\tilde{\pi}_t = (\pi_t^{target})^{\varsigma} (\pi_{t-1})^{1-\varsigma}. \tag{3.4}$$

Here, $\pi_{t-1} \equiv P_{t-1}/P_{t-2}$ and P_t is the price of the final good Y_t. The variable π_t^{target} is the inflation level that the monetary authority targets in its policy rule. The non-optimizing firms thus sets prices more or less to the previous price level adjusted for inflation.

The final goods are converted into consumption goods and investment goods. One unit of goods is converted into C_t unit of consumption or $\Upsilon \mu_{\Upsilon,t}$ unit of investment goods, where $\Upsilon > 1$ is a fixed growth parameter and $\mu_{\Upsilon,t}$ is a shock labeled the investment good

1. Nominal price rigidities can be modeled in several ways. It is now standard in macroeconomics to use the staggered prices model of Calvo (1983), where price changes follow a Poisson process. Calvo builds on the previous work of Taylor (1980), where prices of all firms are sticky for a predetermined number of periods. One reason why prices may be sticky is that changing prices may be costly. In the literature, this concept is typically called the menu cost.

production shock. In other words, CMR assume that consumption goods are converted one-for-one, but not always investment goods. The investment good production shock allows the model to account for the observed trend in the relative price of investment. Also, the trend rise in the technology for producing investment goods provides a second source of growth in the economy. Therefore, the steady state GDP z_t^* is function of Υ, while its growth rate $\mu_{z^*,t}$ is function of the standard technology as well as the investment good technology.

3.2 Labor market

Homogeneous labor services, l_t, are supplied by a representative, competitive household. It corresponds to the aggregation of differentiated labor services provided by household i at time t, $h_{i,t}$. The economy is assumed to be composed of a large number of households. In addition, CMR assume that all the households supply every type of labor services. The aggregation function uses the Dixit-Stiglitz structure, hence the labor input is :

$$l_t = \left[\int_0^1 (h_{i,t})^{\frac{1}{\lambda_w}} di \right]^{\lambda_w}, \qquad 1 \leq \lambda_w. \tag{3.5}$$

Every differentiated labor service i receives a nominal wage $W_{i,t}$ at time t. Nominal wages are not perfectly flexible and face Calvo-type nominal frictions. A random subset of the labor services, $1 - \xi_w$, receive a wage level that is set optimally in the current period. The other subset obtains a wage level set according to the following rule :

$$W_{i,t} = (\mu_{z^*,t})^{\varsigma_\mu} (\mu_{z^*})^{1-\varsigma_\mu} \tilde{\pi}_{w,t} W_{i,t-1}, \tag{3.6}$$

where

$$\tilde{\pi}_{w,t} = (\pi_t^{target})^{\varsigma_w} (\pi_{t-1})^{1-\varsigma_w}. \tag{3.7}$$

Finally, the nominal wages received by each type of labor services are aggregated to W_t, which is earned by the representative supplier of labor for selling its services to the intermediate good firms.

3.3 Financial markets

The financial markets involve three sub-markets. First, households produce raw capital using existing raw capital and investment goods. Second, entrepreneurs borrow from mutual funds in the loan market. Third, entrepreneurs use these loans to purchase raw capital, which they convert into effective capital.

3.3.1 Raw capital market

At the end of every period t, the representative household build the end-of-period raw capital K_{t+1} using the following production function :

$$K_{t+1} = (1-\delta)K_t + (1 - S(\zeta_{I,t} I_t / I_{t-1}))I_t. \tag{3.8}$$

As we can see in this function, the production of raw capital requires two inputs. First, the existing raw capital K_t, which is subject to the depreciation rate δ, where $0 < \delta < 1$. At the end of period t, the quantity of existing raw capital available is thus $(1-\delta)K_t$. The price paid for the existing raw capital is the same as the price received for new raw capital, $Q_{K,t}$, and the transactions take place in a competitive market. The second input is the investment goods, I_t. It is hit by the third technology shock, labeled the marginal efficiency of investment shock in producing capital, $\zeta_{I,t}$. In other words, the shock $\zeta_{I,t}$ affects how much raw capital can be produced with a given amount of investment goods, I_t.

Finally, S is an increasing and convex adjustment cost function for investment :

$$S(x_t) = \frac{1}{2}\left\{exp\left[\sqrt{S''}(x_t - x)\right] + exp\left[-\sqrt{S''}(x_t - x)\right] - 2\right\}, \tag{3.9}$$

where $x_t \equiv \zeta_{I,t} I_t / I_{t-1}$ and x is the steady state of x_t.

3.3.2 Effective capital market

The entrepreneurs are characterized by their networth $N > 0$, which they use to purchased raw capital produced by the representative household at a price $Q_{K,t}$. Net worth is composed of two elements: a end-of-period loan (discussed in next sub-section), B^N_{t+1}, and the networth left over in the previous period. Purchased raw capital is then converted into effective capital in this same period (more on this below). In period $t+1$, entrepreneurs, respectively, supply capital services, earn capital gains, repay their loan and transfer funds between them and their households. It is assumed that every household has a large number of entrepreneurs and that an entrepreneur does not transfer funds to its household. Entrepreneur's networth at the end of period $t+1$ is now determined. It is then added to a new loan for the purchase of raw capital in period $t+2$ and so on and so forth.

Every entrepreneur purchases K^N_{t+1} units of raw capital, such that :

$$Q_{K,t}K^N_{t+1} = N + B^N_{t+1}. \tag{3.10}$$

Here, entrepreneurs face an idiosyncratic financial shock, labeled the risk shock. The K^N_{t+1} units of raw capital are converted into ωK^N_{t+1} units of effective capital, where $\omega =$ [0;1]. As discuss in the chapter 1, the risk shock is the cross sectional standard deviation of the random variable ω and it is denoted σ_t. Therefore, the risk shock affects the transformation of raw capital into effective capital.

CMR justify the introduction of the risk shock with the following intuition. With a given amount of capital, some entrepreneurs create very successful products (e.g., the Apple iPod or the Tesla Motors Model S), while others experience less success (e.g., the Apple III computer or the Hewlett Packard TouchPad). In the former case, a given amount of raw capital is transformed into a large amount of effective capital (i.e., ω is very high), while the opposite happens in the later case. The risk shock, σ_t, corresponds to the cross-sectional standard deviation of the realization of ω. In other words, it is the dispersion of the returns across entrepreneurs in a given period. A negative risk shock increases the dispersion of returns across entrepreneurs forcing some to default and go out of business.

At the end of every period, the information on prices and rates of return are known to entrepreneurs. They choose the utilization rate of their effective capital, u_{t+1}. Thus, the amount of capital services they ultimately supply is $u_{t+1}\omega K_{t+1}$. They earns a competitive market rental rate r^k_{t+1}. At the end of the period, they retrieve their effective capital, $(1-\delta)\omega K_{t+1}$, net of the fixed depreciation rate δ, which is then sold in competitive markets to households at the price $Q_{K,t+1}$. In sum, the rate of return received by the entrepreneur in period $t+1$ is ωR^k_{t+1}, where

$$R^k_{t+1} \equiv \frac{(1-\tau^k)[u_{t+1}r^k_{t+1} - a(u_{t+1})]\Upsilon P_{t+1} + (1-\delta)Q_{K,t+1} + \tau^k \delta Q_{K,t}}{Q_{K',t}}. \tag{3.11}$$

The first part of the equation above corresponds to the revenues from supplying capital services. An entrepreneur gets marginal earnings from supplying capital $u_{t+1}r^k_{t+1}$ minus the increasing and convex cost function of capital utilization $a(u_{t+1})$ (i.e., capital utilization is costly). This amount is also subject to the tax rate on capital income, τ^k, and it is an increasing function of growth rate parameter, Υ, and the price level. The second part correspond to the revenues from selling non-depreciated effective capital to household at the price $Q_{K,t+1}$. The third and last part, $\tau^k\delta Q_{K,t}$, captures the assumption that depreciated capital is tax-deductible at historical cost.

3.3.3 Loan market

In order to produce effective capital, entrepreneurs finance their purchases of raw capital with their networth. Part of this networth comes from a loan, contracted from mutual funds in the form of a debt contract. CMR define the leverage as $L_t \equiv (N + B^N_{t+1})/N$ and the gross nominal rate of interest on debt as Z_{t+1}. These two variables define the debt contract between the entrepreneurs and the mutual funds. Entrepreneurs choose a contract such that the following equality is maximized [2]:

$$E_t\left\{\int_{\bar{\omega}_{t+1}}^{\infty}[R^k_{t+1}\omega Q_{K,t}K_{t+1}-B_{t+1}Z_{t+1}]dF(\omega,\sigma_t)\right\}=E_t[1-\Gamma_t(\bar{\omega}_{t+1})]R^k_{t+1}L_tN, \quad (3.12)$$

where

$$\Gamma_t(\bar{\omega}_{t+1})\equiv[1-F_t(\bar{\omega}_{t+1})]\bar{\omega}_{t+1}+G(\bar{\omega}_{t+1}), \quad (3.13)$$

and

$$G(\bar{\omega}_{t+1})=\int_0^{\bar{\omega}_{t+1}}\omega dF_t(\omega). \quad (3.14)$$

Here, $\bar{\omega}_{t+1}$ denote the value of ω (the idiosyncratic shock) that divides entrepreneurs between those who can repay their loan and those who cannot and thus default. This variable is omnipresent in the most important equilibrium equations of the model (see Appendix III).

The left hand side of equation 3.12 represents the expected networth of an entrepreneur. It corresponds to the integral, over the non-bankrupt entrepreneurs (see the bounds of the integral), of effective capital services, ωK_{t+1}, times its price $Q_{k,t}$ and the rate of return on capital R^K_{t+1} minus the debt burden, $B_{t+1}Z_{t+1}$. The expression $F(\omega,\sigma_t)$ captures the distribution of ω. The right hand side corresponds to the expected average entrepreneurial earnings, $R^k_{t+1}Q_{K',t}K_{t+1}$, received by the entrepreneur times the rate of return on capital, the leverage, L_t, and its networth, N.

Now, the supply for loans. Mutual funds give an amount B_{t+1} of loans per entrepreneurs. They finance these loans by issuing the same amount in deposits to households for a competitive interest rate R_t. An important assumption here is that, apart from the debt contracts with entrepreneurs, the two economic agents do not have access to future information about quantities, prices and uncertainty in this market. As a consequence, R_t is not function of $t+1$ uncertainty. Also, the following cash constraint must hold in every period $t+1$:

$$[1-F_t(\bar{\omega}_{t+1})]Z_{t+1}B_{t+1}+(1-\mu)\int_0^{\bar{\omega}_{t+1}}\omega dF_t(\omega)R^k_{t+1}Q_{K',t}K_{t+1}=B_{t+1}R_t \quad (3.15)$$

2. In equilibrium, each entrepreneur choose the same contract, regardless of their networth N.

Equation 3.15 implies that the total revenue of mutual funds obtained from their loans to entrepreneurs must equates total expanse. The expanses take the form of interest payments on deposits to households, $B_{t+1}R_t$. In other words, this secures that profits are zero in this market (i.e. the market for loans is competitive). The left hand side of equation 3.15 is the mutual funds revenues from its entrepreneurs. These revenues are divided into two parts. The first corresponds to the distribution of non-bankrupt entrepreneurs, $[1 - F_t(\bar{\omega}_{t+1})]$, times the amounts of loans expanded to them and its gross nominal rate of interest, $Z_{t+1}B_{t+1}$. The second is the integral, over the distribution of bankrupt entrepreneurs, of their received effective average entrepreneurial earnings, $\omega R^k_{t+1}Q_{K',t}K_{t+1}$. The term $(1-\mu)$ reflects the monitoring costs faced by mutual funds for the evaluation of the assets of bankrupt entrepreneur. These costs are a fraction μ of entrepreneurs assets.

Finally, at the very end of period $t+1$, entrepreneurs assets are subject to an equity shock. Only a fraction, γ_{t+1}, of these assets stay in their hands. The other fraction $1-\gamma_{t+1}$ is transferred to their households. This shock directly impacts the networth of entrepreneurs. A negative equity shock reduces the value of their networth and negatively impacts investment and output. Also, households give an exogenous lump-sum transfer, W^e_{t+1}, to entrepreneurs. CMR show that the equilibrium aggregate entrepreneurial networth at the end of period t is therefore :

$$N_{t+1} = \gamma_t[1 - \Gamma_{t-1}(\omega_t)]R^k_t Q_{K,t-1}K_t + W^e_t \tag{3.16}$$

In sum, three shocks directly impact the financial markets. Recall that capital is supplied by household and its demand is realized by entrepreneurs. The marginal efficiency of investment shock $\zeta_{I,t}$ affects the supply curve of the market for raw capital. The two financial shocks, the risk shock σ_t and the equity shock γ_t, impact the demand for raw capital. A negative shock to $\zeta_{I,t}$ shifts the supply to the left, reducing the equilibrium quantity of raw capital in the economy. This also means a reduction in the quantity of investment goods purchased by households, since it is an input in the production of raw capital. Therefore, there is a reduction in output and employment. This result - the cyclicality of investment and output - holds in the case of a negative shock to any of the two financial shocks as well. However, their implications for the equilibrium price of capital are different [3]. Indeed a shift to the left of the supply curve implies an increase in the price of capital (i.e. the value of equity is countercyclical), while a shift to the left of the demand curve implies the opposite (i.e. the value of equity is cyclical). As we will see later, the data strongly suggests that the later is right. Furthermore, an analysis of the dynamic responses of the variables in the model to those three shocks confirms these propositions (see Chapter 6).

3.4 The household problem

The representative household maximizes its utility function :

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_{c,t} \left[log(C_t - bC_{t-1}) - \psi_L \int_0^1 \frac{h_{i,t}^{1+\sigma_L}}{1+\sigma_L} di \right], \qquad b, \sigma_L > 0 \quad and \quad 0 < \beta < 1, \tag{3.17}$$

with respect to $C_t, K_{t+1}, K_t, I_t, B_{t+1}, B^L_{t+40}$ subject to the following budget constraint :

$$\begin{aligned} &(1+\tau^c)P_t C_t + B_{t+1} + B^L_{t+40} + (\frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}}) I_t + Q_{K,t}(1-\delta)K_t \leq \\ &(1-\tau^l) \int_0^1 W_t^i h_{i,t} di + R_t B_t + (R_t^L)^{40} B_t^L + Q_{K,t} K_{t+1} + \Pi_t. \end{aligned} \tag{3.18}$$

Equation 3.17 has an infinite horizon. The variable C is the per capita consumption of the households and $h_{i,t}$ is the differentiated labor supply. As we can see, the utility of the representative household increases with consumption and decreases with labor services. The inter-temporal parameter β reflects how impatient the household is. The smaller is β, the less the household values future utility versus current utility. The variable $\zeta_{c,t}$ is a preference shock, E refers to the expectation operator and b, σ_L and Ψ_L are parameters to be calibrated later on.

3. As we will see later, the price of capital is proxied by the value of equity in the stock market, which also represents the networth of entrepreneurs.

The left side of Equation 3.18 indicates that, every period t, household allocates its resources among 5 elements: consumption, one-period bonds B_{t+1}, forty-periods (10 years) bonds B^L_{t+40}, investment, and existing raw capital. The expression $\frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}}$ represents the price of investment good purchases and $Q_{K,t}$ the price of existing raw capital purchases. Consumption is real, therefore it is multiplied by the price level P_t. Also, it is subject to an exogenous and constant tax rate τ^c. The right side indicates that the household has four sources of funds: labor services, revenues from the two types of bonds, the selling of raw capital, and the net amount of lump-sum payments, Π_t. The latter source of funds is composed of several elements including the profits from intermediate good producers, the transfers from entrepreneurs and the net transfers from government. Labor revenues are integrated over all the differentiated labor services and subject to an exogenous and constant tax rates, τ^l. The one-period bonds purchased in the previous period pays a nominal return R_t in period t. The long-term bond B^L_{t+40} , if purchased in period t, will pay a nominal return R^L_t in period $t+40$. Expected returns on both types of bonds are known in the period of the purchase.

3.5 Monetary and fiscal policies

The linearized monetary policy rule is the following :

$$R_t = R + \rho_p(R_{t-1} - R) + (1-\rho_p)[\alpha_\pi(\pi_{t+1} - \pi^*_t) + \alpha_{\Delta y}\frac{1}{4}(g_{y,t} - \mu_{z^*}] + \frac{1}{400}\varepsilon^p_t. \quad (3.19)$$

The monetary authority (i.e. the Central Bank, henceforth CB) changes the interest rate R_t through a monetary shock, ε^p_t. From equation 3.19, we can see that the CB responds to a deviation of anticipated inflation, π_{t+1}, from the CB inflation target π^*_t, as well as to a gap between the observed GDP growth rate $g_{y,t}$ and its steady state growth rate, μ_{z^*}. The policy rule also shows that the CB does not want the interest rate to change too drastically from one period to another. Indeed, the parameter ρ_p weights the policy response of the CB between two elements. The first is the deviation of interest rate in previous period from its steady state, $R_{t-1} - R$, and the second is the deviation in economic fundamentals (GDP growth and inflation). In doing so, the CB smooths its response function over time, preventing R_t to change too abruptly. The higher is ρ_p, the smoother is the CB response. The variables α_π and $\alpha_{\Delta y}$ capture the respective importance placed on the inflation and GDP growth disequilibria. The fraction in front of the policy shock reflects the fact that the variables are quarterly.

Government expenditures is function of the steady state GDP :

$$G_t = z_t^* g_t, \tag{3.20}$$

where g_t is a stationary stochastic shock.

3.6 Resource constraint

The resource constraint in the economy is :

$$Y_t = C_t + \frac{I_t}{\Upsilon \mu_{\Upsilon,t}} + G_t + D_t + a_t(u_t)\Upsilon^{-1} K_t. \tag{3.21}$$

Equation 3.21 is different from the standard resource constraint $Y_t = C_t + I_t + G_t$ because of several features of the model. The relative price of investment goods is seized by $\Upsilon \mu_{\Upsilon,t}$. The expressions D_t and $a_t(u_t)$ capture respectively the costs for the economy of the aggregate monitoring expanses faced by mutual funds and the utilization adjustment cost function faced by entrepreneurs : $D_t = \mu G(\omega_t)\left(1 + R_t^K\right)\frac{Q_{K,t-1}K_t}{P_t}$, $a(u_t) = r^k[exp(\sigma_a(u-1)) - 1]\frac{1}{\sigma_a}$, where $\sigma_a > 0$ denotes the utilization cost function and r^k is the steady-state rental rate of capital.

The model is solved and then log-linearized around its steady state. This results in a list of equilibrium conditions that characterize the solution of the model. The complete list can be found in the Appendix III. It is those equations that are being estimated. They involve a substantial number of parameters, some of which do not appear in the presentation of the model so far. To help understand the list of equilibrium conditions, we refer to the section Data and Parameters (see Chapter 5) where we list the complete set of calibrated and estimated parameters of the model. This list is exhaustive. We also include a complete list of the parameters with their specific name in the CMR Dynare code (alphabetic order with respect to the Dynare name). It can be found in the Appendix IV.

3.7 Exogenous shocks

The model includes 12 aggregate shocks. The markup shock, $\lambda_{f,t}$, affects the final goods producer. The standard technology shock, ε_t, shifts the production function of intermediate producers. $\mu_{\Upsilon,t}$ is a shock to the production of investment goods. $\mu_{z_t^*}$ is a second technology shock that impact the growth rate of non-stochastic steady state GDP. $\zeta_{I,t}$ is a shock to the marginal efficiency of investment in the household production function of raw capital (it is the third technology shock of the model). The utility function of household is subject to a preference shock, $\zeta_{c,t}$. The capital market involving entrepreneurs and mutual funds is affected in several ways by the risk shock, σ_t. The networth of entrepreneurs is also impacted by an equity shock, γ_t. Monetary policy is subject to two shocks, a standard monetary policy shock ε_t^p and a shock to the inflation target π_t^*. g_t denotes the government expenditure shock. Finally, the last shock, η_t, is a measurement error shock on the long-term interest rate R_t^L.

The shocks are represented by an first-order autoregressive (AR) model :

$$x_t = \rho_x x_{t-1} + \xi_t, \tag{3.22}$$

where x_t stands for the log deviation of one of the shock from its non-stochastic steady state and ξ_t is the independent and identically distributed statistical innovation [4]. Here, the innovation is unknown to economic agents until it is realized (i.e. the shock's innovation is unanticipated). CMR argues that recent empirical evidences suggest that at least partial information about period t innovations is known in previous periods (i.e. the shock's innovation is anticipated). On the basis of these results, the representation of one shock is modified to include both unanticipated and anticipated components of the

4. The statistical innovation of a shock corresponds to the forecasting error of the shock in period $t+1$, based on available information up to period t.

shock's statistical innovation :

$$x_t = \rho_x x_{t-1} + \xi_{0,t} + \xi_{1,t} + \xi_{2,t} + \xi_{3,t} + \xi_{4,t} + \xi_{5,t} + \xi_{6,t} + \xi_{7,t} + \xi_{8,t}. \tag{3.23}$$

The unanticipated innovation is $\xi_{0,t}$ and the anticipated innovations, labeled the news (or the signals), are $\xi_{n,t}, n = 1,\ldots,8$. The baseline model puts the news on the risk shock. Therefore, the first shock representation holds for the other eleven shocks, but the risk shock has the second representation. Several alternative models are also considered, where news are put on other shocks [5].

The specification of the shock structure has implication for the number of parameters to estimate. For the eleven shocks with only unanticipated innovation, two parameters are estimated, namely the autocorrelation coefficient, ρ_x, and the standard error of the innovation, σ_x. The shock with news, however, has four parameters to estimate. CMR assume that the correlation structure of the news is :

$$\rho_{x,n}^{|i-j|} = \frac{E\xi_{i,t}\xi_{j,t}}{\sqrt{(E\xi_{i,t}^2)E(\xi_{j,t}^2)}}, i, j = 0,\ldots,8, \tag{3.24}$$

where $\rho_{x,n}$ is a scalar, with $-1 < \rho_{x,n} < 1$. The subscript n stands for news. In addition, CMR assume the following structure of the variance of the news :

$$E\xi_{0,t}^2 = \sigma_x^2, E\xi_{1,t}^2 = E\xi_{2,t}^2 = \cdots = E\xi_{8,t}^2 = \sigma_{x,n}^2. \tag{3.25}$$

The four parameters to estimated are thus the autocorrelation coefficient, ρ_x, the standard error of the unanticipated innovation, $\sigma_{x,0}$, the correlation coefficient of the news, $\rho_{x,n}$, and the standard error of the news, $\sigma_{x,n}$.

3.7.1 Additional details about the news

CMR defends the introduction of a shock's autoregressive law of motion comprising an anticipated component (the news) with the following reasons. First, it improves the

5. Also, CMR use 8 signals because it is the specification with the highest log marginal likelihood in Christiano et al. (2010) (see table A.3).

fit with the data by tackling the problem of mispecification in the model. Recall that this problem is common to all large-scale DSGE models. One thing to note is that the incorporation of the 4 financial variables as observable variables - i.e. the model is forced to fit as closely as possible the fluctuations in those variables during estimation - extends the mispecification in the financial sector. In this case, the modelisation of the anticipated component of the shocks is crucial to lessen model's mispecification. By doing so, the fit of the model to the data is greatly enhanced. It is important to note that as long as an anticipated component is added to one of the 12 shocks, the empirical fit is improved. However, for the sake of parameter parsimony, CMR put the news on one shock only. They show that the specification with the news on the risk shock provides the highest marginal likelihood ratio. It is therefore their baseline model. We show that this is also the case with Canadian data, but we find that a specification with news on both the risk shock and the marginal efficiency of investment shock has the highest likelihood (we discuss this finding in Chapter 6).

Second, CMR argue that the inclusion of news can be motivated by microeconomic foundations. This point is crucial, because it discards any critique stipulating that the model is being arbitrarily manipulated to fit the data. According to CMR, economic agents acquire advance information about future exogenous shocks, thus they know the statistical innovation of the shocks before the innovation realizes. This idea is supported by recent empirical evidence on US data. For instance, Ramey (2011) argues that timing is crucial to understand the impact of government spending shocks on macroeconomic outcomes. The author focuses on consumption because of the mixed results found in the literature on how it responds after such a shock. Ramey (2011) demonstrates that an anticipated government spending shock first reduces consumption until the innovation is actually realized, at which point consumption starts to increase. In contrast, unanticipated government spending shock immediately pushes consumption up. Therefore, different timing can explain why mixed results are found in the literature about the response of consumption to a government spending shock. In our baseline model, we capture this idea by putting the news on the risk shock. In other words, only the risk shock can be anticipated[6]. Entrepreneurs thus routinely revise their own assessment of the risk.

The anticipated and unanticipated risk shocks propagate differently in the economy, as it was the case for the government spending shock discussed above. Figures V.1 and V.3 display the impulse response functions of nine variables of the model to the unanticipated and anticipated risk shocks, respectively. The unanticipated shock is $\xi_{0,0}$ and the anticipated shock is $\xi_{8,0}$. They are assumed to be uncorrelated and we set $\xi_{0,0} = \xi_{8,0} = 0.10$. Both the unanticipated and the anticipated shocks widen the premium (credit spread), but with a delay corresponding to the lag of the anticipated shock. An anticipated risk shock $\xi_{j,t}$ occurring in period t thus means that the premium will widen in period $t + j$, the time at which the risk actually increases. Other than the impact on the premium, the anticipated and unanticipated risk shocks have very similar immediate impact on the main macroeconomic variables.

6. Recall that we also estimate other specifications with the news put on other shocks.

CHAPTER 4

WHAT IS THE BAYESIAN APPROACH

The model is estimated with Bayesian econometrics. This chapter motivates this choice. An implicit objective of this chapter is to show how recent developments in the modelisation of complex Bayesian DSGE models can lead to major improvements in empirical macroeconomic researches. For Fernandez-Villaverde (2010, p. 4), it looks like a revolution in macroeconomics. "…macroeconomists went from writing prototype models of rational expectations to handling complex constructions like the economy in Christiano et al. (2005)." Indeed, the empirical fit and the predictive power of Bayesian DSGE models now surpass in many respects alternative modeling strategies such as time series VAR in the spirit of Sims (1980) (Del Negro et al., 2007, Edge et al., 2010, Smets and Wouters, 2007). They have become so dominant in the macroeconomic literature that Fernandez-Villaverde (2010) speaks of a revolution, labeled the *New Macroeconometrics*.

4.1 Parameters estimation

Conceptually, Bayesian econometrics is simple. First, as for ML, the model must be solved and stacked in a state-space form. This means characterizing the solution of the DSGE model in two vectors of equations: the transition equation and the measurement equation. Second, filtering techniques such as the Kalman Filter are used to derive the likelihood of the variables time series, given the parameters. Third, priors must be specified. This is where the Bayesian approach differs from ML. Fourth, armed with the Baye's theorem, the posterior distributions can be computed (Fernandez-Villaverde, 2010). Draws are then taken from the joint posterior distribution of the parameters using algorithms such as the Random-Walk Metropolis (RWM) algorithm, the Importance Sampling (IS) algorithm and the Gibbs sampler. Once the posteriors are obtained, statistical inference can be performed (Geweke, 2005).

To estimate the model parameters, two elements are required (Lancaster, 2004):

$$p(\theta_A|A), \tag{4.1}$$

$$p(y|\theta_A, A). \tag{4.2}$$

They are, respectively, the prior probability density function (PDF) and the likelihood function (or the observables PDF), where θ_A is a vector of parameters of interest from the model A and y correspond to the dataset of the observables.

The Bayes theorem is used to evaluate the posterior PDF :

$$p(\theta_A|y^0, A) = \frac{p(\theta_A, y^0|A)}{p(y^0|A)} = \frac{p(\theta_A|A)p(y^0|\theta_A, A)}{p(y^0|A)} \propto p(\theta_A|A)p(y^0|\theta_A, A). \tag{4.3}$$

The last step uses the fact that the term in the denominator does not involve θ. The last expression on the right hand side thus approximates the posterior PDF. It is composed only of the two terms just mentioned: the prior PDF and the likelihood function. In contrast to ML, the likelihood function is reweighed by the prior PDF of the parameters to produce the corresponding posterior PDF. The prior density $p(\theta_A|A)$ does not depend on the data, but contains any non-data information available about θ. Hence, it adds information that is not contained in the sample Y. Although the specific choice of prior information can be argued be subjective, it is often the case that uncontroversial information about some parameters is actually available. When this is the case, the inclusion of this information can only improve the estimation results (Koop et al., 2007). Moreover, prior sensitivity analysis is typically conducted. For instance, the priors can be tested by first simulating the prior predictive distribution for different sample moments and then evaluating if they put reasonable weight on important features of the data (An and Schorfheide, 2007, p. 128). Also, if the information in the likelihood dominates the information in the priors, the posterior distribution may be valid even if priors aren't (Canova, 2007).

In fact, the posterior is approximated using simulation methods such as Markov chain Monte Carlo (MCMC). The idea behind MCMC is to produce a Markov chain such that its distribution asymptotically converges to the posterior distribution. The posteriors are approximated by the empirical distribution of the simulated data. Note that this sequence of simulated data constructed by MCMC is neither independent nor identically distributed. Therefore, the convergence of its distribution must always be checked. Finally, draws are taken from the posterior PDF of every parameter, using the RWM algorithm or the Gibbs sampler, to compute measures of central tendency such as the mean, the mode or the median. These measures substitute serve as point estimates for the parameters (Geweke, 2005).

4.2 Model evaluation

In practice, Bayesian models are estimated in order to give an answer to specific economic questions, rather than for the pure sake of estimating parameters. Formally, the interest of the researcher lies in the PDF of the vector of interest v, given a sample y^0 and the model A :

$$p(v|y^0,A). \tag{4.4}$$

In this case, a third element is required in addition to the prior PDF and the likelihood function. It is the PDF of a vector of interest v :

$$p(v|y,\theta_A,A). \tag{4.5}$$

There are only three elements that shall be evaluated to get $p(v|y^0,A)$:

$$p(v|y^0,A) = \int p(\theta_A|y^0,A)p(v|y,\theta_A,A)d\theta_A \propto p(\theta_A|A)p(y^0|\theta_A,A)p(v|\theta_A,y^0,A)d\theta_A, \tag{4.6}$$

respectively, the prior PDF, the likelihood function and the PDF of the vector of interest (Lancaster, 2004).

Model evaluation techniques in Bayesian econometrics are vast. They can be split into two broad categories: the absolute fit of a model and the relative fit of a model against alternative models. The evaluation of the absolute fit of a model resembles the classical hypothesis tests performed in standard econometrics. The objective is to evaluate the prior choices, on the one hand, and the estimated posterior distribution, on the other hand. While several approaches can be used to evaluate the priors, such as the comparison of the prior predictive distribution with the data and the use of training samples, some faith has to be put on the priors choice. In practice, the prior distributions are shown graphically and compared with the posterior distribution. Also, the robustness of the posterior outcomes to the prior choices can be evaluated by changing the prior distributions. This exercise is especially important when the priors reflect subjective assumptions (Canova, 2007).

A lot more effort is put on the evaluation of posterior distributions. First, the posterior predictive distribution can be compared with the data. The idea is to compare picks from the posterior distribution with the actual data. Second, the relative fit of a model can be evaluated in comparison to others. This is usually done by enlarging the model space or by relaxing relevant assumptions. Then, the discrimination between alternative specifications is done using the posterior odds method [1]. It consists of the ratio of the posterior probability of one model to the probability of all the other alternative models that are evaluated. In the simple case of two alternative models A and B, the posterior odds ratio informs us about the evidence found in the data y^0 on the relative posterior probabilities of the two models:

$$\frac{p(A|y^0)}{p(B|y^0)} = \frac{p(A)}{p(B)} \frac{p(y^0|A)}{p(y^0|B)}. \tag{4.7}$$

The first bloc on the right hand side represents the odds ratio, i.e., the unconditional posterior probabilities of the two models. The second shows the ratio of the marginal likelihoods of the two models. It is usually referred to as the Bayes factor. The Bayes factor discriminates in favor of the model which is the closest to the true model by comparing the marginal likelihood of data conditional on each model (Lancaster, 2004).

The difficulty in implementing posterior odds comparisons is the computation of the

1. An alternative method to choose between two models is the ratio of loss functions, also known as the Bayes critical value.

marginal likelihoods. For instance, the marginal likelihood of the model A is

$$p(y^0|A) = \int p(\theta_A, y^0|A) d\theta_A = \int p(\theta_A|A) p(y^0|\theta_A, A) d\theta_A. \tag{4.8}$$

The first term in the integral is the prior distribution of the parameter θ and the second term refers to the density of the observables. Numerical approaches are typically used to evaluate the likelihoods, such as the modified harmonic mean estimator in Geweke (1999) and the algorithm in Chib and Jeliazkov (2001) (An and Schorfheide, 2007). In practice, it is often the case that one evaluates alternative specifications of a model with the posterior odds method assuming that the unconditional posterior probability of every alternative model is identical. The odds ratio is thus equal to 1 and none of the model is favored prior to estimation. In this case, it suffices to compute the Bayes factor and to look for the highest marginal likelihood among the alternative models.

The comparison of marginal likelihoods in Bayesian econometrics is very interesting and powerful. The models do not need to be nested - estimated simultaneously as one model - and you only need to estimate the alternative models with the same data. For instance, the models can have more/less parameters, more/less shocks and different priors Koop et al. (2007). In Chapter 6, we evaluate alternative specifications with the Bayes factor. The marginal likelihoods are computed using two different approaches: the modified harmonic mean estimator and the Laplace approximation.

4.3 Its advantages

The advantage of Bayesian econometrics are often given relative to ML. Indeed, ML was the most popular approach to estimate large-scale DSGE models until recently. However, Bayesian models are so predominant in empirical literature nowadays that estimating a macroeconomic model with ML will invariably be criticized for not using Bayesian econometrics (Fernandez-Villaverde, 2010, p. 7). This revolution is grounded on several elements. Recall that identification problems are more severe for ML than the alternative classical approaches. Indeed, the presence of many variables in DSGE models implies that some of them contain only weak information about the parameters of interest. Therefore, the likelihood function of large-scale DSGE models is typically relatively flat with multiple local maxima and minima. This aspect of the likelihood makes the search for a maximum very difficult and unreliable (An and Schorfheide, 2007). In sum, the two main criticisms of ML are identification problems and computation difficulties during the maximization process. The Bayesian approach can address them.

First, Bayesian estimation deals with identification issues better than any classical approaches. Priors contain information that comes from other datasets and they are used to mitigate partial or weak identification of the parameters. Re-weighting the likelihood function by a prior density restricts the potential range on which the maximization takes place and thus removes the issue surrounding local maxima and minima (Canova, 2007). It allows Bayesian econometrics to address the dilemma of absurd parameter estimates, one major weakness of ML [2] (An and Schorfheide, 2007).

Second, with regard to the computation burden, (Fernandez-Villaverde, 2010) argues that, on top of being merely superior to ML, Bayesian econometrics had become easier to implement. ML maximizes the likelihood functions, while Bayesian integrates it. The later is much easier when the function to be dealt with is high dimensional, as it is the case for most solutions of DSGE models. This is especially true since simulation methods such as MCMC are available to approximate these integrals.

On the other hand, critics argue that priors bring subjectivity in the choice of the restricted range of the likelihood. The results can indeed suffer greatly from bad priors. However, it is easy to test for the sensitivity of the results on the selection of the priors. Furthermore, the fact that the exact same results can be obtained with Bayesian and classical inferences proves the subjective argument wrong (Qin, 1996). Moreover, An and Schorfheide (2007, p. 127) argue that "While, in principle, priors can be gleaned from personal introspection to reflect strongly held beliefs about the validity of economic theories, in practice most priors are chosen based on some observations."

In fact, the advantages of Bayesian econometrics are manifolds. Other than the success of prior information to deal with identification issues and MCMC simulation

2. The optimization of the likelihood function under ML sometimes peaks in areas that suggest values for the estimated parameters that are at odds with accepted economic knowledge.

to facilitate computations, (Qin, 1996) suggests that the early popularity for Bayesian models as substitute for classical methods, was also due to its small sample properties, its potential for full-information estimation and its learning-by-experience characteristics. Moreover, the outcome of Bayesian estimation is an interval estimate. Qin argues that it is more desirable than a point estimate when it comes to evaluate model predictions or public policies [3]. Bayesian econometrics also reserves no role for stationarity, unbiasedness and efficiency concepts (Lancaster, 2004).

Another particularly important distinction between Bayesian and classical methods relies in the assumptions about the parameters. The later treats parameters as fixed, unknown values. The former treats them as random variables and assigns them probability distributions. Hence, it explicitly takes into account parameters uncertainty, while classical approaches construct ex-post confidence intervals to evaluate uncertainty (Koop et al., 2007). This distinction gives to Bayesian inference its philosophical nature. For instance, while p-values give the probability of the data given the hypothesis, Bayesian results present the probability of the hypothesis given the data. Indeed, classical inference makes only pre-sample probability assertions like "a confidence interval contains the true parameter value with probability 95% before the data are observed". After the data are observed, the probability is 0 or 1. Bayesian inference aims to help with the need to characterize uncertainty about parameter values, given the sample that is observed (Sims, 2007). According to Koop et al. (2007), the controversy around the use of Bayesian models is rooted in the acceptance that the unknown (the parameters and the predictions) are random variables. After one accepts that, Bayesian inferences are non-controversial.

3. Bayesian point estimator of the coefficients can be derived, for instance, by taking the mean, mode or median values of the posterior distributions.

CHAPTER 5

DATA AND METHODOLOGY

5.1 Data

As in CMR, we estimate the model with 12 observable variables. We use quarterly observations covering the period 1991Q1 to 2014Q1. It is standard in empirical analysis with Canadian data to start in 1991, the year the Bank of Canada adopted an explicit inflation-control target. All data are taken from Statistics Canada's website.

The observable variables can be split into two categories. The first contains the macroeconomic variables standard in empirical analysis: GDP, consumption, investment, real wage, hours worked, interest rate, inflation, and relative price of investment goods. The second set of variables reflects the importance of financial markets in the model. It is composed of four financial variables: credit to non-financial firms, entrepreneurial networth, slope of the term structure, and credit spread (the premium) [1].

The time series for the variables GDP, consumption and investment are expenditure-based measures in chained-weighted (2007) dollars. Consumption is the sum of household final consumption expenditure of non-durable goods, semi-durable goods and services. Investment is the sum of business gross fixed capital formation (Non-residential structures, machinery and equipment, plus Intellectual property products) and household final consumption expenditure of durable goods. Therefore, we omit gross investment in residential structures as in Christensen et al. (2009) and Nishiyama (2011) [2] [3]. GDP corresponds to the sum of consumption, investment (as they are defined above) and government spending, where government spending is the sum of general governments final consumption expenditure and general governments gross fixed capital formation. [4]. The

1. See Appendix II for a detailed list of the data sources.
2. The model in Christensen et al. (2009) actually contains another observable variable specific for the business residential investment.
3. Dib et al. (2013) use all gross private investment, including residential investments.
4. We do not use the actual data on GDP. Recall that Eq. 21 of the equilibrium conditions (see Appendix III) states that GDP is the sum of consumption, investment and government spending. It omits imports and exports because the model is a closed-economy model. Since Canada is a small-open econ-

real wage corresponds to an index of the total compensation per hour worked in the business sector, divided by the GDP implicit price deflator (IPD). The hours worked variable corresponds to a measure of total actual hours worked in all industries from the Labour force survey estimates by the North American Industry Classification System, as in Christensen et al. (2009). The risk-free interest rate is the three-months bankers' acceptance rate. Inflation is the logarithmic first difference of the Core consumer price index (CPIX). To obtain the relative price of investment goods, we first construct a weighted sum (according to their share, in each period, of total investment as defined above) of the IPDs of business gross fixed capital formation (Non-residential structures, machinery and equipment) and of household final consumption expenditure of durable goods. We refer to this term as the IPD of investment. The relative price of investment corresponds to the logarithmic first difference of the ratio of this IPD of investment over the GDP IPD.

The credit variable is the business credit (excluding short-term) measure of the Bank of Canada, measured in dollar [5]. The entrepreneurial networth is the close value of the Toronto Stock Exchange (TSX) composite index of Standard and Poor's. These two variables are converted into real terms by dividing by the GDP IPD. The slope of the term structure is the difference between the 10-year Government of Canada benchmark bond yield and the risk-free interest rate as defined above. Finally, the credit spread is the difference between the business prime lending rate and the 10-year Government of Canada benchmark bond yield.

Monthly time series are converted into quarterly time series using the mean of every three-months period inside quarters. GDP, consumption, investment, hours, credit and networth are divided by the total Canadian population 15 years and over. The model assumes that all variables are stationary and it considers deviation from steady state values (or constant means). However, it is well known that macroeconomic time series are non-stationary. Therefore, GDP, consumption, investment, real wage, credit and

omy and that international trade represents a large share of Canadian output, using the actual data on GDP biases the results.

5. We use the Other Business Credit measure, which exclude the Short-Term Business Credit because it is less volatile and more coherent with the credit data used in CMR.

networth are transformed in the following way. We take the logarithmic first difference and then remove the sample mean. The variable hours is measured in log, net of its sample mean. Inflation, relative price of investment, risk-free interest rate, credit spread and premium are divided by four to obtained quarterly rates, and we remove their sample means.

It is often the case that there exist several possibilities for the dataset of each observable variable. One has to choose among them and this choice is crucial for the estimation of the unknowns of the model. Hence, we compare our data set (the actual data that are used for estimation) with the U.S. data set from CMR. Figure I.1 plots the two datasets used for the estimation of the Canadian and American models [6]. We plot only the data for the period that is common to the two datasets, 1991Q1 - 2010Q2. Ideally, for the sake of comparability between the results of the two countries, the behavior of the two datasets shall not be too different. For instance, if the path of one of our observables is significantly more or less volatile than the data in CMR, it would be reflected in the estimation results.

Overall, our dataset seems consistent with the dataset in CMR. Focusing on the Great Recession period, we note that, among other things, the drop in GDP is similar in the two countries, investment felt more in Canada than in the U.S., Canadian consumption was more stable and the stock market was hit more severely in Canada. All these observations can be reconcile with empirical facts. Figure I.2 depicts the observed quarter-to-quarter growth rate of real GDP, real consumption, real investment and the stock markets in the U.S. and in Canada. They correspond to raw data taken from the websites of Statistic Canada and the Federal Reserve of St-Louis. The definition of the variables are the same as in the beginning of this section. According to the graph, the drop in Canadian investment is indeed more important than in the United-States. It could be explained by the additional deep contraction of investments in the Canadian energy sector following the crisis. The shrink in consumption was indeed less severe in Canada and was in part compensated with debt. We also observe that the stock market was hit more severely in Canada. The S&P TSX composite index dwindled relatively more than the Dow Jones

6. These data are not the raw data but the transformed data as describe above.

Wilshire index (the data used in CMR) and the S&P 500 index during the last financial crisis.

5.2 Methodology

5.2.1 Calibrated parameters

Table I.I contains the complete list of parameters that are calibrated before the estimation and Tables I.III and I.IV contains the complete list of parameters that are estimated during estimation [7]. Note that it is not all those parameters that appear in Chapter 3 (Model) of this thesis. Recall that the estimated model is actually the complete list of equilibrium conditions in Appendix III). We include the calibration used by CMR to estimate the U.S. economy for the sake of comparison. Also, Table I.II presents steady state properties of the model [8].

The values for the depreciation rate δ and the elasticity of output with respect to capital in the intermediate production technology α are set to 0.025 and 0.36, respectively. These values are similar to the ones used in Bouakez and Rebei (2008), Dib et al. (2013) and Nishiyama (2011). The discount rate β is set to 0.9981. We explain below why this value is somewhat higher than what is being use in the literature. The mean government spending to GDP ratio η_g in our sample period is 24.62%. The value for the steady state (mean) markup of the workers λ_w is set to 1.05. Christiano et al. (2010) set λ_w to 1.05 for both the U.S. and the Euro Area, therefore we do not change it for Canada. The trend rate of investment specific technological change Υ is 0.42%. The calibration of this parameter is important to account for the decline in the price of investment goods relative to the price of output, found in the data. Indeed, Figure I.3 makes it clear that the ratio of the IPD of investment over the GDP IPD shows a downward trend. The quarterly average rate of decline is 0.42% (the same than in CMR).

7. We provide an exhaustive list of the parameters of the model in Appendix IV. The list includes the Dynare code names of all the parameters.

8. An exhaustive list of the parameters of the CMR model can be found in the Manual by Benjamin K. Johannsen provided by CMR along their Dynare code (it is available online). However, the list of values assigned to the calibrated parameters can only be found in the Dynare code itself.

The values for the tax rates on consumption τ^c, capital income τ^k and labor income τ^l are, respectively, 0.1246, 0.2242 and 0.3016. These values were provided by the Bank of Canada. Also, a parameter for the tax rate on bond τ^d is included in the model, but it is set to 0 in CMR.

The remaining economic parameters are given the same values than in CMR. The preference parameter for labor σ_L, the wage bill financing Ψ_L, the transfer received by entrepreneurs W^e and the resources used for state-verification Θ are set to 1, 0.7705, 0.5% and 0.5%, respectively. Note that the fraction of entrepreneurial networth transferred to households $1-\gamma$ is 1.5%. Finally, the parameters τ^o and ζ_t that appear in the equilibrium conditions Eq. 6,9,12,17 of Appendix III are both set to 1.

The parameters of the second group appear in the most general monetary policy rule (Eq. 20 of Appendix III), but they are actually set to 0. We presume CMR defined those parameters in order to be as general as possible for later use. Note that the other relevant parameters in the monetary policy are estimated.

The last group of calibrated parameters are related to the shocks in our model. First, the mean of the process of the shocks are all calibrated. The mean inflation target π^{target} is set to the steady state value for quarterly inflation π. In our sample, the average quarterly inflation rate is 0.5114% (annual value of 2.0057%). The mean quarterly growth rate of real per capita GDP in our sample is 0.28%. As in CMR, we use this value for the mean of the permanent technology shock μ_{z^*} and the average growth rate of steady state GDP. The mean of the process for the equity shock γ and the mean markup of intermediate producers λ_f are set to 0.985 and 1.2, respectively, as in CMR. The mean of the processes for the temporary technology shock ε, the investment good shock μ_Υ, the term structure shock η, the preference shock ζ_c and the marginal efficiency of investment shock ζ_I are all set to 1. Second, the autocorrelations of the equity shock ρ_γ is set to 0, as in CMR.

The autocorrelation of the inflation target shock $\rho_{\pi^{target}}$ and the standard deviation of its innovation $\sigma_{\pi^{target}}$ are set to 0 and 0.000001, respectively. In CMR, these two parameters are set in order to account for the downward trend of inflation in the first years of their sample period. By starting our sample in 1991, the year the Bank of Canada adopted an explicit inflation-control target, we do not observe such a trend. Therefore, we set the autocorrelation to zero and the standard deviation of the innovations to an arbitrary very small value. Note that there is no parameter invoked for the autocorrelation of the monetary policy shock. The autocorrelation and the standard deviation in the processes of the other shocks are estimated and discussed below.

Now, we discuss the calibration of the discount rate in the CMR model. Its value is implied by the following steady-state condition:

$$1+R^s = \frac{\pi^s \mu_{z^*}}{\beta},$$

where R^s and π^s denote steady-state values of the interest rate and the inflation rate. Given our calibration, the derived value for β is 0.9981, which is very close to its value in CMR.

Table I.II presents steady state properties of the model. In Panel A, we list the remaining parameters appearing in the equilibrium conditions that are assigned values before the estimation starts [9]. The mean values of consumption, investment and government spending, respectively c, i and g, and of the inflation rate and the risk-free interest rate, respectively π and R, are all set to their steady state value. Panel B allows us to investigate if the steady state properties of the model match with the data. We compare several steady-state ratios implied by the model with their sample averages. For instance, the implied ratios of consumption, investment and government spending, to GDP,are 0.47, 0.25 and 0.28, respectively [10]. These are close to what is found in our dataset.

5.2.2 Estimated parameters

We give different priors than in CMR on the parameters that are expected to have a value specific to the Canadian case. The priors are based on the existing literature that estimate Bayesian DSGE models with Canadian data. The exhaustive list of estimated

9. They are not calibrated per se, but are set to specific values implied by the model. The values are particularly sensitive to the calibration of the parameter η_g, the mean government spending to GDP ratio.

10. In the model ratios, GDP correspond to the sum of its components $c+\frac{i}{\mu_\Upsilon}+g$, where the value of μ_Υ is set to 1.

parameters is shown in Tables I.III and I.IV. The parameters that are bounded between 0 and 1 are assigned a beta distribution. The positive parameters have an inverted gamma distribution (type 2). Finally, a normal distribution is used for several parameters that can take a negative value. Below we discuss the priors that are different from CMR.

The parameters for the price and wage rigidities are given relatively loose priors around a mean value that imply prices and wages are re-optimized once every 2.5 quarters on average. These values are similar to the ones in Justiniano and Preston (2010a) and represent somewhat a middle ground of what is being used in the literature [11]. The prior given to the consumption habit formation parameter is very close to the ones in Christensen et al. (2009), Nishiyama (2011) and Justiniano and Preston (2010b) [12]. The prior on the monetary policy smoothing parameter are taken from Justiniano and Preston (2010a) and Dib et al. (2013). The priors on the monetary policy weight on inflation and output growth parameters are taken from Justiniano and Preston (2010a). We discuss the posterior estimates in Chapter 6.

5.2.3 Posterior modes computation

In practice, before launching the estimation of the model, one needs to compute the posterior mode of the parameters. It will then be used as starting values in the estimation step. The posterior modes can also substitute the posterior means to perform several statistical exercises with the estimated model. Recall that Bayesian estimation provides interval estimates for the parameters. However, to carry out Bayesian variance or historical decompositions, for instance, every estimated parameter of the model needs to be set to a specific value (i.e. a point estimate). Such value generally corresponds to a measure of the central tendency of the distribution (i.e. the interval estimate) of the parameter. The most popular choices are the arithmetic mean and the mode. A quick survey of the macroeconomic literature is sufficient to understand that there is no consensus on whether we should use the mean or the mode (or other measures of central tendency

11. Nishiyama (2011) gives looser priors around a smaller mean, while Dib et al. (2013) give tighter priors around a higher mean. Christensen et al. (2009) give looser priors for wage stickiness and tighter priors for price stickiness.

12. Justiniano and Preston (2010a) give a tighter prior around the same mean.

such as the median). Some recent academic papers only display the posterior modes in the tables of the posterior estimation results (e.g. CMR, Jermann and Quadrini (2012)), while others display only the posterior means (e.g. Iacoviello (2015), Del Negro et al. (2007)) or both (e.g. Smets and Wouters (2007)) [13].

The right point estimates depend in part on the shape of the posterior distribution of the parameters. For instance, if a posterior distribution is normally distributed, the three measures of central tendency (mean, mode, median) will be identical. However, the distributions of the parameters are usually asymmetric and unknown. In some cases, one might prefer the mode (e.g. with a binomial distribution), and in others one might prefer the mean. One way to visualize the difference between the two measures of central tendency is to compare graphically the priors and posteriors densities. Often, the two measures are quite different. With that in mind, we provide both the posterior modes and means in the results tables. We also plot the historical shocks decompositions when the estimated parameters take the values of their posterior modes and their posterior means, separately. Note that to accomplish the variance decomposition exercises, the estimated parameters take the values of their posterior modes only, as in CMR.

Dynare offers several optimizers for the computation of the mode. We use the Chris Sims optimizer (the default one in Dynare) whenever it is possible. This routine is a derivative-based optimizer that minimizes the negative of the likelihood. We obtain the modes of the baseline model, the specification with signals on the risk and technology shocks and the specification with flexible prices and wages with this optimizer. In the case of the specification with signals on the three technology shocks, the Chris Sims optimizer yields a posterior kernel optimization problem. The minus of the Hessian matrix at the computed mode is not positive definite, which delivers negative posterior variance for the estimated parameters. One solution is to try other optimizer to compute the modes. We use a Monte-Carlo based optimization routine (see Dynare Reference

13. Although it is less frequent, some articles display the posterior median of the parameters (e.g. Justiniano and Preston (2010a), Justiniano and Preston (2010b)).

Manual for details) [14] [15].

5.2.4 Estimation details

As it is the case with most Bayesian DSGE models, we follow the approach reviewed in An and Schorfheide (2007) to estimate our model. The model is solved using Dynare log-linear option. Dynare thus computes a log-linear approximation of the model. The likelihood of the linearized model is evaluated using a Kalman filter. This likelihood is combined with the prior information on the estimated parameters and the Metropolis-Hastings algorithm is used to derive an estimate of the posterior distribution and to evaluate the marginal likelihood of the model. Several diagnostics allow us to determine whether the results of the Bayesian estimation can be trusted. We investigate the multivariate and univariate convergence diagnostics of the Metropolis-Hastings iterations, their acceptance rate, the historical and smoothed variables and the plots of the prior and posterior distributions of the parameters.

Figure V.9 shows the multivariate convergence diagnostic produced by Dynare [16]. The graphs show the 80% interval and quantile range of the posterior likelihood function of the parameters. These functions are aggregated using the posterior kernel. The blue line shows the pooled draws from all MCMC sequences. The red lines show the draws of the individual sequences. The top graph (Interval) shows the deviations from the mean value. The middle (m2) and bottom (m3) graphs show, respectively, the squared and the cubed, absolute deviations from the mean. The desired output is to have the lines stabilizing and converging.

Our sample is composed of 3 chains of 100,000 Metropolis-Hastings iterations each to make sure the distribution of the Markov Chain asymptotically converges to the posterior distributions. We drops the first half of the sample, keeping the last 50,000 draws per chain. As we can see on the plots, rough convergence and stabilization actually occur

14. It is the optimizer number 6. It often solves the problem of non-positive definite Hessian matrix, but it is very long to execute.

15. We do not compute the modes for the specifications with the observable risk shock. Instead, we used the modes of the baseline model. The historical shocks decomposition is thus carried out at the posterior means only.

16. It is based on the Brooks and Gelman (1998, Section 3) convergence diagnostics.

way before the 50,000th draw. If that would not have been the case, we could simply try to run more iterations, until convergence and stabilization do occur.

Figures V.10 to V.13 depict the MCMC univariate diagnostics of a subset of the parameters [17]. This analysis allows to dig deeper into the previous convergence diagnostic. We can observe that most parameters also pass the test of convergence and stabilization with success, although convergence is disputable for some of them.

The scale parameter of the jumping distribution's covariance matrix of the algorithm must also be adjusted to secure satisfactory acceptance rates for every parallel chain. It is generally suggested to have an acceptance rate that is no less than 20% and no more than 40%, with an ideal range lying between one fourth and one third. We got acceptance rates of 0.25%, 0.26% and 0.31%, respectively for the three chains [18].

Figures V.14 and V.15 plot the historical and smoothed variables. The dotted line is the observed data and the red line is the estimate of the smoothed variable given all the observations. Ideally, the two lines match as closely as possible. The difference between them is measurement errors. Recall that we model measurement errors on the networth of entrepreneurs only. As we can observe on the plot, the estimated measurement error is relatively small. Indeed, the two lines closely match.

The priors and posteriors densities are plotted in Figures V.16 to V.19. The densities of the prior (grey) and the posterior (black) are plotted against a targeted range of the prior distribution. The green dotted line is the mode of the posterior. It is possible to note how tight are the priors and posteriors around their mean by looking at the shape of the two densities. Generally, it is desirable to have a tighter posterior distribution (relative to priors). Such an outcome would suggest that the data are informative about the distribution of the parameter in question. In contrast, when the prior and posterior are very similar, it either reflects that priors and data match very well or that, as it is generally the case, the parameter is weakly identified since the data do not provide much information

17. See Appendix IV for the name of the parameters used in the Dynare code.

18. In fact, we obtained the 100,000 Metropolis-Hasting iterations in two distinct simulations of 50,000 draws each. Dynare allows us to combined them easily. The acceptance rate of the 3 chains for the first 50,000 draws are 37%, 39% and 33%. Although these fit in the wider required interval, we slightly increased the scale parameter in the second set of simulations (the last 50,000 draws) to obtain better acceptance rates.

to update the priors (Canova, 2007). Based on this criteria, the plots suggest that the least well-identified parameters are the following: the autocorrelation and standard deviation of the markup shock, the steady state probability of default, the utilization cost, the investment-adjustment cost, the wage indexing weight on inflation target and the monetary policy weight on output growth [19]. However, most parameters seem well-identified overall.

19. These observations are confirmed in Chapter 6 by looking at the estimated standard deviation of the posterior estimates.

CHAPTER 6

RESULTS

We discuss the estimation results around three main elements: the estimated posteriors of the parameters, the variance decomposition of the observable variables, and the historical shock decomposition of GDP. It is standard to compare the results of the baseline model with alternative specifications of the model. It helps to understand the baseline results and to test how robust they are to slight changes in specific assumptions. For instance, in models with financial frictions and financial shocks, alternative specifications typically include one without the financial shocks, without the banking sector, or without the financial observable variables. CMR demonstrate that the inclusion of the four financial observable variables is crucial for the financial shocks to be the prime drivers of business cycle. Without them, the marginal efficiency of investment shock dominates. Here, we focus on a specific feature of the CMR model, the inclusion of signals on the risk shock. The results in CMR suggest that the anticipated component (the signals) of the risk shock explains most of the U.S. business cycle. We test this result with Canadian data and then consider alternative specifications with the news on other shocks. A vast literature exists that found the investment-specific (or neutral) technology shock to be the key driver of business cycle. Therefore, we estimate an alternative model with news on this shock. Actually, we put news on the three technology shocks, to increase as much as possible its chance to beat the others. It turns out that the results are very different. The three technology shocks become the dominant driving forces of macroeconomic fluctuations. With these results in mind, we consider a third specification with news on both the marginal efficiency of investment shock and the risk shock. This alternative model is not estimated in CMR. We find that it has the highest log-marginal likelihood statistic and that the results are almost identical to the results of the baseline model (i.e. the risk shock is the dominant factor behind Canadian business cycle).

In the second section, we explore how the results change when prices and wages are flexible in the model. In the third section, we add a measure for the risk shock in the dataset that is used to estimate the model. This way, the risk shock becomes an observable variable.

6.1 Posteriors

Posterior estimation results for the baseline model are displayed in Tables I.III and I.IV. Overall, the estimation results are consistent with the results in CMR and with the results in the literature using Canadian data. Also, the results suggest that there is a fair amount of information about most parameters in the data. Indeed, the standard deviation of the posterior distributions are generally less than half the standard deviation of the prior distributions. This remark is especially true for the price and wage stickiness parameters, the habit formation parameter, the monetary policy smoothing parameter, the wage indexing weight on persistent technology growth and the autocorrelation coefficients of the shocks. However, there is much less information in the data about the parameters for the steady state probability of default, the utilization cost, the investment adjustment cost, the monetary policy weight on inflation and on output growth and the wage indexing weight on inflation target.

The posterior means for the price and wage stickiness parameters are higher than their priors and suggest that prices are more sticky than wages, a result also found in Christensen et al. (2009) [1]. According to these estimates, prices and wages are re-optimized, respectively, every 9.1 and 3.8 quarters on average. The posterior modes imply that they are re-optimized every 5.9 and 4.2 quarters on average, respectively. Our estimate for price stickiness is close to the estimates in Christensen et al. (2009) and Justiniano and Preston (2010a). Our estimate for wage stickiness appears to be a middle ground among the relatively diverse empirical results found in the literature.

The estimate for the habit formation in consumption parameter is 0.81. It is similar to the literature cited above, as well as to the estimate for the U.S. in CMR. The estimates of the monetary policy parameters are close to the results in Justiniano and

1. The Maximum-likelihood estimates in Dib (2006) suggest otherwise. However, the standard deviation of the estimates are very high.

Preston (2010a). Compared to the results in CMR, monetary policy in Canada is approximately as smooth as in the U.S., it responds less strongly to deviation of inflation from its target, and it responds more strongly to deviation in output growth from its long-term trend. The estimated probability of default of entrepreneurs is 1.04% and the estimated mode is 0.95%, which is higher than in CMR. As in CMR, the estimated value for the monitoring cost parameter is below the 95% lower bound of the prior distribution. The estimated correlation among signals is around 0.44, which is a little higher than the estimate in CMR. This value suggest that the information about risk received by the agents is significantly correlated among consecutive periods.

Overall, the autocorrelation estimates for the shocks in the model show high degree of persistence. The most notable exception is the permanent technology shock, which is almost a white noise process. The markup, the marginal efficiency of investment and the preference shocks are also relatively less persistent. According to our results, the temporary technology, the term structure, the government spending and the risk shocks are particularly persistent. Among these, however, the estimates of the standard deviation of the innovations of the temporary technology and the term structure shocks suggest they are not volatile [2]. The high standard deviation of the innovations to monetary policy suggests this shock is highly volatile, as anticipated. Note that its autocorrelation is zero, therefore it needs a higher standard deviation of its innovations to secure significant weight on the business cycle. The risk shocks, both the unanticipated and the anticipated shocks, are very volatile, as in CMR. Among the three technology shocks, it is the marginal efficiency of investment shock that is the most volatile. Compared to the results in CMR, the price markup shock is more volatile, but less persistent. Most notably, the equity shock is a lot more volatile in our estimated model.

The results for the alternative specification are shown in Tables I.V and I.VI. The estimates of the specification with news on the marginal efficiency of investment shock and the risk shock are extremely similar to the ones of the baseline model. The estimates of the posterior means and modes of all the economic parameters are indeed very close

2. The standard deviation of a shock process directly inform us about how important the shock is for the estimated model. Other things being equal, the higher the standard deviation (i.e. the volatility) of a shock, the greater is its importance.

in both specifications. This is also true for the estimates of the shock processes, with the exception of the estimated autocorrelations of the markup shock and the marginal efficiency of investment shock. They are, respectively, smaller and higher than in the baseline model.

Turning to the specification with signals on the three technology shocks, the estimates of the posterior mean of most parameters differ from the two other specifications. For instance, the estimates of the rigidities in prices and wages are smaller. The posterior mean of the monitoring cost parameter is higher. The utilization cost and the investment adjustment cost parameters are estimated a lot more precisely. The estimates of the correlation among the signals of the marginal efficiency of investment shock is close to zero. The volatility of the three unanticipated technology shocks are very small, but the anticipated technology shocks are very volatile. We note that the estimated measurement error is a lot higher than in the two other specifications. In light of these results, it is clear that the estimated model is sensitive to where we incorporate the news. However, as we will see later in this chapter, formal statistical tests favor the baseline model against the specification with the news on the technology shocks.

6.1.1 Variance decomposition

The first indicator of the importance of the financial shocks for Canadian business cycle appears in Tables I.VII and I.VIII. It shows the unconditional and conditional (1, 4 and 8 periods horizon) variance decomposition of the observable variables forecast error. Unconditional variance decomposition corresponds to the contribution in percent of every exogenous shock in the variance of the variables at an infinite horizon (i.e. over the business cycle). It is distinguish from conditional variance decomposition, which is computed at specific periods.

Clearly, the risk shock is a dominant factor behind the business cycle variance in output, which is explained entirely through the anticipated component [3]. Its contribution at different horizons ranges from 38% up to almost 60% [4]. The risk shock explains more

3. The anticipated component of the risk shock also dominates the unanticipated component in CMR.
4. In CMR, the contribution at business cycle frequencies is around 63%.

than 74% of the long-term business cycle variance in investment and around 70% of the one-year forecast error. It contributes around 30% of the long-term business cycle variance in consumption, but the risk shock has a much lower contribution at smaller horizons. The impact of the risk shock on output is thus channeled mainly through its impact on investment, rather than on consumption.

The contributions of the technology shocks are small overall. As in CMR, the marginal efficiency of investment shock is the most important technology shock. Its contribution to the long-term business cycle variance of output is 16%. Its contribution to the forecast error at lower horizon is higher. Its one period ahead forecast error contribution is about 13% lower than the risk shock, at 25%. It is also the second driving force of investment. Together, the risk shock and the marginal efficiency of investment shock explain around 95% of the forecast error in investment at short and long horizons. The temporary technology shock is a significant source of the variability in consumption, inflation and hours only. Unsurprisingly, the preference shock, the permanent technology shock and the price markup shock are, respectively, the key contributor to the long-term business cycle variance in consumption, wage and inflation. The price markup shock is also the second driving force behind variations in the interest rate at long horizons, while the monetary policy shock is responsible for more than 67% of the one-period forecast error variance. The risk shock is by far the main driving force of the long-term business cycle variance in hours and interest rate.

The importance of the risk shock is relatively high for the financial variables. The risk shock explains more than 80% of the business cycle variances of the premium and networth at any horizon. It is also the main force behind the long-term business cycle variance of the term spread and credit, although it explains a smaller share of their short term forecast error variances. The monetary policy shock and the equity shock are, respectively, the driving force of the short term variability in the term spread and credit. These results confirm that the impact of the financial shocks on investment and output is channeled through the financial markets.

Tables I.IX and I.X depict the variance decomposition of the observable variables based on the model with signals on technology shocks. The results are very different from those of the baseline model. The technology shocks are the main factors behind fluctuations in all variables (except the relative price of investment) at all horizon. The contributions of the other shocks are all reduced to almost nothing. The risk shock explains only a tiny part of the forecast error of all the observable variables. In sum, one should not interpret the results of the baseline model as a robust proof beyond any doubt of the preponderance of the financial shock in Canadian business cycle. This result prompted us to consider a third specification, not explored by CMR, where news are put on both one technology and one financial shocks.

Tables I.XI and I.XII show the variance decomposition of the observable variables for the model with news on the marginal efficiency of investment and the risk shocks. Recall that this specification is meant to give both the risk and the technology shocks a fair chance to end up driving the main macroeconomic variables. If the risk shock remains the main source of economic and financial fluctuations in this specification, the empirical evidence from the results of the baseline model will be strengthened. In fact, it is indeed the case. Overall, the results are remarkably similar to those of the baseline model. First, the risk shock is a prime factor of the variance decomposition of most observable variables. Second, the anticipated components of the two shocks with news dominate the unanticipated components. Third, the contribution of the marginal efficiency of investment shock on the variance decomposition of the 12 variables is very close to its contribution in the baseline model. In other words, its total (anticipated and unanticipated) contribution is not significantly enhanced despite the incorporation of an anticipated component. It is the anticipated component of the risk shock that dominates any other shocks. Fourth, the business cycle variance of the four financial variables are almost entirely monopolized by the risk shock, as it is the case in the baseline model. In other words, the evidence from the baseline model that put forward the risk shock as the main driver of Canadian business cycle is robust to the addition of signals on its most likely contender, namely the marginal efficiency of investment shock.

6.1.2 Historical decomposition

The second experiment to evaluate the importance of the financial shocks in Canadian business cycle is the historical shock decomposition of output. Rather than measuring the deviations from steady-state that cannot be explained by the model (i.e. cannot be forecast), historical decomposition explains all deviations from steady-state. This exercise is useful to understand how the estimated model interprets specific fluctuations of the data during a given period, for instance during the last recession. Figures I.4 to I.9 depict the historical decomposition of GDP over the business cycle for the different specifications. In every period, each column shows the deviation from steady-state due to one specific shock. Some shocks push the data up, others down. In any period, the sum of all the columns adds up to the actual value of the data. The line on the graph thus represents the observed deviation of the data. Note that we grouped the shocks in 5 categories. The financial shock includes the risk and equity shocks. The technology shock includes the temporary and permanent technology shocks and the marginal efficiency of investment shock. The demand shock includes the preference and the government spending shocks. The markup shock includes the price markup shock and the relative price of investment shock. We include the inflation target shock in the monetary policy shock [5].

Figures I.4 and I.5 plot the historical decomposition of output at the posterior means and modes of the parameters. The graphics look very similar. The financial shocks are found again to be a significant driver of fluctuations in output. Their contributions to the deviation from steady-state are generally cyclical, but negative contributions are persistent. This result is consistent with the very high estimated posterior mean for the autocorrelation of the risk shock. Again, the technology shocks are behind the financial shocks as dominant factors behind movements in output. It is worth noting that, as expected, monetary policy shock seems countercyclical. For instance, it contributed positively to the deviation of output during the two last recession.

Now we focus on the period around the Great Recession. The yearly sum of the

5. The term premium shock is left out because it is insignificant.

contribution of each shock to the quarter-on-quarter growth rate of output between 2007 and 2010 is presented in Table I.XIII. Recall that the data are demeaned. The historical shock decomposition at the posterior means and modes of the parameters are given. The results are very similar in both cases, and we discuss mainly the decomposition at parameters mean.

The output growth in 2008 is -1.81% [6]. The financial shocks contributed -2.95% to the deviation from steady-state output. The risk shock alone contributed -4.2%. This result accords well with the recent events in the financial markets. Indeed, the recent financial crisis and the unprecedented decline in the stock market during that time that tightened credit significantly and increased economic and entrepreneurial uncertainty to record heights.

The demand and markup shocks also contributed negatively to output growth in 2008. In particular, the preference shock contributed -1.27% in 2008, which reflects the observed shift in household preferences after the crisis hit from consumption to precautionary savings. Monetary policy and technology shocks contributed positively [7]. In 2009, the financial shocks hit output even more strongly, with the equity shock also contributing negatively. Consistent with the expansionary fiscal policy that year, the government spending shock pushed up output growth by 1.41%. Monetary policy also contributes 1.42% in 2009. Based on these results, the recession in Canada was mainly caused by financial factors and Canadian policy makers succeeded in preventing a more pronounced recession through fiscal and monetary stimulus.

The historical decomposition of output at parameters mean and mode when news are put on technology shocks is presented in Figures I.6 and I.7. It is consistent with the previous results of the variance decomposition. The financial shocks are relegated behind the technology shocks as main drivers of business cycles. In this case, the last two Canadian recessions were caused by the technology shocks. The estimated contribution of the monetary policy shock is highly counter-cyclical over the entire sample. Table I.XIV dig deeper on the main drivers of the recent recession in Canada. According to this

6. Recall that the data are not raw data. See Chapter 5 for the details of the transformation of the data.
7. One possible reason why technology shocks push output growth up is to counter the huge negative contribution of financial shocks.

specification, the main cause of the decline in output in 2008 is the permanent technology shock. In 2009, it is the marginal efficiency of investment shock. The yearly contribution of the risk shock is significantly reduced to less than 1% over this period. Government spending and monetary policy shocks contributed positively to output growth in 2009.

As with the variance decomposition exercise, we obtain dramatically different results from the two previous specifications. This can lead to the belief that the evidence from the baseline model depends crucially on the incorporation of an anticipated component to the risk shock. Again, we consider the historical decomposition of a model with news on marginal efficiency of investment and risk. As we can see in Figures I.8 and I.9, the financial shocks are the main drivers of business cycles in that specification. Overall, the important features outlined for the baseline model hold here. This is specially true when we examine what were the drivers of the recent recession in Canada (Table I.XV).

In sum, we demonstrated that the results in the baseline specification where news are put on the risk shock ought to be taken seriously. While the results favor the technology shocks in one specification, when the news are put on both the risk and the technology shocks, the dominance of the risk shock over the investment-specific technology shock reappears. These observations have been investigated through Bayesian estimation of the parameters, conditional and unconditional variance (second moment) decomposition and historical shock (first moment) decomposition. In the next subsection, we conduct a formal statistical test to discriminate among specifications.

6.1.3 Which model to believe?

Recall that Bayesian econometrics allows us to compare the marginal likelihood of different models, and thus to examine which one is favored by the data. Table I.XVI depicts the log-marginal likelihood of several alternative specifications [8]. We present the Laplace approximation and the Modified harmonic mean. The Bayes factor, discussed in Chapter 4, corresponds to the difference of the log of the marginal likelihood of two

8. Two important notes with regard to this table are: the Laplace approximation estimates are based on posterior modes that are computed using different options in Dynare, since the default option does not work out for all, and the Modified harmonic mean estimates are based on different numbers of MCMC iterations.

alternative specifications. Generally, a Bayes factor greater than 10 provides very strong evidence in favor of the model with the highest likelihood. Based on the marginal likelihood statistics, the model with news on the risk shock fares better than the model with news on technology. Indeed, the marginal likelihood of the model is reduced by about 33 for the later case [9]. Furthermore, the favored model is actually the one with news on both one technology and one financial shocks. Its marginal likelihood is about 4 and 8 points above the baseline model.

In light of the results so far, several conclusions emerge. First, the results in CMR can be replicated with Canadian data. Indeed, the financial shocks, and most notably the risk shock, are the prime drivers of business cycles in the baseline model, far ahead of any technology shocks. This conclusion is supported by both variance decomposition (second moment) and historical shock decomposition (first moment) of the observable variables. However, the results rely heavily on a specific feature of the CMR model. It is the modelisation of an anticipated component on the risk shock. Indeed, when news are put on technology shocks, the variations of macroeconomic variables in the short run and the long run are no longer mainly driven by the risk shock. However, the Bayes factor offers a strong argument in favor of the baseline model. Of all the specifications that put the news on only one shock (which is desirable for the sake of parameters parsimony), it is the one that put the news on the risk shock that is most favored by the data. This is true even if we put news on the three technology shocks, as in CMR. Second, without consideration for parameters parsimony, it is the specification with news on both the risk and the investment-specific technology shocks that is awarded the highest log-marginal likelihood. The results for this specification are very close to the results obtained in the baseline model. Thus, the most likely model is one such that the dominance of the risk shock as a source of economic and financial fluctuations is confirmed [10].

9. Recall that we experienced problem to compute the modes of the specification with the news on the technology shocks using the option 4 of Dynare. We report the value of the Laplace approximation obtained in this case anyway (its value when the modes are computed using the option 6 of Dynare is much lower). The value of the Modified harmonic mean reported is obtained after the estimation of the model with the modes computed using the option 6.

10. Furthermore, in the case of the specifications with news on the risk shock and one of the other technology shocks (temporary and permanent technology), the results of the variance and historical decompositions (not presented) also confirm the risk shock as the main factor behind the volatility of output.

Based on the existing literature reviewed in Chapter 2, the two most likely contenders to the risk shock as the main driver of business cycle are the marginal efficiency of investment shock and the equity shock. To understand why the risk shock is favored, we look at the dynamic responses. Figure V.5 shows the impulse response functions of the observable variables in the model to a negative unanticipated innovation to the marginal efficiency of investment shock, holding everything else constant. At the moment of the shock, we can observe that output, investment and consumption all go down, as expected. However, the value of the stock market, represented by the networth of entrepreneurs, is initially moving up. These results imply that the value of the stock market is countercyclical, which is at odd with what is found in the actual data. Turning to the financial shock, Figure V.7 plot the dynamic response to a positive equity shock. We can note that GDP, investment and consumption increase upon impact, but credit goes down. Hence, the equity shock incorrectly implies that credit is countercyclical.

Figure V.1 displays the dynamic responses to a negative unanticipated risk shock. In this case, GDP, investment, consumption, networth and credit all go down, as in the actual data [11]. Since the estimation forces the model to explain all observable variables, the risk shock, which correctly implies that the values of the stock market and credit are cyclical, is favored when those two variables are incorporated into the dataset. To confirm that networth and credit are cyclical in our dataset, we compute the correlations between output and networth and between output and credit in our dataset. They are indeed positive. Their values are, respectively, 0.42 and 0.22. Also, we plot these data in Figure I.10 for Canada and the United-States [12]. The degree of cyclicality of networth and credit is very similar in the U.S. and in Canada.

One last concern that is worth addressing is the following. As explained by CMR, one could imagine that the risk shock is accompanied with countercyclical consumption, while consumption is in fact cyclical in the actual data. For instance, an increase in risk could be tough to divert resources away from investment toward consumption and leisure. One way this could happen is trough a fall in the real interest rate, which would

11. This observation holds in the case of an anticipated risk shock.
12. The data are not the raw data but the transformed data used in the estimation of our model and the CMR model

stimulate consumption and partly offset the fall in output caused by the decrease in investment. The dynamic responses in Figure V.2 indeed show that the real interest rate goes down following a negative risk shock. However, in our model, nominal interest rate is set by the Central Bank and the price level is subject to nominal rigidity. CMR shows that the monetary policy rule does not respond aggressively enough to a risk shock - i.e. does not cut nominal interest rate enough - for consumption to actually rise. This explains why consumption is cyclical in our estimated model.

6.2 Are price and wage rigidities important?

We now turn to the estimation of a specification without nominal price and wage rigidities. The estimated model is exactly the same, except that the parameters governing the stickiness of prices (ξ_p) and wages (ξ_p) are set to 0. Since these two parameters are estimated in the baseline specification, we estimate two parameters that are calibrated in the baseline specification, namely the autocorrelation and the standard deviation of the inflation target shock.

First, the model without nominal price and wage rigidities has a much lower marginal likelihood (see Table I.XVI). This suggests that the inclusion of these rigidities greatly improve the fit of the model to the data. We briefly discuss the estimates of the posterior means (not presented) for this model. The posterior mean of the real rigidity parameters have significantly increased. This is especially true for the investment adjustment cost parameter, but also for the habit formation, the utilization cost [13] and the monitoring cost parameters. The estimates of the means of the three indexing parameters, l, l_w, and l_μ, are significantly reduced. Also, the monetary policy responds relatively more strongly to deviation in output growth, rather than deviation in inflation from its target, and it is significantly more persistent. These two last remark could be explained by the fact that prices and wages are fully flexible, making the indexations and the response to deviation in inflation, irrelevant. The estimated autocorrelation and standard deviation parameters of the persistent technology shock, the marginal efficiency of investment shock and the

13. The standard error of the posterior mean of the utilization cost parameter is very high.

preference shock are a lot higher. The estimates of the standard deviation of the temporary technology shock and the government spending shock have also increased. Flexible prices and wages therefore mechanically increases the importance of the technology and the demand shocks.

The unconditional variance decomposition makes it clear that the nominal rigidities are crucial for the financial shocks to outstrip technology shocks as the main driver of business cycles (Table I.XVII). This is consistent with the findings in Del Negro et al. (2010), which demonstrate that nominal wage and price rigidities are essential for the financial shock to have significant impact on macroeconomic outcomes. The overall relative contribution of financial shocks to output fluctuation has decreased to less than 2%. Its most important impact is still observed during the recent financial crisis. However, the share of the financial shocks in the fluctuation of output between 2006 and 2010 has significantly diminish. The importance of the demand and technology shocks for business cycles are enhanced, especially around the Great Recession period. The preference shock and the permanent technology shocks are the main factors explaining variations in most observable variables. An important driver of output is the monetary policy shock. This result may seem contradictory, since nominal price or wage rigidities are typically considered essential for monetary policy to be effective [14]. However, one shall not forget the third nominal rigidity present in the model, the financial frictions, as well as the other nominal frictions on the indexation of the inflation target and the persistent technology shock [15]. Therefore, this result suggests that the presence of frictions in the financial market, even when prices and wages are fully flexible, is sufficient for monetary policy to have a significant impact on real output over the business cycle.

In sum, the estimated parameters are not robust to the absence of sticky prices and wages. Furthermore, these nominal rigidities are necessary for the historical shock decomposition to favor the financial shocks over the demand and the technology shocks.

14. In Christiano et al. (2005), wage rigidity is sufficient to capture the dynamic responses to a monetary policy shock. Using Bayesian models comparison, Smets and Wouters (2007) shows that wage and price nominal rigidities are equally important.

15. The model is also characterized by several sources of real rigidities. The presence of real rigidities typically reduce the degree of estimated nominal rigidities to a more reasonable level.

Consequently, and based on the higher marginal likelihood of the baseline specification, sticky prices and wages are highly important to model the Canadian economy with financial factors.

6.3 The risk shock as an observable variable

In the model, the risk shock σ_t is an endogenous variable. Recall that the exogenous part of the process for the risk shock is composed of an unanticipated and an anticipated components, while all the other shocks only have the standard unanticipated component. As explained in Chapter 3, 12 observable variables are mapped to several endogenous variables to estimate the model. An interesting exercise is to map the risk shock to an observable variable. This is made feasible by the availability of actual data that correspond closely to the definition of the risk shock. What we are looking for is a measure of uncertainty (i.e. second moment) in the returns of entrepreneurs. Recall that entrepreneurs take part in both the effective capital market and the loan market. Therefore, the entrepreneurs can be considered as intermediate firms as well as banks. Having that in mind, we use two different proxies for the risk shock [16].

The first is the VIXC index. The second is the Economic Policy Uncertainty (EPU) index. The VIXC index is a measure of the volatility present in Canadian stock markets. The VIXC index and the risk shock are expected to be negatively correlated. A period characterized with a negative risk shock (i.e. an important standard deviation in the returns of entrepreneurs) is accompanied with a relatively high volatility in the stock market, and vice-versa. The EPU index is based on the frequency at which several key words appear in the articles of Canadian newspapers. It is constructed by a group of researchers from various Universities in the United-States. Specifically, the index tracks the amount of articles containing key words that relate to uncertainty such as uncertain,

16. It is important to distinguish between micro (cross-sectional) and macro (aggregate) uncertainty. For instance, Bloom et al. (2012) model both types of uncertainty in the production technology. Although the risk shock in CMR resembles more a micro uncertainty, we assume our proxy for macro uncertainty captures the micro uncertainty. This assumption can actually be reconcile with empirical evidence. Indeed, Bloom (2009) argues that (see p. 628) a number of cross-sectional measures of uncertainty are highly correlated with the volatility in the stock market. Micro uncertainty has also already been proxied by stock market volatility in Bloom et al. (2007), for instance.

uncertainty, economy, policy, tax, spending, regulation, central bank, budget, deficit, and so on. The higher is the frequency of appearance of such key words in the news, the higher is the uncertainty index. The Canadian newspapers that are used to construct the index are: The Gazette, The Vancouver Sun, The Toronto Star, The Ottawa Citizen, and The Globe and Mail [17].

Figure I.11 plots the data of the two proxies for the risk shock, as well as the smoothed risk shock simulated from the baseline model. The two indexes are converted into quarterly data, leaded (i.e. we take the value at $t+1$ for the period t) and smoothed. We take the two periods moving average of the VIXC index and the four periods moving average of the EPU index. We also inverted the sign of the growth rate in the observed measure, to obtain a positive correlation with the model's variable to facilitate comparison. Overall, the fluctuations in the three series are relatively similar. The correlations between the simulated risk shock and, respectively, the VICX index and the EPU index, are around 35%. Although they are far from perfect, this suggests that our proxies can be interpreted as the model's uncertainty.

We still use 12 observable variables to estimate the model. However, we drop the relative price of investment observable variable and add the risk observable variable instead. The equation that map the new observable variable with the data is:

$$risk_t^{obs} = \frac{\sigma_t}{\sigma_{t-1}} \tag{6.1}$$

The time-series of the observed measures are transformed accordingly. We take the logarithmic first-difference and subtract the sample mean.

6.3.1 Posteriors

The estimation results of the model with the dataset containing the VIXC and EPU indexes are shown in Tables I.XVIII and I.XIX. Overall, the results are similar and very close to the results obtained in the baseline model. The estimates of the monetary policy parameters and the rigidity parameters are very similar to the baseline results. Excep-

17. Details can be found on the official website: http://www.policyuncertainty.com/index.html.

tions includes the investment adjustment cost and the utilization cost. Their posterior means change significantly across specifications and their estimates are imprecise. This provides evidence on the importance of the relative price of investment as an observable variable to correctly identify those two parameters.

The most interesting estimates are the ones relating to the financial factors. If we believe the VIXC and EPU indexes are good proxies for the risk shock, the new observable variable should help to obtain better estimates for those parameters. For instance, the estimated probability of default is reduced by more than half in both specification, relative to the baseline model. According to the model with the EPU index, the standard deviation of the anticipated risk shock is more than doubled and the estimated correlation among signals is almost unchanged. In the case of the model with the VIXC index, the standard deviation of the anticipated risk shock is similarly augmented, but the estimated correlation among signals is reduced by almost half compared to the baseline model, i.e. the risk shock is more volatile but less persistent. These observations seem to indicate that the baseline model overestimate the importance of the risk shock. Overall, the parameters regarding the stochastic processes of the others shocks are relatively similar with the results of the baseline model. Finally, it is worth noting that the estimates of the measurement error on networth is approximately doubled. As a consequence, it is important to interpret the results in this section with precaution.

6.3.2 Variance and historical decompositions

We briefly touch on the variance decomposition, before moving to a more thorough analysis of the historical decomposition exercises. The variance decomposition exercises when the risk shock is observable are displayed in Tables I.XXII, I.XXIII, **??**and **??**. Overall, the results share most of the important features of the baseline case. First, the risk shock is the major factor of the business cycle variance of GDP, investment and the financial variables, entirely through its anticipated component. In all three cases, the long-term variance of wage is driven by the permanent technology shock. The preference, temporary technology and markup shocks all contribute significantly to the business cycle variance of consumption.

The historical decomposition of GDP in the specification with the VIXC index, although clearly not perfect, is actually very similar to the baseline case (Figure I.12). In both cases, the financial shocks contribute positively to output growth for several years before the recent recession and then negatively for most of the post-2008 period. It is interesting to note that the financial shocks, although they are key drivers of fluctuations in output, are sharing this role with the technology shocks. Indeed, the main difference with the baseline results is the significant contributions of the technology shocks. They are major factors of the drop in output in 2008 and 2009, while in the baseline model, they contribute either positively or marginally during that period. This result seems to confirm that the baseline model overestimate the dominance of the financial shocks.

Similarly to the results of the baseline model, the markup shock contributed negatively to the slow growth in Canada since the last financial crisis in the United-States. Demand shocks push output growth up for several quarters after 2009q1, before fiscal contraction push it down for most of the rest of the sample period. Its contribution before 2009 is also very similar across the two specifications. Monetary policy seems effective at boosting output growth in the wake of the recession. It contributed negatively before the crisis.

Table I.XXIV displays the historical shock decomposition around the Great Recession. Most contributions are very similar to the baseline model except for the marginal efficiency of investment and the financial shocks. We observe that the risk shock contributed -2.77% and -3.69% to the output growth in 2008 and 2009, respectively, which is lower than its contribution in the baseline case. This suggest that the baseline model slightly overestimate the role of the risk shock during the previous recession in Canada. The contribution of the equity shock is higher and positive during those two years, which reduces the overall contribution of the financial shocks in Figure I.12. The marginal efficiency of investment is the most important technology shock. It contributes -2.21% and -1.61% in 2008 and 2009, respectively.

Figure I.13 (see also Table I.XXV) present the historical shock decomposition of output when we use the EPU index. In the portion of the graph before 2008, we can see that the importance of the risk shock is overestimated. Its contribution is also generally in the opposite direction, compared to the baseline case. In response, the importance of the technology shocks are also overestimated during that period. This result can be explained by the relatively high volatility of the index compared to the simulated risk shock before 2008. However, after 2008, the graph looks similar to the baseline case. In particular, at the beginning of 2009, the only positive contribution to output growth come from the monetary shock. The financial, technology, markup and demand shocks all contribute negatively. At the very end of the sample, the financial shocks are pushing down output growth again due to a surge in uncertainty, as observed in Figure I.4.

6.3.3 Concluding remarks

To assess the validity of our proxies, we estimate three first-order autoregressive (AR) models, one for the two proxies (observable risk shocks) and one for the endogenous risk shock obtained from the baseline model (unobservable risk shock). Then, we use a simple statistical test on the coefficients of the three models to test their equality. If our proxies are valid, we would expect those coefficient to be statistically non-different across models.

The estimated coefficients of the first-order lag are 0.914, 0.961 and 0.841 for the observable risk shock, the unobservable risk shock based on the EPU index and unobservable risk shock based on the VIXC index, respectively. The mean squared error obtained from the two AR models of the proxies are approximately ten times higher. Finally, linear hypothesis tests fail to confirm that the parameters of the observable risk shocks are statistically identical to ones in the case of the unobservable risk shock. One reason is that the time-series of the proxies are significantly more volatile than the measures of the risk shock simulated endogenously by the model.

In sum, although the results are far from perfect, it seems a promising avenue to include an actual measure for the risk shock into the dataset used to estimate the model. We are indeed able to replicate several important results obtained with the baseline model when we enrich the dataset with a proxy for the risk shock. However, more work has to be done to find a measure that produces better results overall.

CHAPTER 7

CONCLUSION

The main objective of this thesis is to find what are the drivers of Canadian business cycle. More specifically, are the financial shocks important to explain the dynamics of the Canadian economy. We answer these questions by estimating the model in Christiano et al. (2014) with Canadian data. We quantify the relative importance of the financial shocks through variance (second moment) decomposition and historical shock (first moment) decomposition of the macroeconomic and financial variables. Our results suggest that the financial shocks, in particular the risk shock, are the main driver of economic fluctuation in Canada, ahead of the technology shocks. The risk shock explains up to 60% of the volatility of output and up to 74% of volatility of investment. The risk shock is also the main cause of the last recession in 2008-2009. The impact of the risk shock on output fluctuations occurs through its impact on investment, mainly. In fact, a negative risk shock increases the credit spread (the premium). The cost of borrowing is higher, the amount of credit available to entrepreneurs is highly restricted, the networth (the value of the stock market) initially plummets and investment, consumption and output all drop. In sum, the risk shock correctly implies that both credit and the value of stock market are cyclical, whereas the equity shock and the investment specific technology shock imply incorrect co-movements for one of them. Hence, when the dataset includes those two variables, the risk shock is highly favored by the data.

One important element in the CMR model is the incorporation of an anticipated (news) shock. The baseline model put the news on the risk shock. However, we find that the results are sensitive to which shock is awarded an anticipated component. We consider two alternative models: one with the news on the three technology shocks and one with the news on one technology shock and one financial shock. In the former case, the results are dramatically changed. The main drivers of the Canadian economy become the technology shocks. In the later case, the results are very similar to the results in the baseline model. That begs the question of why specification to believe? Bayesian econometrics offers a powerful statistical test to discriminate among alternative models. We find that the specification with the news on the technology shocks is the least favored by the data. Furthermore, the most favored is the model with news on both the risk and the technology shocks and this specification support the baseline results.

Finally, we endogenize the risk shock by incorporating a proxy into the dataset. We estimate the model with the updated dataset. In other words, instead of simulating the risk shock from the solution of the estimated model, we use an actual measure of financial uncertainty. We consider two proxies, the VIXC index and the EPU index. If we believe the VIXC and EPU indexes are good proxies for the risk shock, the new observable variable should help to identify better estimates for the parameters of the model. The results suggest that the baseline model slightly overestimate the importance of the risk shock for the dynamics of the Canadian economy. Overall, the results are nonetheless similar to the baseline case and it seems a promising avenue to include an actual measure for the risk shock into the dataset used to estimate the model. However, more work has to be done to find a proxy that delivers better outcomes.

Overall, this thesis contributes to the flourishing literature that investigate the role of financial factors for the business cycles with complex Bayesian DSGE models. We provide an extensive review of the related literature in order to emphasize the potential of Bayesian DSGE models characterized with financial frictions and financial shocks to study the dynamics of an economy. Our objective is also to shed light on the very few empirical works that focus on the case of Canada. So far, the dynamics of the Canadian economy have scarcely been investigated using the tools of Bayesian DSGE models with (or even without) financial factors. Yet, the recession that followed the recent financial crisis was very painful in Canada. The non-energy export sector was severely hit and the stock market collapsed. The unemployment rate (in American standard) rose by 2.6 percentage points and the rate of job destruction was greater than in the two previous recessions. These events evoke the importance of improving our knowledge on the link between the financial markets and the real economy in Canada. Canada is a very interesting case to study more thoroughly because it integrates several specific features not present in the United-States, for example. This leads us to the many ways we can improve our results by considering these particularities. First, the model should be extended to include a foreign sector. Trade represents a significant share of the Canadian economy. Therefore, shocks happening in the foreign markets have important impact on domestic output. Furthermore, the model can be extended to include an energy sector. Recent events convey that the Canadian economy is vulnerable to changes in the international price of commodities. Finally, Christensen et al. (2009) show that the housing sector is an important factor behind Canadian business cycles. In sum, we show that financial shocks cannot be left behind when it comes to study the dynamics of the Canadian economy, but several features specific to the case of Canada have to be considered in future works.

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Appendix I

List of the figures and tables

Figure I.1: **Comparison of the datasets (Canada and United-States) used for the estimation of the model** The U.S. dataset is taken from CMR

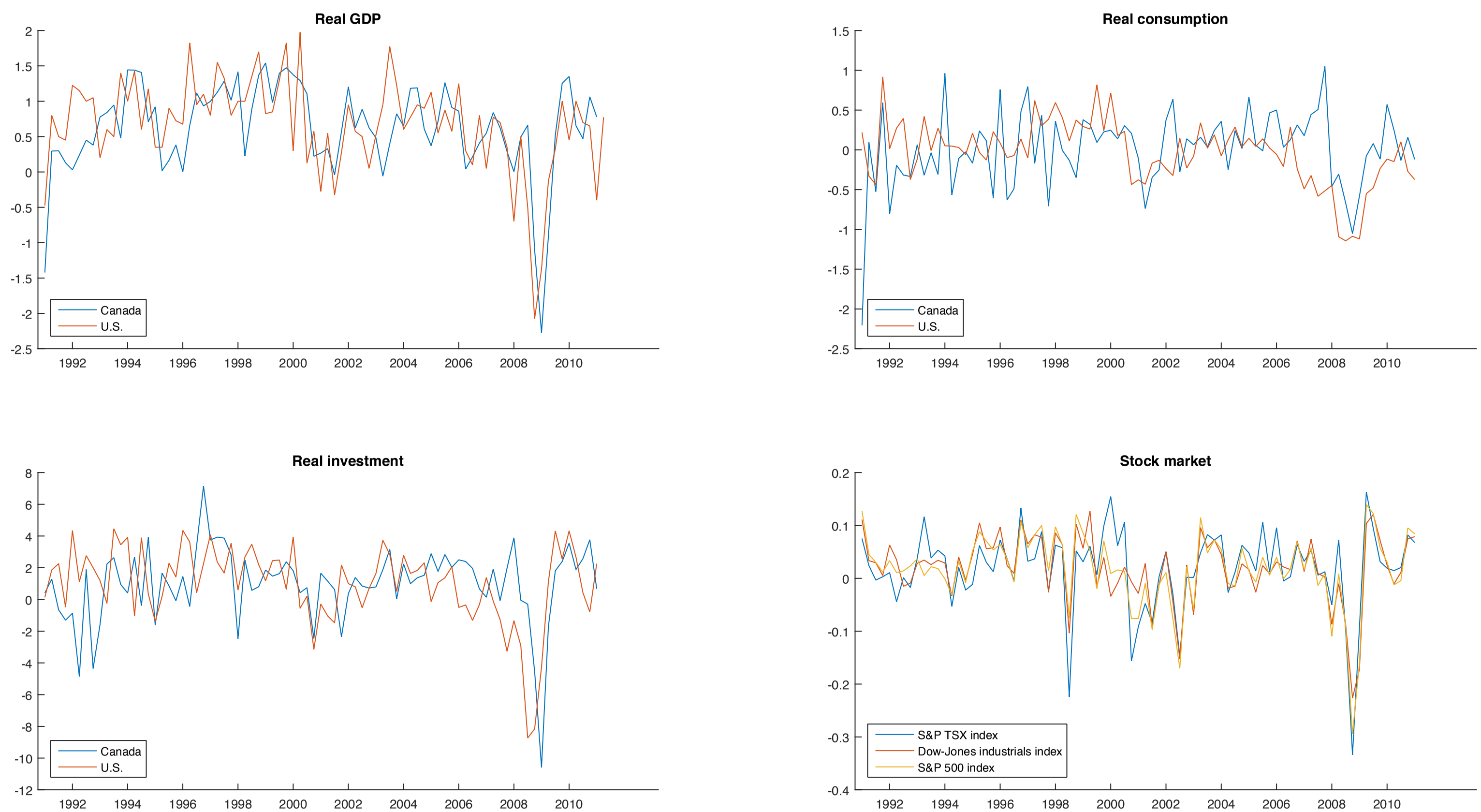

Figure I.2: **Comparison of the macroeconomic trends in Canada and the U.S.** Real, log first-difference data of consumption, investment, GDP and stock market indexes

Figure I.3: **Evolution of the relative price of investment** The mean quarter-to-quarter change is the same in Canada and in the U.S.

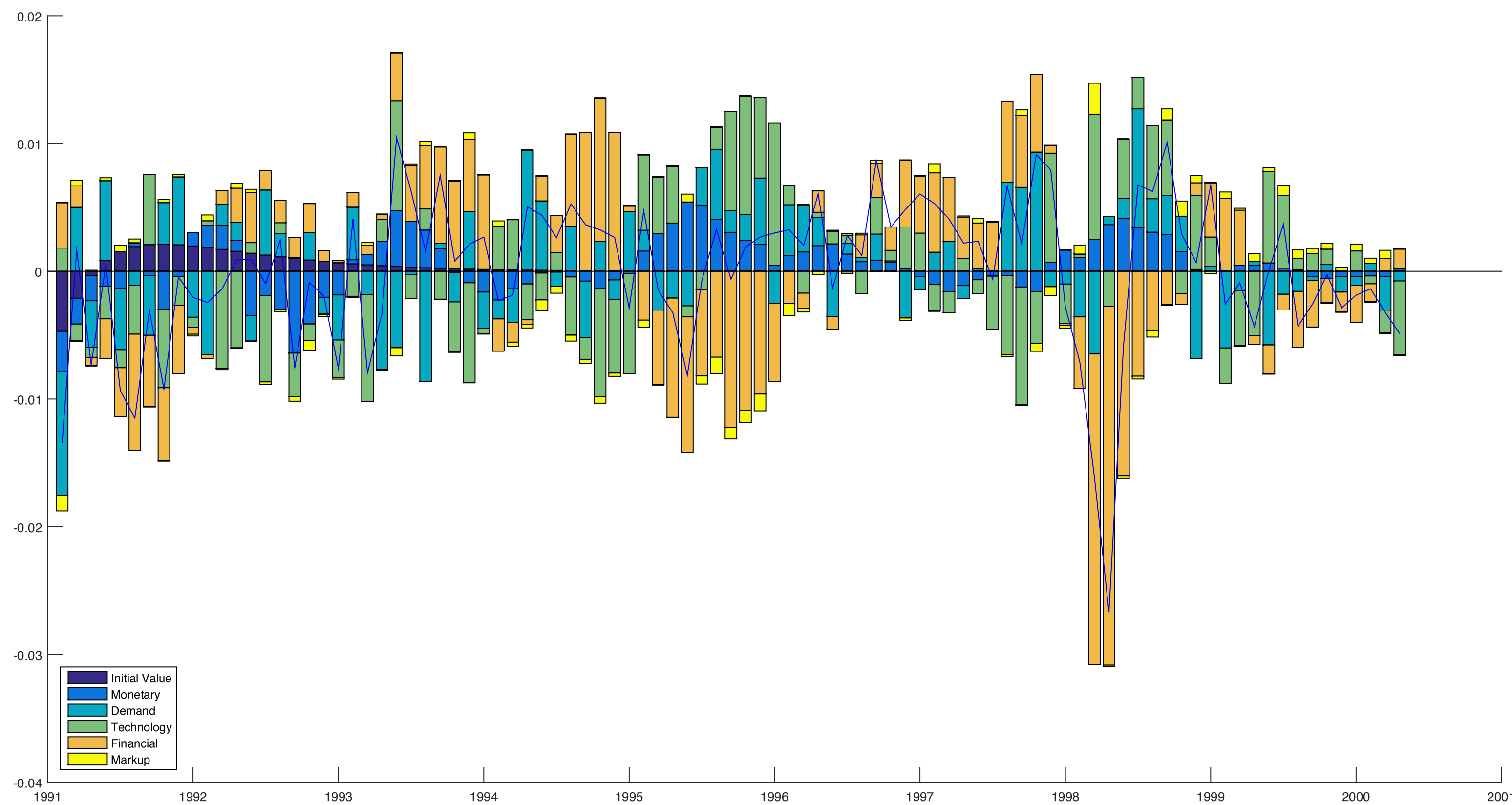

Figure I.4: **Historical decomposition of GDP at posterior means** Baseline model

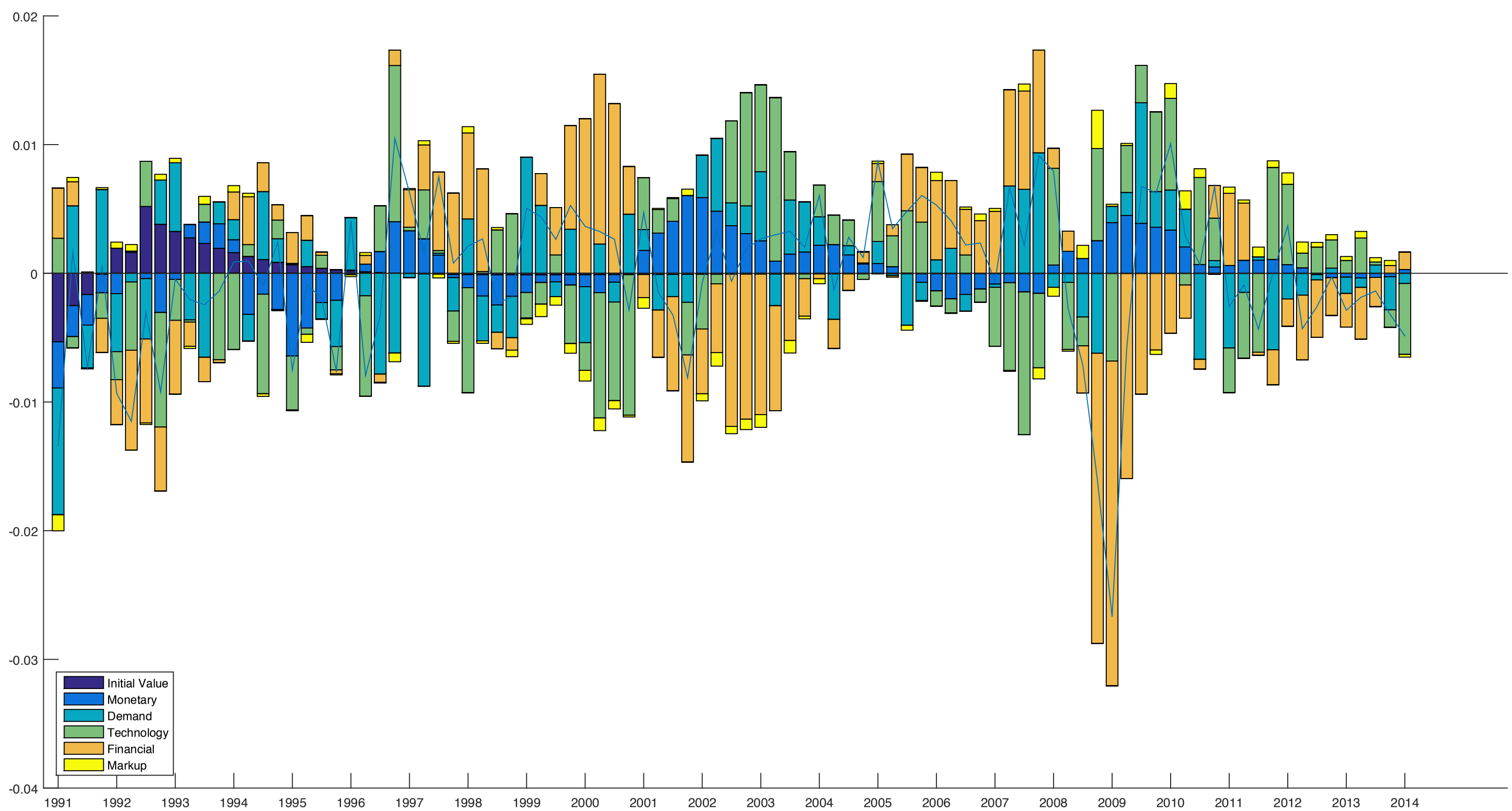

Figure I.5: **Historical decomposition of GDP at posterior modes** Baseline model

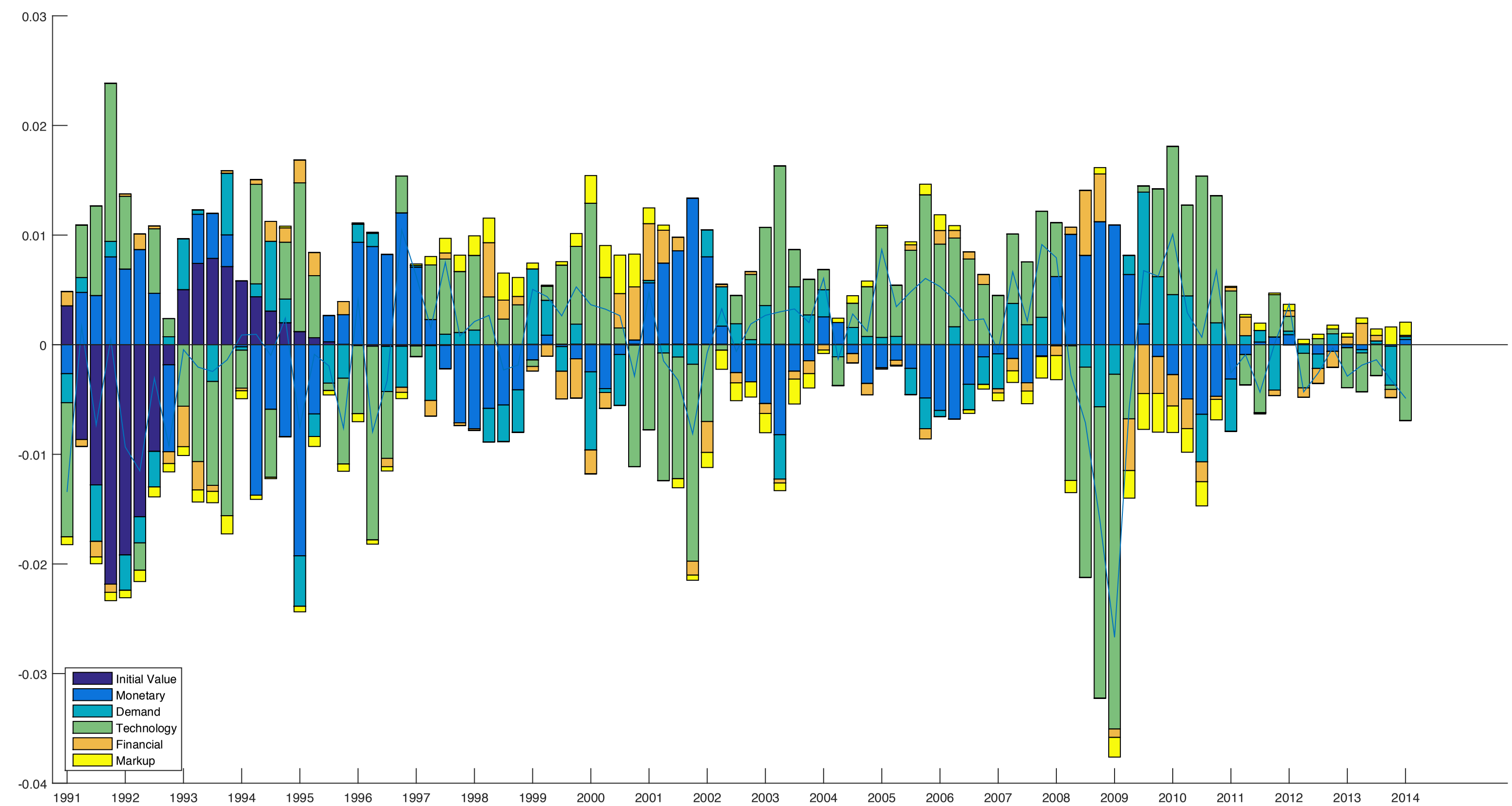

Figure I.6: **Historical decomposition of GDP at posterior means** Signals on the technology shocks

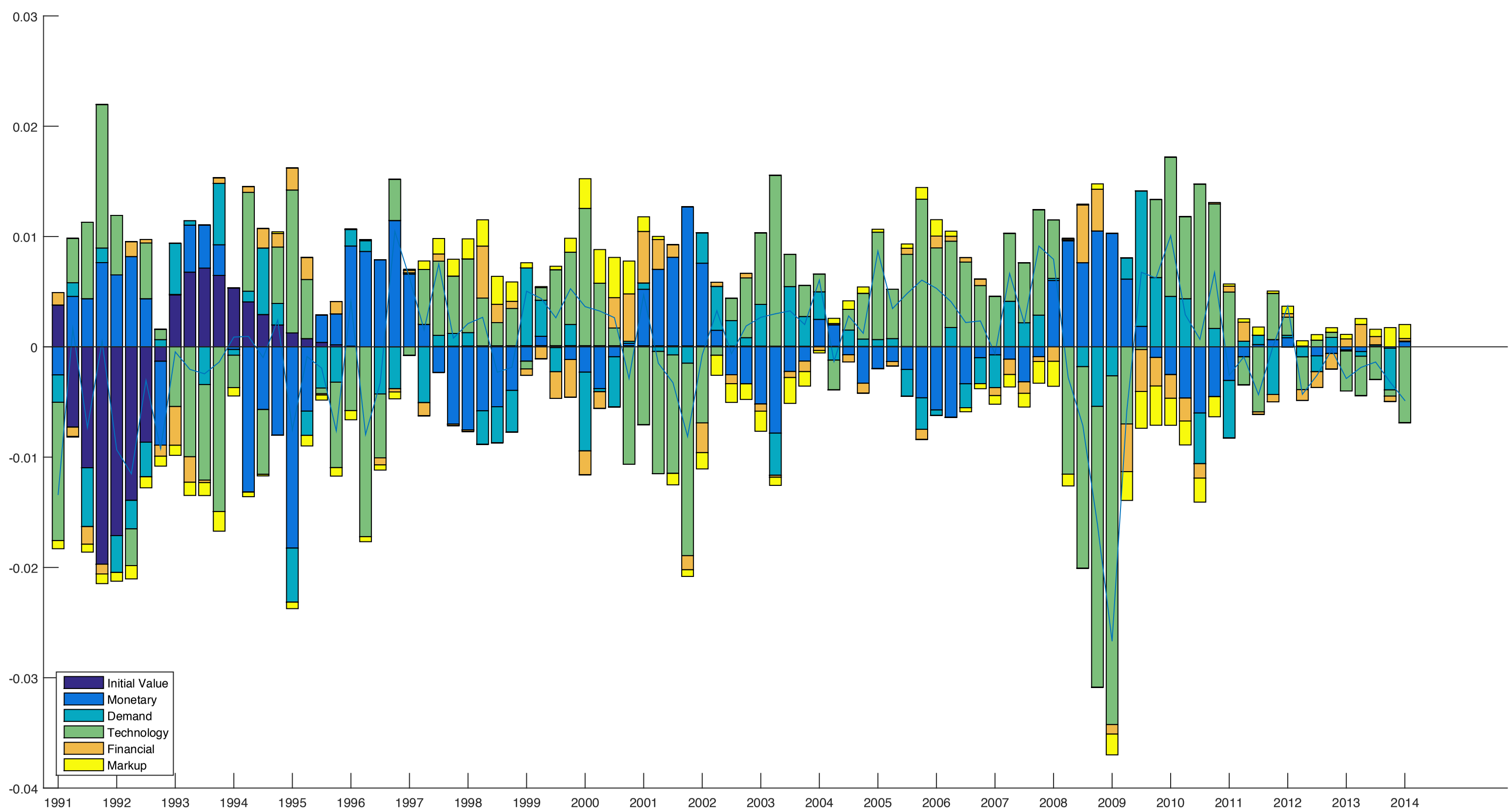

Figure I.7: **Historical decomposition of GDP at posterior modes** Signals on the technology shocks

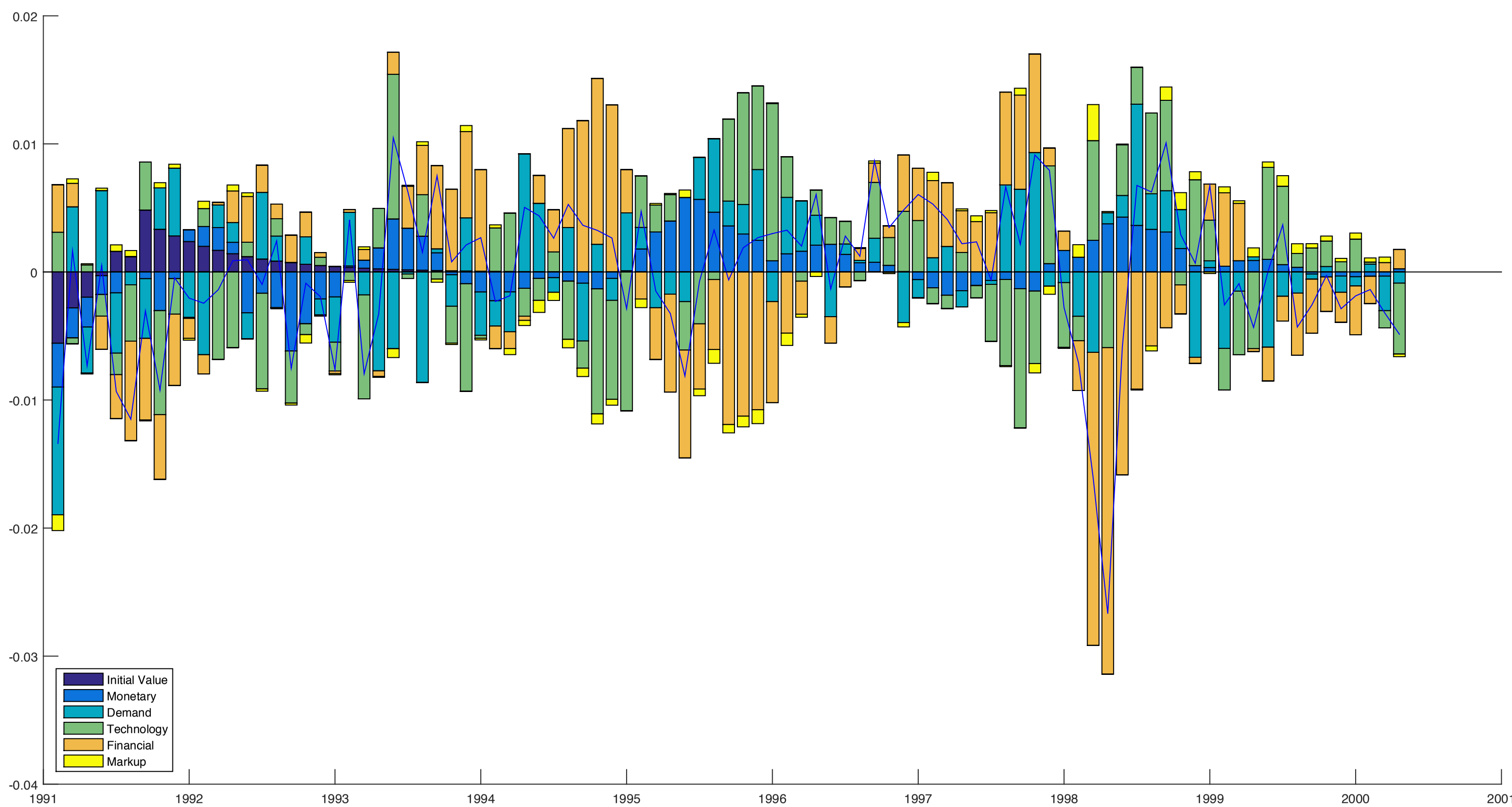

Figure I.8: **Historical decomposition of GDP at posterior means** Signals on the technology and risk shocks

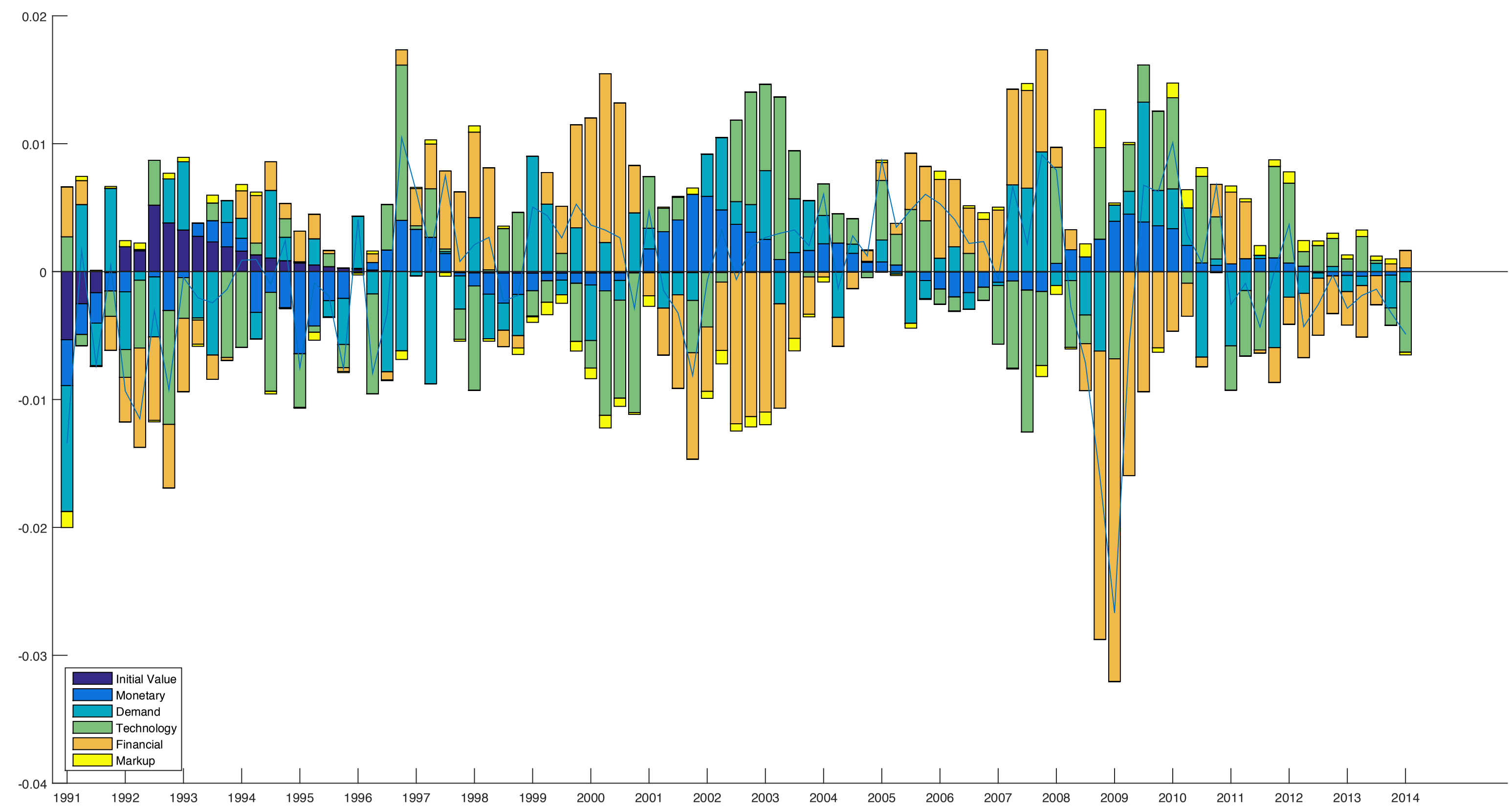

Figure I.9: **Historical decomposition of GDP at posterior modes** Signals on the technology and risk shocks

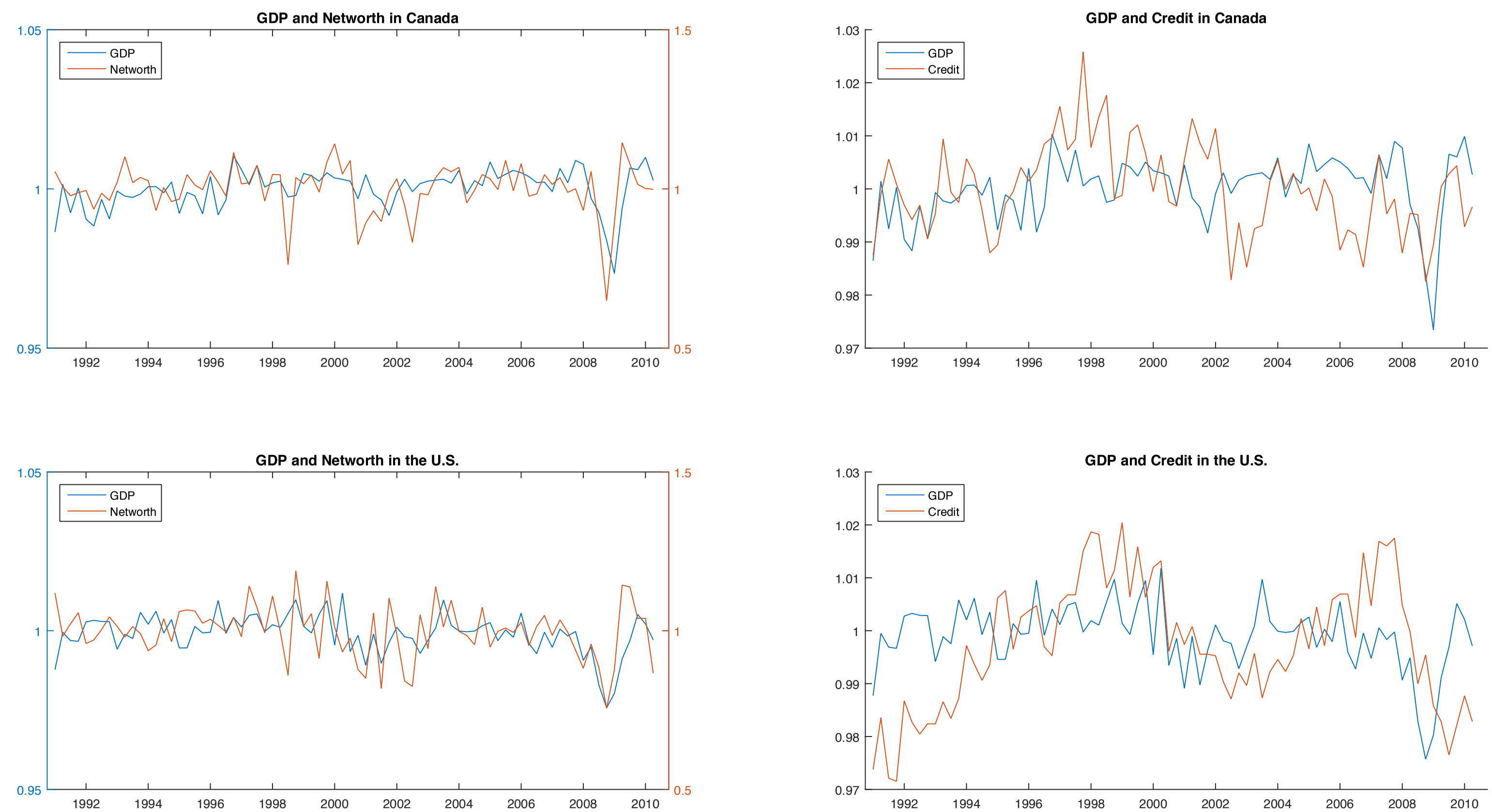

Figure I.10: **Credit and networth are cyclical in Canada and in the U.S.**

Figure I.11: **The model's risk shock and the observed measures of uncertainty** Transformed to have positive correlation

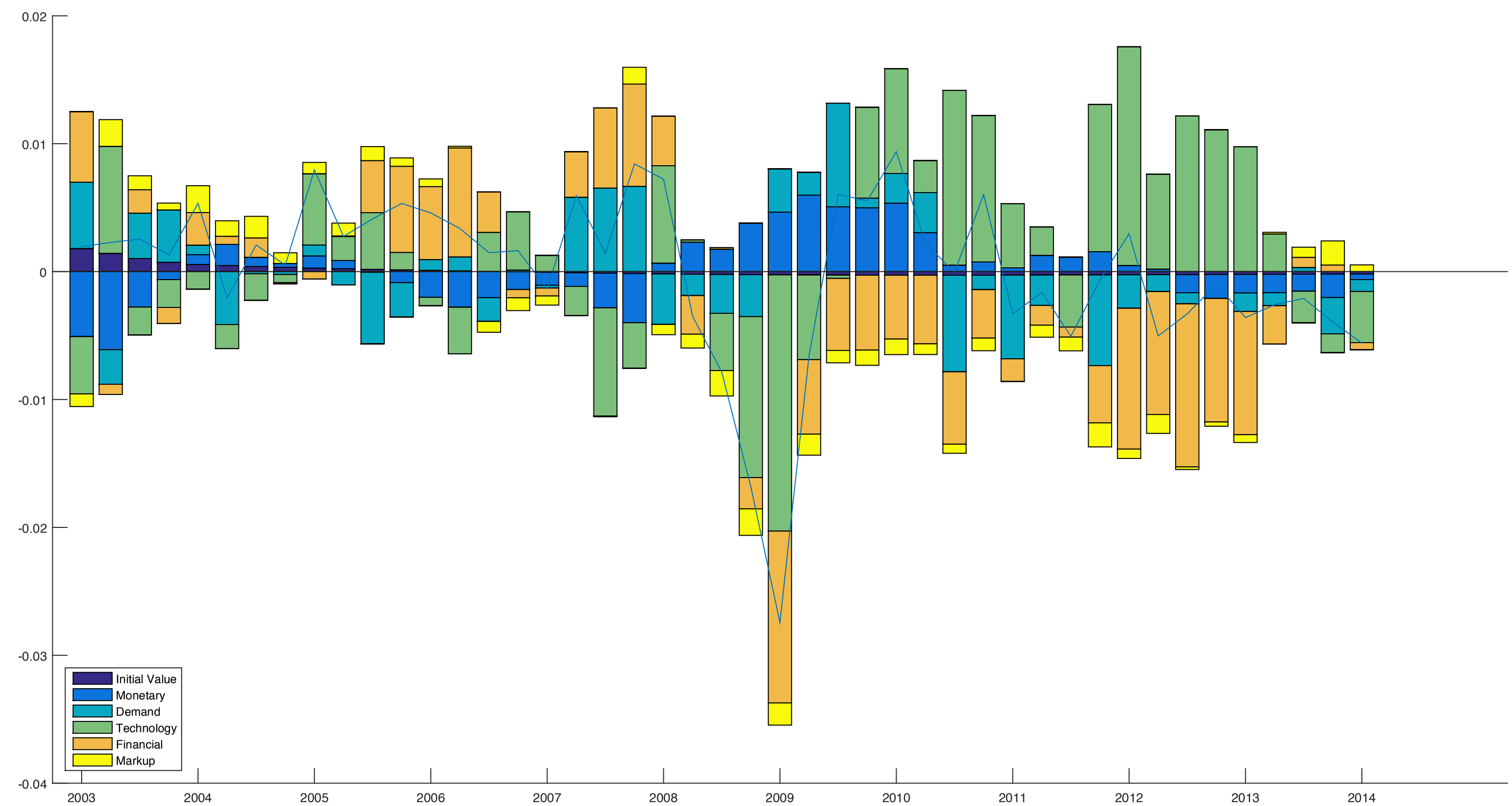

Figure I.12: **Historical decomposition of GDP at posterior means** Observable risk shock, VIXC index

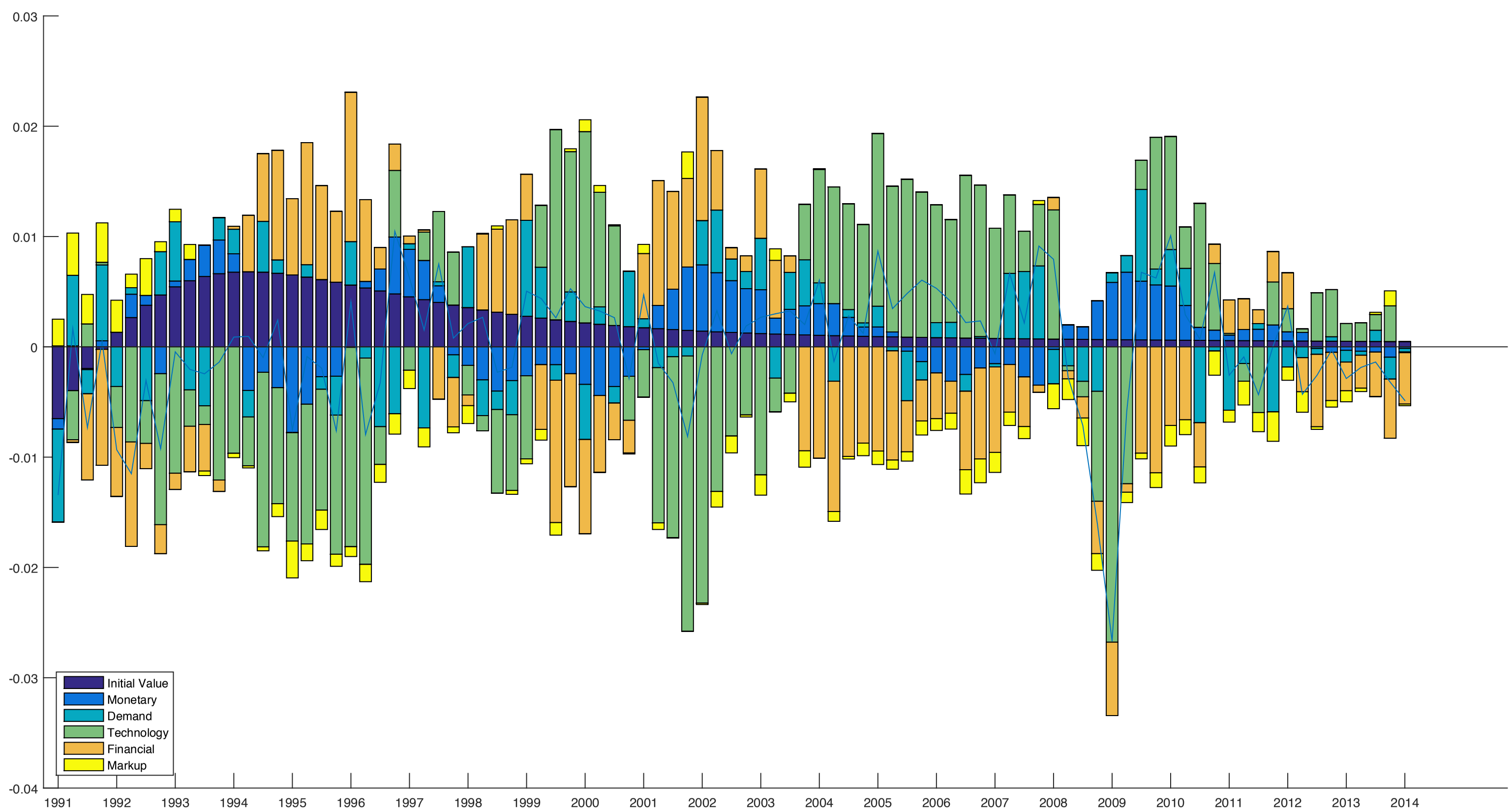

Figure I.13: **Historical decomposition of GDP at posterior means** Observable risk shock, EPU index

Table I.I: Calibrated parameters

		Canada	U.S.(CMR)
	A. Economic parameters		
β	Discount rate in utility	0.9981	0.9987
δ	Depreciation rate on capital	0.025	0.025
α	Power on capital in production function	0.36	0.40
η_g	Steady state gov. spending to GDP ratio	0.28	0.20
λ_w	Mean markup of suppliers of labor	1.05	1.05
Υ	Trend rate of invest.-specific techno. change	1.0028	1.0042
τ^c	Tax rate on consumption	0.13	0.05
τ^k	Tax rate on capital income	0.40	0.32
τ^l	Tax rate on labor income (wage)	0.31	0.24
τ^d	Tax rate on bond	0	0
σ_L	Preference parameter for labor	1	1
Ψ_L	Wage bill financing	0.7705	0.7705
w^e	Household lump-sum transfer to entrepreneur	0.005	0.005
Θ	Resources used for state-verification	0.005	0.005
τ^o	Parameter in Eq. 9,12,17 (Appendix III)	1	1
ζ_t	Parameter in Eq. 6 (Appendix III)	1	1
	B. Monetary policy		
$\tilde{\alpha}_c$	Parameter in the monetary policy	0	0
$\tilde{\alpha}_d$	Parameter in the monetary policy	0	0
$\tilde{\alpha}_y$	Parameter in the monetary policy	0	0
	C. Shock processes		
π_t^{target}	Mean value of target inflation	1.0050	1.0041
μ_{z^*}	Mean of the process for the S.S. GDP growth shock	1.0050	1.0041
γ	Mean of the process for the equity shock	0.985	0.985
λ_f	Mean of the process for the markup shock	1.2	1.2
ε	Mean of the process for the technology shock	1	1
μ_Υ	Mean of the process for the invest. good shock	1	1
η	Mean of the process for the term structure shock	1	1
ζ_c	Mean of the process for the preference shock	1	1
ζ_I	Mean of the process for the marg. eff. of invest.	1	1
ρ_γ	Autocorrelation of the equity shock	0	0
$\rho_{\pi^{target}}$	Autocorrelation of the target inflation shock	0	0.975
$\sigma_{\pi^{target}}$	St. deviation, innovation to the target infl. shock	0.000001	0.0001

Table I.II: Steady-state values and ratios

A. Steady-state parameters			
		Canada	U.S. (CMR)
c	Consumption	1.1371	1.5469
i	Investment	0.5889	0.7394
g	Government spending	0.6716	0.5868
π	Inflation	1.0050	1.0061
R	Risk free rate	0.0097	0.0115
$\bar{\pi}$	Parameter in $\tilde{\pi}_t$ and $\tilde{\pi}_{w,t}$	1.0050	1.0061
B. Steady-state ratios			
		Model	Data
$\frac{c}{y}$	Consumption to GDP	0.47	0.52
$\frac{i}{y}$	Investment to GDP	0.25	0.20
$\frac{g}{y}$	Gov. spending to GDP	0.28	0.28
π_t	Inflation, annualized	2.02	2.01
R_t	Risk-free rate, annualized	3.94	3.88

Table I.III: Estimated parameter priors and posteriors

			Priors-Canada		Posterior-Canada			Priors-U.S.(CMR)	
		dist.	mean	stdv	mean	mode	stdv	mean	stdv
	Economic parameters								
ξ_p	Calvo price rigidity	beta	0.6	0.15	0.89	0.83	0.05	0.5	0.1
ξ_w	Calvo wage rigidity	beta	0.6	0.15	0.74	0.76	0.06	0.75	0.1
b	Habit parameter	beta	0.5	0.2	0.81	0.81	0.05	0.5	0.1
$F(\bar{\omega})$	Steady state probability of default	beta	0.007	0.0037	0.0104	0.0095	0.0036	0.007	0.0037
μ	Monitoring cost	beta	0.275	0.15	0.217	0.199	0.05	0.275	0.15
σ_a	Curvature, utilization cost	normal	1	1	1.44	1.96	0.77	1	1
S''	Curvature, invest. adjust. cost	normal	5	3	15.24	14.84	2.69	5	3
l_w	Wage indexing weight on inflation target	beta	0.5	0.15	0.43	0.43	0.14	0.5	0.15
l	Price indexing weight on inflation target	beta	0.5	0.15	0.77	0.86	0.06	0.5	0.15
l_μ	Wage indexing weight on $\mu_{z^*,t}$	beta	0.5	0.15	0.94	0.94	0.03	0.5	0.15
α_π	Monetary policy weight on inflation	normal	1.8	0.3	2.26	2.22	0.23	1.5	0.25
$\alpha_{\Delta y}$	Monetary policy weight on output growth	normal	0.3	0.2	0.44	0.41	0.19	0.25	0.1
$\tilde{\rho}$	Monetary policy smoothing parameter	beta	0.6	0.2	0.85	0.86	0.02	0.75	0.1

Table I.IV: Estimated parameter priors and posteriors (continued)

			Priors-Canada		Posteriors-Canada			Priors-U.S.(CMR)	
		dist.	mean	stdv	mean	mode	stdv	mean	stdv
	Shock processes								
ρ_ε	Autocorrelation, temporary tech. shock	beta	0.5	0.2	0.91	0.92	0.03	0.5	0.2
$\rho_{\mu_{z^*}}$	Autocorrelation, permanent tech. shock	beta	0.5	0.2	0.08	0.06	0.04	0.5	0.2
ρ_{μ_Υ}	Autocorrelation, invest. good shock	beta	0.5	0.2	0.96	0.96	0.02	0.5	0.2
ρ_{λ_f}	Autocorrelation, markup shock	beta	0.5	0.2	0.36	0.80	0.09	0.5	0.2
ρ_{ζ_I}	Autocorrelation, marg. eff. of invest.	beta	0.5	0.2	0.54	0.56	0.21	0.5	0.2
ρ_{ζ_c}	Autocorrelation, preference shock	beta	0.5	0.2	0.39	0.39	0.14	0.5	0.2
ρ_η	Autocorrelation, term structure shock	beta	0.5	0.2	0.96	0.97	0.07	0.5	0.2
ρ_g	Autocorrelation, govern. spending shock	beta	0.5	0.2	0.97	0.97	0.01	0.5	0.2
ρ_σ	Autocorrelation, risk shock	beta	0.5	0.2	0.96	0.97	0.01	0.5	0.2
$\rho_{\sigma,n}$	Correlation, signals (anticipated)	normal	0	0.5	0.44	0.44	0.08	0	0.5
	Standard deviation of shock innovations								
σ_ε	Temporary tech. shock	invgam2	0.002	0.0033	0.0052	0.0051	0.0004	0.002	0.0033
$\sigma_{\mu_{z^*}}$	Permanent tech. shock	invgam2	0.002	0.0033	0.0072	0.0069	0.0006	0.002	0.0033
σ_{μ_Υ}	Invest. good shock	invgam2	0.002	0.0033	0.0025	0.0025	0.0002	0.002	0.0033
σ_{λ_f}	Markup shock	invgam2	0.002	0.0033	0.1164	0.0224	0.113	0.002	0.0033
σ_{ζ_I}	Marg. eff. of invest. shock	invgam2	0.002	0.0033	0.0210	0.0206	0.0039	0.002	0.0033
σ_{ζ_c}	Preference shock	invgam2	0.002	0.0033	0.0209	0.0196	0.0045	0.002	0.0033
σ_η	Term structure shock	invgam2	0.002	0.0033	0.0015	0.0013	0.0015	0.002	0.0033
σ_g	Govern. spending shock	invgam2	0.002	0.0033	0.0108	0.0104	0.0008	0.002	0.0033
σ_γ	Equity shock	invgam2	0.002	0.0033	0.0134	0.0131	0.0021	0.002	0.0033
σ_{ε^p}	Monetary pol. shock	invgam2	0.583	0.825	0.5498	0.5363	0.0462	0.583	0.825
$\sigma_{\sigma,0}$	Risk shock (unanticipated)	invgam2	0.002	0.0033	0.0194	0.0011	0.0006	0.002	0.0033
$\sigma_{\sigma,n}$	Signals (anticipated)	invgam2	0.001	0.0012	0.0296	0.0308	0.0038	0.001	0.0012
	Measurement error on networth	Weibull	0.01	5	0.0176	0.0177	0.0011	0.01	5

Table I.V: Estimated parameter posteriors, alternative specifications

		Signals on risk and techno.			Signals on techno.		
		mean	mode	stdv	mean	mode	stdv
	Economic parameters						
ξ_p	Calvo price rigidity	0.91	0.91	0.01	0.28	0.30	0.03
ξ_w	Calvo wage rigidity	0.71	0.71	0.05	0.61	0.61	0.02
b	Habit parameter	0.80	0.81	0.04	0.90	0.90	0.01
$F(\bar{\omega})$	Steady state probability of default	0.0102	0.0096	0.0034	0.0115	0.0120	0.0002
μ	Monitoring cost	0.192	0.187	0.06	0.382	0.395	0.012
σ_a	Curvature, utilization cost	1.52	1.31	0.73	5.95	5.51	0.04
S''	Curvature, invest. adjust. cost	15.79	15.76	1.75	3.34	3.36	0.22
l_w	Wage indexing weight on inflation target	0.45	0.47	0.15	0.40	0.37	0.01
l	Price indexing weight on inflation target	0.74	0.77	0.10	0.50	0.55	0.01
l_μ	Wage indexing weight on $\mu_{z^*,t}$	0.94	0.95	0.03	0.85	0.84	0.00
α_π	Monetary policy weight on inflation	2.32	2.29	0.23	1.46	1.49	0.03
$\alpha_{\Delta y}$	Monetary policy weight on output growth	0.45	0.48	0.19	0.60	0.57	0.01
$\tilde{\rho}$	Monetary policy smoothing parameter	0.83	0.83	0.02	0.96	0.96	0.00

Table I.VI: Estimated parameter posteriors, alternative specifications (continued)

		Signals on risk and techno.			Signals on techno.		
		mean	mode	stdv	mean	mode	stdv
	Shock processes						
ρ_{ε}	Autocorrelation, temporary tech. shock	0.91	0.92	0.02	0.35	0.30	0.03
$\rho_{\mu_{z^*}}$	Autocorrelation, permanent tech. shock	0.09	0.06	0.04	0.03	0.04	0.00
$\rho_{\mu_{\Upsilon}}$	Autocorrelation, invest. good shock	0.96	0.96	0.02	0.96	0.97	0.02
ρ_{λ_f}	Autocorrelation, markup shock	0.18	0.15	0.11	0.96	0.96	0.03
ρ_{ζ_I}	Autocorrelation, marg. eff. of invest.	0.79	0.85	0.06	0.90	0.93	0.01
ρ_{ζ_c}	Autocorrelation, preference shock	0.39	0.36	0.12	0.99	0.99	0.02
ρ_{η}	Autocorrelation, term structure shock	0.96	0.97	0.02	0.88	0.87	0.01
ρ_{g}	Autocorrelation, govern. spending shock	0.97	0.97	0.01	0.91	0.92	0.01
ρ_{σ}	Autocorrelation, risk shock	0.96	0.97	0.01	0.88	0.91	0.01
$\rho_{\sigma,n}$	Correlation, signals on risk	0.43	0.42	0.08	-	-	-
$\rho_{\zeta_I,n}$	Correlation, signals on marg. eff. of invest.	-0.17	-0.22	0.13	-0.06	-0.12	0.06
$\rho_{\varepsilon,n}$	Correlation, signals on temporary tech.	-	-	-	0.96	0.97	0.02
$\rho_{\mu_{z^*},n}$	Correlation, signals on permanent tech.	-	-	-	0.96	0.97	0.04
	Standard deviation of shock innovations						
$\sigma_{\varepsilon,0}$	Temporary tech. (unantic.)	0.0052	0.0051	0.0004	0.0011	0.0010	0.0001
$\sigma_{\varepsilon,n}$	Temporary tech. (antic.)	-	-	-	0.0230	0.0240	0.0002
$\sigma_{\mu_{z^*},0}$	Permanent tech. (unantic.)	0.0073	0.0070	0.0006	0.0009	0.0007	0.0002
$\sigma_{\mu_{z^*},n}$	Permanent tech. (antic.)	-	-	-	0.0232	0.0234	0.0002
$\sigma_{\mu_{\Upsilon}}$	Invest. good shock	0.0025	0.0025	0.0002	0.0026	0.0025	0.0001
σ_{λ_f}	Markup shock	0.2235	0.2145	0.0766	0.0058	0.0055	0.0006
$\sigma_{\zeta_I,0}$	Marg. eff. of invest. (unantic.)	0.0016	0.0010	0.0005	0.0010	0.0008	0.0001
$\sigma_{\zeta_I,n}$	Marg. eff. of invest. (antic.)	0.0070	0.0068	0.0006	0.0307	0.0307	0.0001
σ_{ζ_c}	Preference shock	0.0196	0.0185	0.0041	0.0239	0.0226	0.0003
σ_{η}	Term structure shock	0.0015	0.0013	0.0006	0.0057	0.0056	0.0002
σ_{g}	Govern. spending shock	0.0109	0.0106	0.0009	0.0110	0.0111	0.0002
σ_{γ}	Equity shock	0.0145	0.0145	0.0019	0.0038	0.0033	0.0005
σ_{ε^p}	Monetary pol. shock	0.5574	0.5402	0.0455	0.4815	0.4672	0.0417
$\sigma_{\sigma,0}$	Risk shock (unantic.)	0.0096	0.0011	0.0006	0.0177	0.0157	0.0006
$\sigma_{\sigma,n}$	Signals (antic.)	0.0301	0.0310	0.0031	-	-	-
	Measurement error on networth	0.0172	0.0171	0.0009	0.0225	0.0230	0.0004

Table I.VII: **Variance decomposition (in percent)** Baseline model, signals on risk shock

GDP	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	1.89	6.73	1.20	2.30	0.26	5.99	0.00	0.00	59.90	0.00	2.17	3.21	16.34
1	1.19	13.53	0.95	1.61	0.42	10.78	0.00	0.00	38.1	0.00	2.25	5.72	25.45
4	1.77	8.10	1.22	2.19	0.28	6.86	0.00	0.00	55.17	0.00	2.38	3.60	18.46
8	1.79	7.41	1.21	2.07	0.27	6.42	0.00	0.00	57.83	0.00	2.20	3.51	17.30
Investment	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.43	0.00	1.50	1.00	0.04	0.21	0.00	0.00	74.12	0.00	1.39	0.00	21.29
1	0.23	0.00	1.43	0.75	0.02	0.13	0.00	0.00	56.23	0.00	1.52	0.00	39.69
4	0.37	0.00	1.57	0.96	0.03	0.18	0.00	0.00	70.52	0.00	1.53	0.00	24.84
8	0.41	0.00	1.52	0.92	0.04	0.21	0.00	0.00	71.65	0.00	1.43	0.00	23.80
Consumption	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	9.25	1.71	0.50	6.22	0.04	4.36	0.00	0.00	30.18	0.00	3.29	42.69	1.77
1	7.08	1.30	0.05	5.00	0.00	2.03	0.00	0.00	2.45	0.00	4.20	77.28	0.61
4	12.08	2.22	0.11	8.04	0.00	3.81	0.00	0.00	5.59	0.00	4.97	61.93	1.25
8	11.30	2.16	0.19	7.23	0.00	4.36	0.00	0.00	10.83	0.00	4.36	57.92	1.65
Spread	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	3.56	0.16	0.90	9.66	0.05	0.42	0.00	0.00	60.24	17.62	5.44	0.12	1.84
1	0.12	0.00	0.01	7.95	0.03	0.11	0.00	0.00	2.59	26.45	60.92	0.07	1.74
4	3.54	0.07	0.33	22.23	0.01	0.08	0.00	0.00	27.94	18.21	24.00	0.20	3.38
8	4.56	0.12	0.67	17.69	0.01	0.19	0.00	0.00	49.34	13.62	10.72	0.18	2.90
Premium	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.04	0.02	3.43	0.03	0.05	0.06	0.00	0.01	94.39	0.00	1.40	0.01	0.57
1	0.00	0.03	3.71	0.15	0.14	0.18	0.00	0.01	89.05	0.00	5.57	0.02	1.14
4	0.00	0.02	7.89	0.10	0.10	0.13	0.00	0.03	86.92	0.00	3.86	0.01	0.93
8	0.01	0.02	4.94	0.05	0.06	0.08	0.00	0.02	92.04	0.00	2.13	0.01	0.65
Networth	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.01	0.02	8.48	0.33	0.13	0.15	0.00	0.01	84.63	0.00	5.09	0.01	1.14
1	0.00	0.02	8.87	0.33	0.14	0.16	0.00	0.01	84.04	0.00	5.25	0.01	1.16
4	0.01	0.02	8.88	0.33	0.14	0.16	0.00	0.01	83.95	0.00	5.33	0.01	1.15
8	0.01	0.02	8.68	0.33	0.13	0.15	0.00	0.01	84.30	0.00	5.22	0.01	1.14

Table I.VIII: **Variance decomposition (in percent)** Baseline model, signals on risk shock (continued)

Credit	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	1.01	0.03	21.53	2.94	0.03	0.23	0.00	0.00	72.77	0.00	0.53	0.02	0.92
1	1.87	0.06	77.20	6.74	0.02	0.02	0.00	0.00	13.34	0.00	0.68	0.04	0.03
4	2.24	0.06	48.38	6.31	0.02	0.02	0.00	0.00	41.55	0.00	0.82	0.05	0.56
8	1.45	0.04	31.61	4.20	0.01	0.04	0.00	0.00	61.09	0.00	0.54	0.03	0.97
Inflation	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	10.87	0.48	0.60	41.53	0.04	0.89	0.00	0.00	41.53	0.00	2.03	0.23	1.79
1	12.31	0.31	0.17	68.34	0.00	0.40	0.00	0.00	15.84	0.00	0.91	0.23	1.49
4	12.72	0.38	0.34	54.72	0.01	0.57	0.00	0.00	27.67	0.00	1.58	0.27	1.76
8	12.20	0.42	0.49	46.79	0.02	0.70	0.00	0.00	35.47	0.00	2.03	0.26	1.61
Wage	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	2.77	0.05	0.13	12.82	0.01	76.47	0.00	0.00	7.26	0.00	0.11	0.00	0.38
1	2.27	0.04	0.00	12.48	0.00	85.11	0.00	0.00	0.08	0.00	0.00	0.00	0.01
4	2.75	0.05	0.01	13.19	0.00	82.94	0.00	0.00	0.90	0.00	0.04	0.00	0.12
8	2.77	0.05	0.04	13.00	0.00	81.31	0.00	0.00	2.49	0.00	0.07	0.00	0.26
Hours	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	3.53	3.34	1.10	3.02	0.06	1.15	0.00	0.00	74.14	0.00	2.10	0.84	10.72
1	46.98	11.53	0.17	0.87	0.16	5.79	0.00	0.00	0.74	0.00	0.01	4.83	28.93
4	15.21	5.40	0.16	3.30	0.05	2.14	0.00	0.00	39.60	0.00	1.65	3.25	29.24
8	6.68	3.36	0.59	4.12	0.02	0.97	0.00	0.00	60.98	0.00	2.37	1.70	19.20
Interest rate	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	7.52	0.73	1.05	13.00	0.09	1.94	0.00	0.00	66.76	0.00	6.81	0.19	1.91
1	3.59	0.36	0.14	16.36	0.00	0.41	0.00	0.00	10.39	0.00	67.22	0.21	1.30
4	8.25	0.48	0.48	27.86	0.01	0.82	0.00	0.00	34.33	0.00	25.10	0.32	2.35
8	9.15	0.53	0.78	22.38	0.02	1.12	0.00	0.00	51.47	0.00	12.31	0.28	1.96
Rel. price	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table I.IX: **Variance decomposition (in percent)** Signals on the technology shocks

GDP	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^{p}	$\zeta_{c,t}$
∞	0.49	0.03	0.06	0.01	0.06	0.00	0.00	0.00	0.00	9.26	77.87	11.56	0.00	0.59	0.08
1	3.01	0.11	0.08	0.02	0.22	0.00	0.00	0.00	0.00	7.95	85.53	0.41	0.00	2.38	0.30
4	0.83	0.04	0.09	0.01	0.08	0.00	0.00	0.00	0.00	7.13	83.91	6.85	0.00	0.92	0.12
8	0.57	0.03	0.07	0.01	0.06	0.00	0.00	0.00	0.00	9.55	81.54	7.42	0.00	0.66	0.08
Invest.	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^{p}	$\zeta_{c,t}$
∞	0.02	0.10	0.11	0.01	0.21	0.00	0.00	0.00	0.00	34.81	36.67	26.30	0.00	1.62	0.16
1	0.05	0.22	0.06	0.02	0.44	0.00	0.00	0.00	0.00	16.38	77.96	0.90	0.00	3.63	0.34
4	0.03	0.15	0.15	0.02	0.27	0.00	0.00	0.00	0.00	25.04	60.22	11.61	0.00	2.27	0.21
8	0.02	0.12	0.12	0.02	0.23	0.00	0.00	0.00	0.00	37.21	45.13	15.14	0.00	1.85	0.18
Consump.	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^{p}	$\zeta_{c,t}$
∞	0.01	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.20	91.16	8.33	0.00	0.16	0.08
1	0.01	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	88.43	10.74	0.00	0.51	0.21
4	0.01	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.03	86.92	12.46	0.00	0.32	0.15
8	0.01	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.09	89.14	10.35	0.00	0.23	0.11
Spread	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^{p}	$\zeta_{c,t}$
∞	0.06	0.02	0.07	0.01	0.03	0.00	0.00	0.00	0.00	2.73	29.38	64.01	2.52	0.87	0.30
1	0.05	0.03	0.12	0.00	0.05	0.00	0.00	0.00	0.00	2.16	30.79	16.70	28.12	19.73	2.25
4	0.08	0.03	0.18	0.00	0.04	0.00	0.00	0.00	0.00	2.3	8.94	77.17	7.39	3.50	0.37
8	0.06	0.02	0.08	0.00	0.02	0.00	0.00	0.00	0.00	1.70	14.16	79.62	3.07	1.13	0.12
Premium	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^{p}	$\zeta_{c,t}$
∞	0.15	0.80	0.29	0.03	3.24	0.00	0.00	0.00	0.00	1.63	24.53	67.42	0.00	1.42	0.49
1	0.17	0.17	0.27	0.02	0.45	0.00	0.00	0.00	0.00	0.30	56.53	37.25	0.00	4.34	0.50
4	0.20	1.45	0.29	0.03	6.72	0.00	0.00	0.00	0.00	0.61	48.28	38.20	0.00	3.79	0.44
8	0.21	1.44	0.34	0.03	6.16	0.00	0.00	0.00	0.00	1.56	34.90	52.30	0.00	2.72	0.33
Networth	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^{p}	$\zeta_{c,t}$
∞	0.11	0.41	0.12	0.02	0.49	0.00	0.00	0.00	0.00	1.02	49.32	44.17	0.00	3.90	0.43
1	0.13	0.50	0.08	0.03	0.53	0.00	0.00	0.00	0.00	0.54	55.72	37.55	0.00	4.45	0.49
4	0.13	0.45	0.13	0.02	0.52	0.00	0.00	0.00	0.00	0.51	51.54	42.06	0.00	4.19	0.46
8	0.12	0.44	0.12	0.02	0.52	0.00	0.00	0.00	0.00	0.73	50.39	43.05	0.00	4.15	0.46

Table I.X: **Variance decomposition (in percent)** Signals on the technology shocks (continued)

Credit	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$
∞	0.03	1.61	0.26	0.00	0.17	0.00	0.00	0.00	0.00	2.73	13.07	81.93	0.00	0.19	0.02
1	0.27	34.58	3.07	0.01	1.21	0.00	0.00	0.00	0.03	1.97	34.73	20.20	0.00	3.73	0.20
4	0.08	4.56	0.76	0.00	0.31	0.00	0.00	0.00	0.00	1.32	5.00	87.44	0.00	0.48	0.03
8	0.05	2.64	0.43	0.00	0.22	0.00	0.00	0.00	0.00	2.60	4.84	88.88	0.00	0.28	0.02
Inflation	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$
∞	0.07	0.01	0.50	0.00	0.01	0.00	0.00	0.00	0.00	2.01	19.72	76.33	0.00	1.06	0.30
1	0.57	0.02	5.72	0.00	0.03	0.00	0.00	0.00	0.03	1.90	55.56	32.74	0.00	2.92	0.52
4	0.12	0.01	0.85	0.00	0.01	0.00	0.00	0.00	0.00	0.83	28.97	67.38	0.00	1.52	0.30
8	0.09	0.01	0.69	0.00	0.01	0.00	0.00	0.00	0.00	1.56	27.19	68.63	0.00	1.48	0.33
Wage	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$
∞	0.02	0.00	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.59	68.04	30.94	0.00	0.04	0.00
1	0.69	0.02	12.15	0.00	0.03	0.00	0.00	0.02	0.04	2.23	22.07	62.15	0.00	0.54	0.07
4	0.06	0.00	1.02	0.00	0.00	0.00	0.00	0.00	0.00	0.45	56.93	41.45	0.00	0.06	0.01
8	0.03	0.00	0.49	0.00	0.00	0.00	0.00	0.00	0.00	0.54	74.58	24.30	0.00	0.05	0.01
Hours	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$
∞	0.51	0.05	0.61	0.01	0.06	0.00	0.00	0.00	0.00	8.08	56.65	32.61	0.00	1.18	0.28
1	3.68	0.07	0.16	0.02	0.17	0.00	0.00	0.00	0.04	10.62	82.02	1.00	0.00	1.96	0.26
4	0.88	0.05	0.26	0.00	0.06	0.00	0.00	0.00	0.00	7.39	46.26	43.13	0.00	1.75	0.24
8	0.76	0.06	0.54	0.00	0.06	0.00	0.00	0.00	0.00	10.25	42.14	44.04	0.00	1.86	0.27
Int. rate	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$
∞	0.04	0.01	0.14	0.01	0.02	0.00	0.00	0.00	0.00	1.26	58.35	36.71	0.00	0.63	2.88
1	0.14	0.01	0.53	0.00	0.01	0.00	0.00	0.00	0.00	0.73	23.99	52.85	0.00	21.52	0.21
4	0.08	0.01	0.25	0.00	0.01	0.00	0.00	0.00	0.00	0.76	33.11	62.83	0.00	2.65	0.31
8	0.06	0.01	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.72	37.30	60.38	0.00	0.99	0.41
Rel. price	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	σ_t	π_t^{target}	$\zeta_{i,t}^{unant}$	$\mu_{z^*,t}^{unant}$	ε_t^{unant}	$\zeta_{i,t}^{ant}$	$\mu_{z^*,t}^{ant}$	ε_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$
∞	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table I.XI: **Variance decomposition (in percent)** Signals on the technology and risk shocks

GDP	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	6.40	1.42	0.01	0.24	0.73	0.00	0.00	0.02	58.86	21.7	0.00	1.90	2.82	5.89
1	17.57	1.44	0.00	0.54	0.63	0.00	0.00	0.03	49.41	6.54	0.00	2.62	6.95	14.26
4	8.93	1.63	0.00	0.30	0.78	0.00	0.00	0.03	61.75	12.64	0.00	2.39	3.70	7.86
8	7.40	1.48	0.01	0.26	0.73	0.00	0.00	0.02	58.68	19.46	0.00	2.01	3.24	6.68
Investment	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.00	1.70	0.01	0.04	0.13	0.00	0.00	0.03	68.17	28.48	0.00	1.23	0.00	0.20
1	0.00	2.59	0.01	0.03	0.10	0.00	0.01	0.05	83.75	11.14	0.00	2.14	0.00	0.19
4	0.00	2.17	0.01	0.04	0.12	0.00	0.00	0.04	78.31	17.48	0.00	1.63	0.00	0.20
8	0.00	1.84	0.01	0.04	0.13	0.00	0.00	0.03	69.13	27.26	0.00	1.33	0.00	0.22
Consumption	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	1.66	0.60	0.08	0.05	5.62	0.00	0.00	0.01	29.73	3.40	0.00	3.78	48.42	6.65
1	1.17	0.10	0.03	0.00	3.91	0.00	0.00	0.00	6.21	1.30	0.00	4.36	79.48	3.43
4	1.97	0.22	0.04	0.00	6.64	0.00	0.00	0.00	12.99	2.32	0.00	5.18	64.25	6.38
8	1.91	0.32	0.07	0.00	6.25	0.00	0.00	0.00	17.86	2.32	0.00	4.55	59.74	6.97
Term spread	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.16	1.09	0.88	0.08	2.16	0.00	0.00	0.02	53.06	5.05	26.77	10.29	0.08	0.35
1	0.01	0.01	3.25	0.04	0.03	0.00	0.00	0.00	1.88	1.11	26.61	66.95	0.07	0.04
4	0.05	0.36	3.38	0.02	1.05	0.00	0.00	0.01	22.92	1.29	28.42	42.29	0.15	0.05
8	0.09	0.83	1.93	0.01	2.21	0.00	0.00	0.02	45.49	1.99	24.56	22.61	0.13	0.13
Premium	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.01	4.26	0.09	0.06	0.03	0.00	0.01	0.00	93.82	0.26	0.00	1.42	0.00	0.04
1	0.01	4.45	0.29	0.16	0.00	0.00	0.01	0.01	88.99	0.77	0.00	5.17	0.01	0.12
4	0.01	9.16	0.20	0.12	0.00	0.00	0.02	0.01	86.25	0.49	0.00	3.64	0.01	0.09
8	0.01	5.92	0.12	0.07	0.01	0.00	0.02	0.00	91.41	0.27	0.00	2.09	0.01	0.06
Networth	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.01	9.94	0.13	0.15	0.00	0.00	0.01	0.01	84.21	0.72	0.00	4.72	0.01	0.11
1	0.01	10.36	0.13	0.15	0.00	0.00	0.01	0.01	83.60	0.74	0.00	4.86	0.01	0.11
4	0.01	10.38	0.14	0.15	0.00	0.00	0.01	0.01	83.52	0.73	0.00	4.93	0.01	0.11
8	0.01	10.16	0.13	0.15	0.00	0.00	0.01	0.01	83.87	0.71	0.00	4.83	0.01	0.11

Table I.XII: **Variance decomposition (in percent)** Signals on the technology and risk shocks (continued)

Credit	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.01	24.03	1.07	0.03	0.29	0.00	0.00	0.00	70.71	3.12	0.00	0.52	0.01	0.21
1	0.02	79.34	3.25	0.02	0.40	0.00	0.00	0.00	15.64	0.53	0.00	0.77	0.01	0.00
4	0.02	49.78	2.15	0.02	0.57	0.00	0.00	0.00	44.86	1.80	0.00	0.79	0.01	0.01
8	0.01	33.59	1.51	0.02	0.40	0.00	0.00	0.00	61.43	2.47	0.00	0.53	0.01	0.03
Inflation	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.65	0.90	43.89	0.09	6.88	0.00	0.00	0.02	40.29	4.61	0.00	1.56	0.13	0.99
1	0.10	0.12	90.25	0.01	2.74	0.00	0.00	0.00	5.99	0.3	0.00	0.30	0.05	0.12
4	0.32	0.45	67.58	0.02	7.03	0.00	0.00	0.01	21.66	1.31	0.00	1.09	0.14	0.39
8	0.45	0.69	55.68	0.04	7.87	0.00	0.00	0.01	30.40	2.60	0.00	1.54	0.15	0.57
Wage	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.01	0.23	7.69	0.01	0.53	0.00	0.00	0.00	10.74	0.57	0.00	0.31	0.05	79.86
1	0.00	0.01	7.93	0.00	0.25	0.00	0.00	0.00	0.82	0.07	0.00	0.08	0.05	90.78
4	0.00	0.08	8.18	0.00	0.41	0.00	0.00	0.00	4.25	0.21	0.00	0.24	0.06	86.56
8	0.00	0.15	7.98	0.00	0.47	0.00	0.00	0.00	7.18	0.30	0.00	0.29	0.05	83.57
Hours	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	3.26	1.47	0.04	0.08	4.22	0.00	0.00	0.04	75.61	11.52	0.00	1.91	0.73	1.10
1	15.78	0.28	0.07	0.20	65.52	0.00	0.00	0.05	1.05	3.77	0.00	0.00	6.14	7.13
4	6.92	0.26	0.03	0.06	22.30	0.00	0.00	0.07	50.22	12.49	0.00	1.80	3.64	2.20
8	3.75	0.85	0.01	0.02	9.19	0.00	0.00	0.06	67.93	13.48	0.00	2.29	1.62	0.80
Int. rate	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.99	1.49	1.11	0.17	5.84	0.00	0.00	0.02	65.82	7.94	0.00	14.22	0.14	2.23
1	0.41	0.14	4.25	0.00	1.01	0.00	0.00	0.00	6.03	0.04	0.00	87.54	0.18	0.38
4	0.64	0.72	4.19	0.02	4.63	0.00	0.00	0.01	31.92	0.89	0.00	55.72	0.30	0.97
8	0.74	1.24	2.45	0.05	6.76	0.00	0.00	0.02	52.75	3.06	0.00	31.33	0.25	1.37
Rel. price	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	ε_t	π_t^{target}	σ_t^{unant}	$\zeta_{i,t}^{unant}$	σ_t^{ant}	$\zeta_{i,t}^{ant}$	η_t	ε_t^p	$\zeta_{c,t}$	$\mu_{z^*,t}$
∞	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table I.XIII: **Historical shock decomposition, Contribution to GDP** Baseline model, signals on risk shock

	2007		2008		2009		2010	
	mean	mode	mean	mode	mean	mode	mean	mode
Financial shocks	2.19	1.71	-2.95	-2.67	-5.70	-5.19	0.18	0.17
$\sigma_t^{unantic}$	-0.40	0.00	-0.41	0.00	0.16	0.00	0.46	0.00
σ_t^{antic}	1.15	0.33	-4.23	-4.35	-5.30	-4.72	1.01	1.4
γ_t	1.43	1.39	1.69	1.68	-0.56	-0.48	-1.30	-1.23
Technology shocks	-2.36	-1.93	1.55	1.91	1.01	0.84	1.23	1.56
ε_t	0.61	0.79	0.71	0.93	-0.10	-0.25	0.94	1.23
$\mu_{z^*,t}$	-0.68	-0.64	0.33	0.34	-0.01	-0.01	-0.53	-0.47
$\zeta_{I,t}$	-2.29	-2.08	0.52	0.65	1.12	1.10	0.82	0.80
Demand shocks	2.27	2.17	-1.22	-1.26	1.41	1.48	-0.06	-0.12
g	1.28	1.71	0.05	0.04	1.41	1.45	-0.25	-0.35
$\zeta_{c,t}$	1.00	0.91	-1.27	-1.30	0.00	0.03	0.19	0.23
Markup shocks	-0.03	0.10	0.22	-0.50	-0.10	-0.65	0.24	-0.17
$\mu_{\Upsilon,t}$	-0.02	-0.04	0.32	0.31	-0.03	-0.04	0.23	0.24
$\lambda_{f,t}$	0.00	0.14	-0.10	-0.80	-0.07	-0.61	0.01	-0.42
Monetary shocks ε^p	-0.35	-0.33	0.59	0.70	1.42	1.56	0.45	0.60
All shocks (data)	1.73	1.73	-1.81	-1.81	-1.95	-1.95	2.04	2.04

Table I.XIV: **Historical shock decomposition, Contribution to GDP** Signals on the technology shocks

	2007		2008		2009		2010	
	mean	mode	mean	mode	mean	mode	mean	mode
Financial shocks	-0.23	-0.36	1.00	0.78	-1.33	-1.15	-0.76	-0.54
σ_t	-0.62	-0.62	0.29	0.18	-0.10	-0.13	-0.52	-0.42
γ_t	0.39	0.26	0.71	0.60	-1.23	-1.03	-0.25	-0.12
Technology shocks	2.62	2.57	-5.31	-5.00	-3.05	-3.18	4.88	4.61
$\varepsilon_t^{unantic}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ε_t^{antic}	-0.53	-0.44	-2.06	-1.80	1.39	1.28	2.45	2.25
$\mu_{z^*,t}^{unantic}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mu_{z^*,t}^{antic}$	4.27	3.94	-4.67	-4.43	-0.76	-0.70	2.80	2.49
$\zeta_{I,t}^{unantic}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\zeta_{I,t}^{antic}$	-1.12	-0.93	1.41	1.23	-3.68	-3.76	-0.38	-0.12
Demand shocks	0.48	0.62	-0.79	-0.69	1.73	1.78	0.67	0.60
g	0.89	0.94	-0.79	-0.69	1.73	1.78	0.67	0.60
$\zeta_{c,t}$	-0.41	-0.32	-0.29	-0.22	-0.10	-0.08	0.27	0.22
Markup shocks	-0.49	-0.51	-0.27	-0.28	-1.11	-1.14	-0.86	-0.86
$\mu_{\Upsilon,t}$	0.00	0.00	0.35	0.35	-0.10	-0.10	0.12	0.13
$\lambda_{f,t}$	-0.49	-0.51	-0.62	-0.63	-1.01	-1.04	-0.99	-0.99
Monetary shocks ε^p	-0.66	-0.59	3.56	3.37	1.81	1.73	-1.88	-1.77
All shocks (data)	1.73	1.73	-1.81	-1.81	-1.95	-1.95	2.04	2.04

Table I.XV: **Historical shock decomposition, Contribution to GDP** Signals on the technology and risk shocks

	2007		2008		2009		2010	
	mean	mode	mean	mode	mean	mode	mean	mode
Financial shocks	2.69	2.79	-2.39	-2.31	-5.63	-5.65	-0.43	-0.54
$\sigma_t^{unantic}$	-0.11	0.00	-0.12	0.00	0.04	0.00	0.12	0.00
σ_t^{antic}	1.12	1.01	-4.23	-4.38	-5.29	-5.31	0.79	0.85
γ_t	1.68	1.78	1.96	2.07	-0.37	0.34	-1.34	-1.40
Technology shocks	-2.77	-2.83	0.85	0.72	0.72	0.60	1.59	1.63
ε_t	0.48	0.50	0.65	0.68	-0.07	-0.06	0.83	0.86
$\mu_{z^*,t}$	-0.62	-0.59	0.31	0.31	-0.03	-0.03	-0.45	-0.45
$\zeta_{I,t}^{unantic}$	-0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
$\zeta_{I,t}^{antic}$	-2.62	-2.73	-0.12	-0.27	0.81	0.68	1.20	1.23
Demand shocks	2.23	2.24	-1.17	-1.13	1.48	1.52	0.01	-0.01
g	1.35	1.35	0.10	0.11	1.49	1.53	-0.34	-0.37
$\zeta_{c,t}$	0.88	0.90	-1.27	-1.24	-0.01	-0.01	0.35	0.36
Markup shocks	-0.01	-0.01	0.31	0.32	-0.03	0.00	0.29	0.32
$\mu_{\Upsilon,t}$	-0.03	-0.04	0.32	0.31	-0.03	-0.03	0.24	0.26
$\lambda_{f,t}$	0.02	0.02	-0.01	0.00	0.00	0.03	0.04	0.06
Monetary shocks ε^p	-0.41	-0.45	0.60	0.60	1.50	1.59	0.58	0.66
All shocks (data)	1.73	1.73	-1.81	-1.81	-1.95	-1.95	2.04	2.04

Table I.XVI: Mariginal Likelihood of the baseline model and the alternative specifications based

Model	*Marginal Likelihood*	
	Laplace approximation	Modified harmonic mean
Parsimonious models		
News on risk shock (Baseline)	3502.94	3506.55
News on equity shock	3471.89	3437.77
News on monetary policy shock	3438.48	3417.77
News on marginal eff. of invest. shock	3402.09	3379.33
Non-parsimonious models		
News on marginal eff. of invest. and risk shocks	3510.78	3510.88
News on permanent technology and risk shocks	3510.22	3487.11
News on temporary technology and risk shocks	3502.58	3473.63
News on technology (3) shocks	3469.43	2935.14

Table I.XVII: **Unconditional Variance decomposition (in percent)** Flexible price and wage

	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
GDP	2.72	0.86	0.02	0.32	0.01	31.23	0.00	0.04	1.81	0.00	20.23	41.75	1.00
Investment	3.52	0.30	0.02	0.47	0.00	18.92	0.00	0.04	2.24	0.00	23.86	49.15	1.48
Consumption	2.93	0.45	0.01	0.62	0.00	42.27	0.00	0.07	2.38	0.00	15.90	32.73	2.63
Term spread	3.36	0.36	0.02	0.62	0.00	18.96	0.00	0.05	2.21	12.80	19.10	39.79	2.74
Premium	3.97	0.32	0.02	0.62	0.00	18.22	0.00	0.10	1.76	0.00	24.36	50.42	0.19
Networth	3.81	0.32	0.02	0.60	0.00	18.10	0.00	0.02	0.55	0.00	24.90	51.51	0.17
Credit	6.84	0.34	0.04	1.07	0.00	22.40	0.00	0.26	3.43	0.00	20.85	43.50	1.26
Inflation	5.77	0.32	0.05	0.94	0.00	19.96	0.00	0.13	1.47	0.00	21.37	49.09	0.90
Wage	3.62	0.10	0.01	3.65	0.00	40.37	0.00	0.08	0.96	0.00	16.51	34.14	0.57
Hours	3.31	0.89	0.02	0.41	0.00	16.34	0.00	0.09	2.61	0.00	23.83	49.03	3.47
Interest rate	0.15	0.02	0.00	0.02	0.00	0.74	0.00	0.00	0.07	0.00	0.89	97.98	0.12
Rel. price of invest.	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table I.XVIII: **Estimated parameter posteriors** Observable risk shock

		EPU index			VIXC index		
		mean	90% c.i.	90% c.i.	mean	90% c.i.	90% c.i.
	Economic parameters						
ξ_p	Calvo price rigidity	0.86	0.83	0.89	0.82	0.75	0.89
ξ_w	Calvo wage rigidity	0.77	0.73	0.80	0.69	0.60	0.77
b	Habit parameter	0.87	0.84	0.89	0.75	0.62	0.88
$F(\bar{\omega})$	Steady state probability of default	0.0044	0.0036	0.0053	0.0043	0.0026	0.0061
μ	Monitoring cost	0.196	0.170	0.229	0.107	0.072	0.139
σ_a	Curvature, utilization cost	0.04	-0.01	0.09	1.13	-0.0053	2.35
S''	Curvature, invest. adjust. cost	18.02	16.08	21.23	9.13	6.63	11.56
l_w	Wage indexing weight on inflation target	0.44	0.28	0.65	0.53	0.30	0.77
l	Price indexing weight on inflation target	0.85	0.75	0.97	0.83	0.75	0.93
l_μ	Wage indexing weight on $\mu_{z^*,t}$	0.92	0.87	0.97	0.90	0.84	0.95
α_π	Monetary policy weight on inflation	2.26	1.58	3.03	1.95	1.65	2.34
$\alpha_{\Delta y}$	Monetary policy weight on output growth	0.65	0.46	0.87	0.55	0.29	0.79
$\tilde{\rho}$	Monetary policy smoothing parameter	0.87	0.84	0.90	0.80	0.75	0.86

Table I.XIX: **Estimated parameter posteriors** Observable risk shock (continued)

		EPU index			VIXC index		
		mean	90% c.i.	90% c.i.	mean	90% c.i.	90% c.i.
	Shock processes						
ρ_{ε}	Autocorrelation, temporary tech. shock	0.96	0.95	0.97	0.87	0.79	0.97
$\rho_{\mu_{z^*}}$	Autocorrelation, permanent tech. shock	0.14	0.11	0.17	0.10	0.01	0.16
$\rho_{\mu_{\Upsilon}}$	Autocorrelation, invest. good shock	0.96	0.94	0.97	0.82	0.75	0.95
ρ_{λ_f}	Autocorrelation, markup shock	0.82	0.78	0.87	0.73	0.45	0.99
ρ_{ζ_I}	Autocorrelation, marg. eff. of invest.	0.82	0.79	0.86	0.80	0.75	0.85
ρ_{ζ_c}	Autocorrelation, preference shock	0.39	0.24	0.51	0.62	0.44	0.89
ρ_{η}	Autocorrelation, term structure shock	0.89	0.85	0.94	0.93	0.90	0.98
ρ_{g}	Autocorrelation, govern. spending shock	0.99	0.98	0.99	0.91	0.87	0.96
ρ_{σ}	Autocorrelation, risk shock	0.96	0.95	0.97	0.95	0.90	0.98
$\rho_{\sigma,n}$	Correlation, signals (anticipated)	0.41	0.32	0.47	0.25	0.07	0.41
	Standard deviation of shock innovations						
σ_{ε}	Temporary tech. shock	0.0071	0.0068	0.0074	0.0075	0.0059	0.0089
$\sigma_{\mu_{z^*}}$	Permanent tech. shock	0.0068	0.0062	0.0074	0.0070	0.0056	0.0081
$\sigma_{\mu_{\Upsilon}}$	Invest. good shock	0.0023	0.0019	0.0028	0.0017	0.0010	0.0026
σ_{λ_f}	Markup shock	0.0303	0.0176	0.0424	0.0354	0.0078	0.0691
σ_{ζ_I}	Marg. eff. of invest. shock	0.0373	0.317	0.407	0.0467	0.0402	0.0532
σ_{ζ_c}	Preference shock	0.0261	0.0216	0.0294	0.0187	0.0095	0.0276
σ_{η}	Term structure shock	0.0034	0.0019	0.0048	0.0017	0.0008	0.0026
σ_{g}	Govern. spending shock	0.0108	0.0089	0.0134	0.0128	0.0110	0.0153
σ_{γ}	Equity shock	0.0251	0.0236	0.0264	0.0476	0.0437	0.0510
σ_{ε^p}	Monetary pol. shock	0.5238	0.4435	0.5772	0.4038	0.3367	0.4807
$\sigma_{\sigma,0}$	Risk shock (unanticipated)	0.0014	0.0007	0.0025	0.0019	0.0004	0.0035
$\sigma_{\sigma,n}$	Signals (anticipated)	0.0634	0.0585	0.0668	0.0886	0.0781	0.0971
	Measurement error on networth	0.0375	0.0375	0.0375	0.0339	0.0335	0.0344

Table I.XX: **Variance decomposition (in percent)** Observable risk shock, VICX index

GDP	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	4.39	4.28	2.18	14.30	0.01	4.80	0.00	0.00	49,57	0.00	2.46	0.93	17.07
1	3.79	8.43	2.08	12.84	0.01	8.60	0.00	0.00	39,31	0.00	3.12	1.30	20.53
4	4.42	4.84	2.22	15.10	0.01	5.37	0.00	0.00	46,56	0.00	2.64	0.83	17.99
8	4.41	4.64	2.18	15.35	0.01	5.18	0.00	0.00	47,6	0.00	2.51	0.95	17.16
Investment	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.75	0.00	2.97	6.03	0.00	0.21	0.00	0.00	56,84	0.00	2.13	0.03	31.02
1	1.23	0.01	2.76	7.27	0.00	0.26	0.00	0.00	63,37	0.00	1.82	0.07	23.20
4	1.11	0.00	2.89	7.56	0.00	0.26	0.00	0.00	61,28	0.00	1.94	0.05	24.90
8	1.24	0.01	2.81	8.16	0.00	0.30	0.00	0.00	61,56	0.00	1.87	0.06	24.00
Consumption	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	19.35	0.84	0.70	28.22	0.00	4.34	0.00	0.00	21,53	0.00	2.47	17.22	5.33
1	23.81	1.06	0.02	35.77	0.00	5.02	0.00	0.00	1,32	0.00	4.34	27.61	1.04
4	26.49	1.12	0.03	39.15	0.00	5.39	0.00	0.00	1,85	0.00	3.22	21.45	1.30
8	24.94	1.05	0.11	36.89	0.00	5.33	0.00	0.00	4,46	0.00	3.16	21.82	2.24
Spread	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	1.66	0.15	2.33	3.17	0.00	0.31	0.00	0.00	72,12	1.50	1.98	0.36	16.43
1	0.58	0.21	0.06	13.26	0.00	0.17	0.00	0.00	6,62	13.06	58.02	0.07	7.94
4	3.74	0.24	1.36	8.00	0.00	0.08	0.00	0.00	50,32	4.06	8.72	0.58	22.88
8	2.65	0.18	1.96	3.27	0.00	0.14	0.00	0.00	64,96	2.00	2.91	0.50	21.43
Premium	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.01	0.01	6.13	1.45	0.00	0.11	0.00	0.00	84,57	0.00	2.58	0.00	5.12
1	0.01	0.02	5.62	2.98	0.00	0.22	0.00	0.00	76,82	0.00	5.09	0.00	9.25
4	0.00	0.01	9.04	2.43	0.00	0.18	0.00	0.00	76,45	0.00	4.17	0.00	7.71
8	0.00	0.01	7.33	1.81	0.00	0.14	0.00	0.00	81,52	0.00	3.16	0.00	6.01
Networth	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.01	0.01	11.40	2.76	0.00	0.19	0.00	0.00	72,48	0.00	4.57	0.00	8.55
1	0.01	0.01	11.84	2.91	0.00	0.20	0.00	0.00	71,4	0.00	4.74	0.00	8.87
4	0.01	0.01	11.79	2.87	0.00	0.20	0.00	0.00	71,61	0.00	4.73	0.00	8.77
8	0.01	0.01	11.58	2.81	0.00	0.20	0.00	0.00	72,09	0.00	4.65	0.00	8.63

Table I.XXI: **Variance decomposition (in percent)** Observable risk shock, VIXC index (continued)

Credit	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	2.27	0.05	22.47	5.92	0.00	0.45	0.00	0.00	60,9	0.00	0.93	0.13	6.88
1	4.35	0.13	80.07	6.47	0.00	0.01	0.00	0.00	4,08	0.00	0.19	0.19	4.51
4	5.90	0.14	57.00	9.02	0.00	0.02	0.00	0.00	22,45	0.00	0.98	0.33	4.16
8	3.62	0.08	36.11	6.02	0.00	0.10	0.00	0.00	47,29	0.00	0.72	0.21	5.86
Inflation	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	9.59	0.37	1.81	9.52	0.00	0.67	0.00	0.00	56,78	0.00	2.62	0.77	17.87
1	20.42	0.52	0.82	22.11	0.00	0.29	0.00	0.00	33,74	0.00	1.89	0.87	19.34
4	14.07	0.44	1.33	11.73	0.00	0.37	0.00	0.00	47,57	0.00	2.55	0.94	20.99
8	10.97	0.39	1.69	8.66	0.00	0.44	0.00	0.00	54,45	0.00	2.78	0.88	19.73
Wage	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	6.15	0.03	0.24	30.95	0.00	54.64	0.00	0.00	6,52	0.00	0.13	0.04	1.32
1	4.72	0.03	0.00	16.78	0.00	78.28	0.00	0.00	0,05	0.00	0.00	0.01	0.12
4	6.42	0.03	0.02	27.96	0.00	64.80	0.00	0.00	0,49	0.00	0.03	0.02	0.21
8	6.36	0.03	0.07	30.84	0.00	60.08	0.00	0.00	1,93	0.00	0.06	0.02	0.61
Hours	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	1.66	0.74	1.13	41.50	0.00	0.55	0.00	0.00	34,54	0.00	1.13	0.24	18.53
1	31.26	7.81	0.70	4.26	0.01	2.66	0.00	0.00	1,53	0.00	0.02	1.26	50.49
4	6.43	2.64	0.38	18.40	0.00	0.54	0.00	0.00	23,95	0.00	1.25	1.01	45.39
8	2.44	1.32	0.92	24.98	0.00	0.23	0.00	0.00	35,36	0.00	1.49	0.49	32.76
Interest rate	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	4.61	0.35	2.35	4.30	0.00	1.34	0.00	0.00	69	0.00	1.73	0.64	15.68
1	6.43	0.85	0.91	4.49	0.00	0.75	0.00	0.00	30,82	0.00	39.76	0.80	15.18
4	7.24	0.53	1.78	3.13	0.00	0.76	0.00	0.00	56,96	0.00	6.20	1.01	22.40
8	5.41	0.40	2.18	1.35	0.00	0.78	0.00	0.00	65,94	0.00	2.43	0.85	20.65

Table I.XXII: **Variance decomposition (in percent)** Observable risk shock, EPU index

GDP	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	2.09	2.44	0.89	0.80	0.18	1.80	0.00	0.00	71,41	0.00	1.67	0.93	17.79
1	1.06	6.28	0.91	0.48	0.35	4.05	0.00	0.00	61,65	0.00	1.83	2.13	21.26
4	1.59	2.95	0.94	0.68	0.19	2.08	0.00	0.00	69,13	0.00	1.79	1.04	19.61
8	2.03	2.68	0.94	0.71	0.19	1.94	0.00	0.00	70,26	0.00	1.73	0.99	18.52
Investment	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.71	0.01	1.01	0.36	0.04	0.00	0.00	0.00	76,47	0.00	1.37	0.00	20.03
1	0.30	0.00	1.11	0.21	0.02	0.00	0.00	0.00	71,18	0.00	1.56	0.00	25.61
4	0.48	0.00	1.07	0.30	0.03	0.00	0.00	0.00	74,39	0.00	1.48	0.00	22.25
8	0.68	0.01	1.07	0.33	0.04	0.00	0.00	0.00	75,36	0.00	1.45	0.00	21.07
Consumption	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	21.20	0.84	0.18	4.99	0.04	11.70	0.00	0.00	6,67	0.00	1.14	50.17	3.08
1	9.54	0.37	0.05	2.44	0.01	4.75	0.00	0.00	0,55	0.00	1.04	80.22	1.03
4	19.39	0.74	0.10	4.58	0.02	9.89	0.00	0.00	0,76	0.00	1.31	61.38	1.82
8	21.81	0.86	0.09	4.38	0.02	12.00	0.00	0.00	0,85	0.00	1.18	57.01	1.78
Spread	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	10.70	0.02	0.37	26.83	0.03	0.06	0.00	0.00	35,69	5.92	12.77	0.04	7.58
1	1.55	0.05	0.07	5.01	0.06	0.10	0.00	0.00	1,39	24.86	66.16	0.03	0.70
4	1.78	0.04	0.04	32.91	0.03	0.04	0.00	0.00	5,44	16.89	41.56	0.06	1.21
8	5.53	0.02	0.13	39.40	0.02	0.03	0.00	0.00	17,11	10.40	23.69	0.05	3.63
Premium	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.04	0.00	2.02	0.03	0.02	0.01	0.00	0.00	91,71	0.00	1.49	0.00	4.68
1	0.00	0.00	1.90	0.03	0.04	0.01	0.00	0.00	87,63	0.00	2.98	0.00	7.40
4	0.00	0.00	3.08	0.02	0.03	0.01	0.00	0.01	87,82	0.00	2.52	0.00	6.49
8	0.00	0.00	2.43	0.02	0.03	0.01	0.00	0.01	90,59	0.00	1.84	0.00	5.08
Networth	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.00	0.00	3.59	0.02	0.04	0.01	0.00	0.00	86,42	0.00	2.82	0.00	7.11
1	0.00	0.00	3.71	0.01	0.04	0.01	0.00	0.00	85,99	0.00	2.91	0.00	7.32
4	0.00	0.00	3.72	0.02	0.04	0.01	0.00	0.00	86.00	0.00	2.93	0.00	7.27
8	0.00	0.00	3.64	0.02	0.04	0.01	0.00	0.00	86,28	0.00	2.87	0.00	7.15

Table I.XXIII: **Variance decomposition (in percent)** Observable risk shock, EPU index (continued)

Credit	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	0.99	0.01	8.96	2.16	0.04	0.01	0.00	0.00	81,61	0.00	0.55	0.00	5.66
1	1.01	0.00	48.68	6.39	0.01	0.00	0.00	0.00	41,54	0.00	1.17	0.00	1.18
4	1.34	0.00	19.99	5.03	0.01	0.00	0.00	0.00	72,01	0.00	0.50	0.00	1.11
8	1.01	0.00	11.98	2.90	0.01	0.00	0.00	0.00	80,70	0.00	0.37	0.00	3.03
Inflation	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	19.10	0.07	0.25	58.03	0.02	0.18	0.00	0.00	15,81	0.00	1.21	0.03	5.29
1	11.39	0.00	0.05	83.39	0.00	0.09	0.00	0.00	3,52	0.00	0.28	0.01	1.27
4	15.59	0.01	0.09	74.76	0.00	0.13	0.00	0.00	6,54	0.00	0.52	0.02	2.33
8	18.68	0.01	0.15	65.80	0.01	0.17	0.00	0.00	10,65	0.00	0.83	0.03	3.70
Wage	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	5.86	0.00	0.02	16.27	0.00	75.14	0.00	0.00	1,92	0.00	0.13	0.04	0.62
1	2.85	0.00	0.00	15.06	0.00	82.01	0.00	0.00	0.00	0.00	0.01	0.03	0.02
4	4.36	0.00	0.00	15.89	0.00	78.61	0.00	0.00	0,68	0.00	0.08	0.04	0.33
8	5.10	0.00	0.01	15.66	0.00	77.29	0.00	0.00	1,30	0.00	0.11	0.04	0.49
Hours	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	5.07	2.42	1.33	0.92	0.18	0.87	0.00	0.00	56,51	0.00	1.99	0.16	30.54
1	31.47	4.71	0.73	0.39	0.08	2.00	0.00	0.00	12,52	0.00	0.51	1.58	46.02
4	10.75	2.24	0.22	1.06	0.02	0.92	0.00	0.00	30,57	0.00	0.73	1.02	52.47
8	4.05	1.25	0.43	1.32	0.01	0.39	0.00	0.00	48,64	0.00	1.36	0.49	42.05
Interest rate	ε_t	g_t	γ_t	$\lambda_{f,t}$	$\mu_{\Upsilon,t}$	$\mu_{z^*,t}$	π_t^{target}	σ_t^{unant}	σ_t^{ant}	η_t	ε_t^p	$\zeta_{c,t}$	$\zeta_{i,t}$
∞	18.65	0.16	0.63	22.40	0.06	0.06	0.00	0.00	37,49	0.00	9.09	0.05	11.41
1	2.55	0.20	0.07	15.91	0.00	0.03	0.00	0.00	5,21	0.00	74.06	0.09	1.85
4	8.55	0.11	0.23	35.60	0.00	0.01	0.00	0.00	17,50	0.00	32.32	0.09	5.59
8	13.03	0.08	0.37	34.31	0.01	0.02	0.00	0.00	27,34	0.00	16.64	0.07	8.14

Table I.XXIV: **Historical shock decomposition, Contribution to GDP** VIXC index

	2007	2008	2009	2010
Financial shocks	1.72	-0.15	-3.08	-1.98
$\sigma_t^{unantic}$	0.00	0.00	0.00	0.00
σ_t^{antic}	-0.02	-2.77	-3.69	0.18
γ_t	1.74	2.62	0.61	-2.16
Technology shocks	-1.30	-0.93	-1.98	3.58
ε_t	0.43	0.94	-0.54	1.06
$\mu_{z^*,t}$	-0.44	0.35	0.17	-0.41
$\zeta_{I,t}$	-1.29	-2.21	-1.61	2.93
Demand shocks	1.88	-1.19	1.40	-0.32
g	1.12	0.27	1.52	-0.79
$\zeta_{c,t}$	0.76	-1.46	-0.12	0.46
Markup shocks	0.05	-0.59	-0.55	-0.38
$\mu_{\Upsilon,t}$	0.02	0.00	0.01	-0.02
$\lambda_{f,t}$	0.04	-0.59	-0.56	-0.35
Monetary shocks ε^p	-0.86	0.85	2.07	0.97
All shocks (data)	1.45	-2.10	-2.24	1.76

Table I.XXV: **Historical shock decomposition, Contribution to GDP** EPU index

	2007	2008	2009	2010
Financial shocks	-1.72	-0.63	-2.85	-1.60
$\sigma_t^{unantic}$	0.00	0.00	0.00	0.00
σ_t^{antic}	-1.17	-0.96	-3.06	-0.20
γ_t	-0.56	0.33	0.21	-1.80
Technology shocks	2.63	-0.01	-2.46	3.12
ε_t	1.43	1.89	0.61	2.53
$\mu_{z^*,t}$	-0.56	0.06	-0.58	-0.93
$\zeta_{I,t}$	1.76	-1.96	-2.49	1.53
Demand shocks	1.83	-1.20	1.21	-0.06
g	1.09	0.39	1.62	-0.46
$\zeta_{c,t}$	0.75	-1.59	-0.41	0.40
Markup shocks	-0.38	-0.81	-0.28	-0.68
$\mu_{\Upsilon,t}$	0.05	0.01	0.05	-0.02
$\lambda_{f,t}$	-0.42	-0.82	-0.33	-0.66
Monetary shocks ε^p	-0.93	0.57	2.16	1.02
All shocks (data)	1.73	-1.81	-1.95	2.04

Appendix II

Details on the dataset used for the estimation of the model

Consumption : The sum of household final consumption expenditure of non-durable goods, semi-durable goods and services from Cansim Table 380-0064 Gross domestic product, expenditure-based, quarterly (dollars x 1,000,000), chained (2007) dollars, seasonally adjusted at annual rates.

Investment : The sum of business gross fixed capital formation (Non-residential structures, machinery and equipment, plus Intellectual property products) and household final consumption expenditure of durable goods from Cansim Table 380-0064 Gross domestic product, expenditure-based, quarterly (dollars x 1,000,000), chained (2007) dollars, seasonally adjusted at annual rates

GDP : Sum of consumption, investment (as they are defined above) and government spending. Government spending is the sum of General governments final consumption expenditure and General governments gross fixed capital formation from Cansim Table 380-0064 Gross domestic product, expenditure-based, quarterly (dollars x 1,000,000), chained (2007) dollars, seasonally adjusted at annual rates.

Real wage : Total compensation per hour worked from Cansim Table 383-0008 Indexes of labour productivity, unit labour cost and related variables, seasonally adjusted, quarterly (index, 2007=100), business sector.

Hours worked : Total actual hours worked all industries from the Cansim Table 282-0092 Labour force survey estimates (LFS), actual hours worked at main job by North American Industry Classification System (NAICS), seasonally adjusted, montly (hours x 1,000) Canada [1].

Interest rate : Bankers' acceptances 3 month from the Cansim Table 176-0043 Financial market statistics, last Wednesday unless otherwise stated, Bank of Canada, monthly (percent unless otherwise noted) [2].

---

1. Another candidate for the hours worked is an index for the total hours worked in the business sector from the Cansim Table 383-0008. The two series are very similar.
2. Other candidates for the risk-free interest rate are the Overnight money market financing, the the

Relative price of investment : The logarithmic first difference of the ratio of the IPD of investment over the GDP IPD. The IPD of investment is a weighted sum of the IPDs of business gross fixed capital formation (Non-residential structures, machinery and equipment) and of household final consumption expenditure of durable goods. All IPDs are from Cansim Table 380-0066 Price indexes, gross domestic product, quarterly (2007=100 unless otherwise noted).

Inflation : The logarithmic first difference of the Bank of Canada's core index from Cansim Table 326-0022 Consumer Price Index, seasonally adjusted, monthly (2002=100).

Net worth : Standard and Poor's/Toronto Stock Exchange Composite Index, close from Cansim Table 176-0047 Toronto Stock Exchange statistics, Bank of Canada, monthly (index, 2000=1000 unless otherwise noted).

Credit: Other business credit from the Cansim Table 176-0032 Credit measures, Bank of Canada, monthly (dollars x 1,000,000).

Slope of the term structure : The difference between the 10-year Government of Canada benchmark bond yield from the Cansim Table 176-0043 Financial market statistics, last Wednesday unless otherwise stated, Bank of Canada, monthly (percent unless otherwise noted) and the risk-free interest rate as defined above.

Credit spread : The difference between the Chartered bank administered interest rates - prime business and the 10-year Government of Canada benchmark bond yield, both from the Cansim Table 176-0043 Financial market statistics, last Wednesday unless otherwise stated, Bank of Canada, monthly (percent unless otherwise noted).

Bank rate or the Canadian three months Treasury bill as in Dib et al. (2013). They are all very similar.

Appendix III

Exhaustive list of the equilibrium conditions of the model

This appendix provides the exhaustive list of equations that characterize the estimated model. We present them as they appear in the Dynare code [1]. When we think it is useful, we provide simplified versions of the equations. The estimated model is composed of 4 groups of equations. First, auxiliary equations are used to simplify the equilibrium conditions without using additional variables. The second group is composed of the 23 equilibrium conditions from the solution of the model, plus three additional equations. The third group contains the equations that relate the observable variables to the model variables. The idea is to make sure that the same transformation are performed to the data (observable variables) and the variables of the model. The fourth group of equations characterizes the shock processes [2].

Auxiliary equations

a- Definition of $\tilde{\pi}_t$ [3]:

$$\tilde{\pi}_t = (\pi_t^{target})^l (\pi_{t-1})^{1-l} (\bar{\pi})^{1-l-(1-l)} \tag{III.1}$$

which simplifies to (as in the model part of the paper):

$$\tilde{\pi}_t = (\pi_t^{target})^l (\pi_{t-1})^{1-l} \tag{III.2}$$

1. CMR provides an Online Technical Appendix along their paper. Section B lists the equilibrium conditions. However, these equations do not always directly map with the equilibrium conditions in the code. Our objective here is to represent all the equations in the model part of the code, as they appear in the Dynare code. When we refer to the CMR Appendix below, we mean the section B of the Online Technical Appendix.

2. In the Dynare code, an expression, ending with p1 means it is lead(+1). For instance, Kp = lag(Kpp1) and pitildew = lag(pitildewp1).

3. It appears in the price setting of non-optimizing intermediate firms.

b- Definition of several variables[4]:

$$F_t(\omega_{t+1}) = \Phi\left(\frac{\omega_{t+1} + \frac{\sigma^2}{2}}{\sigma}\right) \tag{III.3}$$

$$F_{t-1}(\omega_t) = \Phi\left(\frac{\omega_t + \frac{\sigma^2}{2}}{\sigma}\right) \tag{III.4}$$

$$G_t(\omega_{t+1}) = \Phi\left(\frac{\omega_{t+1} + \frac{\sigma^2}{2}}{\sigma} - \sigma\right) \tag{III.5}$$

$$G_{t-1}(\omega_t) = \Phi\left(\frac{\omega_t + \frac{\sigma^2}{2}}{\sigma} - \sigma\right) \tag{III.6}$$

c- The definition of d, the resources lost in monitoring:

$$d_t = \frac{\{[G_t(\omega_{t+1}) + \omega_{t+1}(1 - F_t(\omega_{t+1}))] - [(1-\mu)G_t(\omega_{t+1}) + \omega_{t+1}(1 - F_t(\omega_{t+1}))]\}(1 + R_t^k)q_{t-1}k_t}{\pi_t \mu_{z^*,t}} \tag{III.7}$$

which simplify to

$$d_t = \frac{[\mu G_t(\omega_{t+1}) + \omega_{t+1}(1 - F_t(\omega_{t+1}))](1 + R_t^k)q_{t-1}k_t}{\pi_t \mu_{z^*,t}} \tag{III.8}$$

In the CMR Appendix, it is:

$$d_t = \frac{\mu G_t(\omega_{t+1})(1 + R_t^k)q_{t-1}k_t}{\pi_t \mu_{z^*,t}} \tag{III.9}$$

d- Definition of $\pi_{w,t}$:

$$\pi_{w,t} = \pi \mu_{z^*,t} \frac{\tilde{w}_t}{\tilde{w}_{t-1}} \tag{III.10}$$

e- Definition of $\tilde{\pi}_{w,t}$[5]:

$$\tilde{\pi}_{w,t} = (\pi_t^{target})^{l_w}(\pi_{t-1})^{1-l_w}(\bar{\pi}_t)^{1-l_w-(1-l_w)} \tag{III.11}$$

4. They relate to the distribution of the risk shock. In the code, they are, respectively, Fp1, F, Gp1, G. Note that Gprp1 in the code is the derivative of Gp1

5. It appears in the price setting of non-optimizing intermediate firms.

which simplifies to (as in the model part of the paper):

$$\tilde{\pi}_{w,t} = (\pi_t^{target})^{l_w} (\pi_{t-1})^{1-l_w} \tag{III.12}$$

f- The definition of S, the adjustment cost function:

$$S = exp\left[\sqrt{\frac{S''}{2}}\left(\zeta_{I,t}\mu_{z^*}\Upsilon\frac{i_t}{i_{t-1}} - \mu_{z^*}\Upsilon\right)\right] + exp\left[-\sqrt{\frac{S''}{2}}\left(\zeta_{I,t}\mu_{z^*}\Upsilon\frac{i_t}{i_{t-1}} - \mu_{z^*}\Upsilon\right)\right] - 2 \tag{III.13}$$

g- The definition of S'_t [6]:

$$S'_t = \sqrt{\frac{S''}{2}}\left\{exp\left[\sqrt{\frac{S''}{2}}\left(\zeta_{I,t}\mu_{z^*}\Upsilon\frac{i_t}{i_{t-1}} - \mu_{z^*}\Upsilon\right)\right] + exp\left[-\sqrt{\frac{S''}{2}}\left(\zeta_{I,t}\mu_{z^*}\Upsilon\frac{i_t}{i_{t-1}} - \mu_{z^*}\Upsilon\right)\right]\right\} \tag{III.14}$$

f- The definition of $\Gamma_t(\omega_{t+1})$

$$\Gamma_t(\omega_{t+1}) = \omega_{t+1}[1 - F_t(\omega_{t+1})] + G_t(\omega_{t+1}) \tag{III.15}$$

Equilibrium conditions

The 23 equilibrium conditions as they appear in the Dynare code [7].

6. It is Spr in the code.
7.
- Eq. 12 (resource constraint) in the CMR Appendix is the CEE version. The Eq. B23 in the CMR Appendix is the correct one.
- Eq. 16 (FOC for capiltal) in the CMR Appendix is the CEE version. The one in the code is a lot different.
- Eq. 22 (zero profit condition) is a little different in the CMR Appendix. However, it can be simplified to the one in the code using the definition of the share of entrepreneurial earnings received by bank (p.9).
- Eq. 23 (law of motion of networth) is different in the CMR Appendix. However, it can be simplified using the definition of G and the share of entrepreneurial earnings (p.9).
- Eq. 20 (monetary policy) is very different in the CMR Appendix. It is a lot more complicated in the code and it uses additional parameters (not defined, and calibrated). Also, the monetary policy in the code expand y_t using Eq. 21.

Eq. 1 Law of motion for p^*:

$$p_t^* - \left[(1-\xi_p(\frac{K_{p,t}}{F_{p,t}})^{\frac{\lambda_f}{1-\lambda_f}} + \xi_p(\frac{\tilde{\pi}_t}{\pi_t}p_{t-1}^*)^{\frac{\lambda_f}{1-\lambda_f}}\right]^{\frac{1-\lambda_f}{\lambda_f}} = 0 \tag{III.16}$$

Eq. 2 Law of motion for F_p:

$$E_t\left\{\zeta_{c,t}\lambda_{z,t}y_{z,t} + \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}}\right)^{\frac{1}{1-\lambda_f}}\beta\xi_p F_{p,t+1} - F_{p,t}\right\} = 0s \tag{III.17}$$

Eq. 3 Law of motion for K_p

$$\zeta_{c,t}\lambda_{z,t}\lambda_f y_{z,t}s_t + \beta\xi_p(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}})^{\frac{\lambda_f}{1-\lambda_f}}K_{p,t+1} - K_{p,t} = 0 \tag{III.18}$$

Eq. 4 Relationship between K_p and F_p:

$$K_{p,t} = F_{p,t}\left\{\frac{\left[1-\xi_p\left(\frac{\tilde{\pi}_t}{\pi}\right)^{\frac{1}{1-\lambda_f}}\right]}{1-\xi_p}\right\}^{1-\lambda_f} \tag{III.19}$$

Eq. 5 Law of motion for F_w:

$$\begin{aligned} &\zeta_{c,t}\lambda_{z,t}\frac{(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}h_t(1-\tau_t^l)}{\lambda_w} + \\ \beta\xi_w(\mu_{z^*})^{\frac{1-l\mu}{1-\lambda_w}}E_t(\mu_{z^*,t+1})^{\frac{l\mu}{1-\lambda_w}-1}&\left(\frac{1}{\pi_{w,t+1}}\right)^{\frac{\lambda_w}{1-\lambda_w}}\frac{\tilde{\pi}_{w,t+1}^{\frac{1}{1-\lambda_w}}}{\pi_{t+1}}F_{w,t+1} - F_{w,t} = 0 \end{aligned} \tag{III.20}$$

Eq. 6 Law of motion for K_w:

$$\zeta_{c,t}\zeta_t\left[(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}h_t\right]^{1+\sigma_L} + \beta\xi_w\left(\frac{\tilde{\pi}_{w,t+1}}{\pi_{w,t+1}}(\mu_{z,t+1}^*)^{l_\mu}(\mu_z^*)^{1-l_\mu}\pi_{w,t+1}\right)^{\frac{\lambda_w}{1-\lambda_w}(1+\sigma_L)}K_{w,t+1} - K_{w,t} = 0 \tag{III.21}$$

Eq. 7 Relationship between F_w and K_w:

$$K_{w,t} = \frac{\tilde{w}_t F_{w,t}}{\Psi_L} \left\{ \frac{1 - \xi_w \left[\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}} \mu_{z^*}^{1-l_w} \mu_{z^*,t}^{l_w} \right]^{\frac{1}{1-\lambda_w}}}{1 - \xi_w} \right\}^{1-\lambda_w(1+\sigma_L)} \tag{III.22}$$

Eq. 8 Law of motion of w^*:

$$w_t^* = \left[(1-\xi_w) \left(\frac{1 - \xi_w \left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}} (\mu_{z^*})^{1-l_\mu} (\mu z^*, t)^{l_\mu} \right)}{1 - \xi_w} \right)^{\lambda_w} + \xi_w \left(\frac{\tilde{\pi}_{w,t} (\mu_{z^*,t})^{l_\mu} (\mu_z^*)^{1-l_\mu}}{\pi_{w,t}} w_{t-1}^* \right)^{\frac{\lambda_w}{1-\lambda_w}} \right]^{\frac{1-\lambda_w}{\lambda_w}} \tag{III.23}$$

Eq. 9 Efficiency condition for setting capital utilization:

$$r_t^k = \tau^o r^k exp(\sigma_\alpha [u-1]) \tag{III.24}$$

Eq. 10 Rental rate on capital:

$$r_t^k = \frac{\alpha \varepsilon_t}{[1 + \Psi_{k,t} R_t]} \left(\frac{\Upsilon \mu_{z^*,t} L_t (w_t^*)^{\frac{\lambda_w}{\lambda_w - 1}}}{u_t k_t}^{1-\alpha} s_t \right) \tag{III.25}$$

Eq. 11 Marginal cost:

$$s_t = \frac{1}{\varepsilon_t} \left(\frac{r_t^k}{\alpha} \right)^{\alpha} \left(\frac{\tilde{w}_t}{1-\alpha} \right)^{1-\alpha} \tag{III.26}$$

Eq. 12 Resource constraint (Eq. B23 in the CMR Appendix):

$$y_{z,t} = d_t + c_t + g_t + \frac{i_t}{\mu_{\Upsilon,t}} + \Theta \frac{1-\gamma_t}{\gamma_t} [n_{t+1} - w^e] + \tau^o a(u_t) \frac{k_t}{\Upsilon \mu_{z^*,t}} \tag{III.27}$$

Eq. 13 Law of motion for capital:

$$k_{t+1} = (1-\delta) \frac{1}{\mu_{z^*,t} \Upsilon} k_t + [1-S]\, i_t \tag{III.28}$$

Eq.14 Household First order condition (FOC) with respect to risk-free bonds:

$$E_t \left\{ \beta \frac{1}{\pi_{t+1}\mu_{z^*,t+1}} \zeta_{c,t+1}\lambda_{z,t+1}(1+R_t) - \zeta_{c,t}\lambda_{z,t} \right\} = 0 \tag{III.29}$$

Eq.15 Household FOC with respect to consumption:

$$E_t \left[(1+\tau^C)\zeta_{c,t}\lambda_{z,t} - \frac{\mu_{z^*,t}\zeta_{c,t}}{c_t\mu_{z^*,t} - bc_{t-1}} + b\beta \frac{\zeta_{c,t+1}}{c_{t+1}\mu^*_{z,t+1} - bc_t} \right] = 0 \tag{III.30}$$

Eq. 16 FOC for capital (Not in the CMR Appendix):

$$\begin{gathered} \frac{(1-\Gamma_t(\omega_{t+1}))(1+R^k_{t+1})}{1+R_t} + \\ \frac{1-\Gamma_t(\omega_{t+1})}{1-\Gamma_t(\omega_{t+1}) - \mu\frac{F_t(\omega_{t+1})}{\sigma}} \left(\frac{(1+R^k_{t+1})}{1+R_t}(\Gamma_t(\omega_{t+1}) - \mu G'_t(\omega_{t+1})) - 1 \right) = 0 \end{gathered} \tag{III.31}$$

Eq. 17 Definition of R^k_t, the return of entrepreneurs

$$1+R^k_t = \frac{(1-\tau^k_{t-1})[u_t r^k_t - \tau^o a(u_t)] + (1-\delta)q_t}{\Upsilon q_{t-1}}\pi_t + \tau^k_{t-1}\delta \tag{III.32}$$

Eq. 18 Household FOC with respect to investment:

It is slightly different in the CMR Appendix (Spr is S'_t and Sprp1 is S'_{t+1}):

$$\begin{gathered} \zeta_{c,t}\lambda_{z,t}q_t \left\{ 1 - S_t - S'_t \left[\frac{\zeta_{i,t}\mu_{z^*,t}\Upsilon i_t}{i_{t-1}} \right] \right\} - \frac{\zeta_{c,t}\lambda_{z,t}}{\mu_{\Upsilon,t}} + \\ \frac{\beta\lambda_{z,t+1}\zeta_{c,t+1}q_{t+1}}{\mu_{z^*,t+1}\Upsilon} S'_{t+1} \left[\frac{\zeta_{i,t+1}\mu_{z^*,t+1}\Upsilon i_{t+1}}{i_t} \right]^2 = 0 \end{gathered} \tag{III.33}$$

Eq. 19 Definition of the scaled representation of aggregate output:

$$y_{z,t} = (p^*_t)^{\frac{\lambda_f}{\lambda_f - 1}} \left\{ \left[\varepsilon \frac{uk_t}{\mu_{z^*,t}\Upsilon} \right]^{\alpha} \left[(h_t)(w^*_t)^{\frac{\lambda_f}{\lambda_f - 1}} \right]^{1-\alpha} - \phi \right\} \tag{III.34}$$

Eq. 20 Monetary policy rule [8]:

$$
\begin{aligned}
log(\frac{R_t}{R}) &= \tilde{\rho} log(\frac{R_{t-1}}{R}) \\
&+ \frac{1}{R}(1-\tilde{\rho})\pi log(\frac{\pi_t^{target}}{\pi}) \\
&+ \frac{1}{R}(1-\tilde{\rho})\tilde{\alpha}_\pi \pi (log(\pi_{t+1}) - log(\pi_t^{target})) \\
&+ \frac{1}{4*R}(1-\tilde{\rho})\alpha_{\Delta y}\mu_{z^*}\left\{ \frac{c*log(\frac{c_t}{c_{t-1}}) + i*[log(\frac{i_t}{i_{t-1}}) - log(\frac{\mu_{\Upsilon,t}}{\mu_{\Upsilon,t-1}})] + g*log(\frac{g_t}{g_{t-1}})}{\frac{c+i}{1-\eta_g}} + log(\frac{\mu_{z^*,t}}{\mu_{z^*,t}}) \right\} \\
&+ \frac{1}{R}(1-\tilde{\rho})\tilde{\alpha}_c^{pp}\mu_{z^*}\left[log(\frac{q_t k_{t+1} - n_{t+1}}{q_{t-1}k_t - n_t}) + log(\frac{\mu_{z^*,t}}{\mu_{z^*}}) \right] \\
&+ \frac{1}{R}(1-\tilde{\rho})\tilde{\alpha}_d^{pp} log(\frac{\pi_t}{\pi_{t-1}}) \\
&- \frac{1}{4*R}(1-\tilde{\rho})\tilde{\alpha}_y^{pp}\left[\frac{c*log(\frac{c_t}{c}) + i*[log(\frac{i_t}{i}) - log(\mu_{\Upsilon,t})] + g*log(\frac{g_t}{g})}{\frac{c+i}{1-\eta_g}} \right] \\
&+ \frac{1}{400*R}\varepsilon_t^p
\end{aligned}
\tag{III.35}
$$

which reduces to [9]:

$$
\begin{aligned}
log\left(\frac{R_t}{R}\right) &= \tilde{\rho} log\left(\frac{R_{t-1}}{R}\right) \\
&+ \frac{1}{R}(1-\tilde{\rho})\pi log\left(\frac{\pi_t^{target}}{\pi}\right) \\
&+ \frac{1}{R}(1-\tilde{\rho})\tilde{\alpha}_\pi \pi log\left(\frac{\pi_{t+1}}{\pi_t^{target}}\right) \\
&+ \frac{1}{4*R}(1-\tilde{\rho})\mu_{z^*}\alpha_{\Delta y}\left\{ \frac{c*log\left(\frac{c_t}{c_{t-1}}\right) + i*log\left(\frac{i_t}{i_{t-1}} - \frac{\mu_{\Upsilon,t}}{\mu_{\Upsilon,t-1}}\right) + g*log\left(\frac{g_t}{g_{t-1}}\right)}{\frac{c+i}{1-\eta_g}} + log\left(\frac{\mu_{z^*,t}}{\mu_{z^*,t}}\right) \right\} \\
&+ \frac{1}{400*R}\varepsilon_t^p
\end{aligned}
\tag{III.36}
$$

8. Actually, three parameters are set to 0 in the calibration, which simplifies the equation.
9. Because the calibration is such that $\tilde{\alpha}_c^{pp} = \tilde{\alpha}_d^{pp} = \tilde{\alpha}_y^{pp} = 0$.

which can further be simplified to:

$$\begin{aligned} log\left(\frac{R_t}{R}\right) &= \tilde{\rho} log\left(\frac{R_{t-1}}{R}\right) \\ +\frac{1}{R}(1-\tilde{\rho})\pi\left[log\left(\frac{\pi_t^{target}}{\pi}\right)+\tilde{\alpha}_\pi log\left(\frac{\pi_{t+1}}{\pi_t^{target}}\right)\right] \\ +\frac{1}{4*R}(1-\tilde{\rho})\mu_{z^*}\alpha_{\Delta y} log\left(\frac{y_t}{y}\right) \\ +\frac{1}{400*R}\varepsilon_t^p \end{aligned} \tag{III.37}$$

Eq. 21 The definition of GDP:

$$y_t = g_t + c_t + \frac{i_t}{\mu_{\Upsilon,t}} \tag{III.38}$$

Eq. 22 Zero profit condition:

$$q_{t-1}k_t(1+R_t^k)\left[\frac{(1-\mu)G_{t-1}(\omega_t)+\bar{\omega}_t(1-F_{t-1}(\omega_t))}{n_t(1+R_{t-1})}\right] - \frac{q_{t-1}k_t}{n_t} + 1 = 0 \tag{III.39}$$

Using little algebra, we can get the equation in the CMR Appendix:

$$q_t k_{t+1}(1+R_{t+1}^k)\left[\frac{\Gamma_t(\omega_{t+1})-\mu G_t(\omega_{t+1})}{n_t(1+R_{t-1})}\right] - \frac{q_t k_{t+1}}{n_{t+1}} + 1 = 0 \tag{III.40}$$

Eq. 23 Law of motion of networth

$$\begin{aligned} n_{t+1} = \frac{\gamma_t}{\pi_t\mu_{z^*,t}}\left\{R_t^k - R_{t-1} - \left[(G_{t-1}(\omega_t)+\bar{\omega}_t(1-F_{t-1}(\omega_t))) - ((1-\mu)G_{t-1}(\omega_t)+\bar{\omega}_t(1+F_{t-1}(\omega_t)))\right](1+R_t^k)\right\} k_t \\ +w^e + \gamma_t\left(\frac{1+R_t}{\pi_t\mu_{z^*}} \right. \end{aligned} \tag{III.41}$$

which simplifies to:

$$n_{t+1} = \frac{\gamma_t}{\pi_t\mu_{z^*,t}}\left\{R_t^k - R_{t-1} + \mu G_t(\omega_{t+1})\right\} k_t q_{t-1} + w^e + \gamma_t\left(\frac{1+R_{t-1}}{\pi_t\mu_{z^*,t}}\right) n_t \tag{III.42}$$

Using little algebra, we can get the equation in the CMR Appendix:

$$n_{t+1} = \frac{\gamma_t}{\pi_t \mu_{z^*,t}} \left\{ R_t^k - R_{t-1} - \mu \int_0^{\omega_{t+1}} \omega dF_{t-1}(\omega) \left(1 + R_t^k\right) \right\} k_t q_{t-1} + w^e + \gamma_t \left(\frac{1 + R_{t-1}}{\pi_t \mu_{z^*,t}} \right) n_t \tag{III.43}$$

The equation for the long term (40 years) bond rate:

$$\zeta_{c,t} \lambda_{z,t} = [(1 + R_t^L)\beta]^{40} \zeta_{c,t+40} \lambda_{z,t+40} \frac{\eta_{t+1} \eta_{t+2} \dots \eta_{t+40}}{(\pi_{t+1} \mu_{z^*,t+1})(\pi_{t+2} \mu_{z^*,t+2}) \dots (\pi_{t+40} \mu_{z^*,t+40})} \tag{III.44}$$

The equation for the real risk free 10 year rate:

$$\zeta_{c,t} \lambda_{z,t} = \frac{(r_t^L \beta)^{40} \zeta_{c,t+40} \lambda_{z,t+40}}{\mu_{z^*,t+1} \mu_{z^*,t+2} \dots \mu_{z^*,t+40}} \tag{III.45}$$

To ensure that profits are zero in equilibrium:

$$\phi = \phi^{ss} \tag{III.46}$$

Observable equations

Consumption:

$$c_t^{obs} = \frac{c_t}{c_{t-1}} \frac{\mu_{z^*,t}}{\mu_{z^*}} \tag{III.47}$$

Credit:

$$credit_t^{obs} = \frac{q_t k_{t+1} n_{t+1}}{q_{t-1} k_t n_t} \frac{\mu_{z^*,t}}{\mu_{z^*}} \tag{III.48}$$

GDP:

$$GDP_t^{obs} = \frac{c_t + \frac{i_t}{\mu_{\Upsilon,t}} + g_t}{c_{t-1} + \frac{i_{t-1}}{\mu_{\Upsilon,t-1}} + g_{t-1}} \frac{\mu_{z^*,t}}{\mu_{z^*}} \tag{III.49}$$

Hours:

$$h_t^{obs} = \frac{h_t}{h^{ss}} \tag{III.50}$$

Inflation:

$$\pi_t^{obs} = \frac{\pi_t}{\pi_{t-1}} \tag{III.51}$$

Investment:

$$i_t^{obs} = \frac{i_t}{i_{t-1}} \frac{\mu_{z^*,t}}{\mu_{z^*}} \tag{III.52}$$

Net worth:

$$networth_t^{obs} = \frac{n_t}{n_{t-1}} \frac{\mu_{z^*,t}}{\mu_{z^*}} \tag{III.53}$$

Premium:

$$premium_t^{obs} = exp\left\{ \left([G_t(\omega_{t+1}) + \omega_{t+1}(1 - F_t(\omega_{t+1}))] - [(1-\mu)G_t(\omega_{t+1}) + \omega_{t+1}(1 - F_t(\omega_{t+1}))] \frac{1 + R_t^k q_{t-1} k_t}{q_{t-1} k_t - n_t} \right) - \right. \tag{III.54}$$

where G^{ss} is a normal cumulative density function of ω_{t+1} and σ_t, which reduces to

$$premium_t^{obs} = exp\left\{ \left([\mu G_t(\omega_{t+1}) + \omega_{t+1}(1 - F_t(\omega_{t+1}))] \frac{1 + R_t^k q_{t-1} k_t}{q_{t-1} k_t - n_t} \right) - \frac{\mu G^{ss}(1 + (R^k)^{ss}) k^{ss}}{k^{ss} - n^{ss}} \right\} \tag{III.55}$$

Relative price of investment:

$$pinvest_t^{obs} = \frac{\mu_{\Upsilon,t-1}}{\mu_{\Upsilon,t}} \tag{III.56}$$

Interest rate:

$$R_t^{obs} = exp(R_t - R) \tag{III.57}$$

and the real interest rate:

$$r_t^{obs} = \frac{\frac{1+R_t}{\pi_{t+1}}}{\frac{1+R}{\pi}} \tag{III.58}$$

Spread:

$$spread_t^{obs} = 1 + R_t^L - R_t \tag{III.59}$$

Wage:

$$w_t^{obs} = \frac{\tilde{w}_t}{\tilde{w}_{t-1}} \frac{\mu_{z^*,t}}{\mu_{z^*}} \tag{III.60}$$

Shock equations

Temporary technology shock:

$$log\left(\frac{\varepsilon_t}{\varepsilon}\right) = \rho_\varepsilon * log\left(\frac{\varepsilon_{t-1}}{\varepsilon}\right) + e_{\varepsilon,t} \tag{III.61}$$

Government spending shock:

$$log\left(\frac{g_t}{g}\right) = \rho_g * log\left(\frac{g_{t-1}}{g}\right) + e_{g,t} \tag{III.62}$$

Equity shock:

$$log\left(\frac{\gamma_t}{\gamma}\right) = \rho_\gamma * log\left(\frac{\gamma_{t-1}}{\gamma}\right) + e_{\gamma,t} \tag{III.63}$$

Markup shock:

$$log\left(\frac{\lambda_{f,t}}{\lambda_f}\right) = \rho_{\lambda_f} * log\left(\frac{\lambda_{f,t-1}}{\lambda_f}\right) + e_{\lambda_f,t} \tag{III.64}$$

Investment good shock:

$$log\left(\frac{\mu_{\Upsilon,t}}{\mu_\Upsilon}\right) = \rho_{\mu_\Upsilon} * log\left(\frac{\mu_{\Upsilon,t-1}}{\mu_\Upsilon}\right) + e_{\mu_\Upsilon,t} \tag{III.65}$$

Persistent technology shock (to steady state GDP):

$$log\left(\frac{\mu_{z^*,t}}{\mu_{z^*}}\right) = \rho_{\mu_{z^*}} * log\left(\frac{\mu_{z^*,t-1}}{\mu_{z^*}}\right) + e_{\mu_{z^*},t} \tag{III.66}$$

Target inflation shock:

$$log\left(\frac{\pi_t^{target}}{\pi^{target}}\right) = \rho_{\pi^{target}} * log\left(\frac{\pi_{t-1}^{target}}{\pi^{target}}\right) + e_{\pi^{target},t} \tag{III.67}$$

Term structure (of long term interest rate) shock:

$$log\left(\frac{\eta_t}{\eta}\right) = \rho_\eta * log\left(\frac{\eta_{t-1}}{\eta}\right) + e_{\eta,t} \tag{III.68}$$

Preference shock (in utility function):

$$log\left(\frac{\zeta_{c,t}}{\zeta_c}\right) = \rho_{\zeta_c} * log\left(\frac{\zeta_{c,t-1}}{\zeta_c}\right) + e_{\zeta_c,t} \tag{III.69}$$

Marginal efficient of investment shock:

$$log\left(\frac{\zeta_{I,t}}{\zeta_I}\right) = \rho_{\zeta_I} * log\left(\frac{\zeta_{I,t-1}}{\zeta_I}\right) + e_{\zeta_I,t} \tag{III.70}$$

Risk shock:

$$\begin{aligned} log\left(\frac{\sigma_t}{\sigma}\right) = \rho_\sigma * log\left(\frac{\sigma_{t-1}}{\sigma}\right) + log(\xi_{0,t}) \\ + log(\xi_{1,t}) + log(\xi_{2,t}) + log(\xi_{3,t}) + log(\xi_{4,t}) + log(\xi_{5,t}) + log(\xi_{6,t}) + log(\xi_{7,t}) + log(\xi_{8,t}), \end{aligned} \tag{III.71}$$

where

$$\begin{aligned} log(\xi_{8,t}) = \sigma_{\sigma,n} * e_{\xi_8,t} \\ log(\xi_{7,t}) = \rho_{\sigma,n}\sigma_{\sigma,n} * e_{\xi_8,t} + \sqrt{1-\rho^2_{\sigma,n}} * \sigma_{\sigma,n} * e_{\xi_7,t} \\ log(\xi_{6,t}) = \rho^2_{\sigma,n}\sigma_{\sigma,n} * e_{\xi_8,t} + \sqrt{1-\rho^2_{\sigma,n}} * \rho_{\sigma,n}\sigma_{\sigma,n} * e_{\xi_7,t} + \sqrt{1-\rho^2_{\sigma,n}} * \rho^2_{\sigma,n}\sigma_{\sigma,n} * e_{\xi_6,t} \\ log(\xi_{5,t}) = \dots \end{aligned} \tag{III.72}$$

Equilibrium conditions with price and wage rigidity parameters are set to 0

Eq. 1 Law of motion for p^*:

$$p^*_t = 1 \tag{III.73}$$

Eq. 2 Law of motion for F_p:

$$E_t\left\{\zeta_{c,t}\lambda_{z,t}y_{z,t} - F_{p,t}\right\} = 0 \tag{III.74}$$

Eq. 3 Law of motion for K_p

$$\zeta_{c,t}\lambda_{z,t}\lambda_f y_{z,t}s_t - K_{p,t} = 0 \tag{III.75}$$

Eq. 4 Relationship between K_p and F_p:

$$K_{p,t} = F_{p,t} \tag{III.76}$$

Eq. 5 Law of motion for F_w:

$$\zeta_{c,t}\lambda_{z,t}\frac{h_t(1-\tau_t^l)}{\lambda_w} - F_{w,t} = 0 \tag{III.77}$$

Eq. 6 Law of motion for K_w:

$$\zeta_{c,t}\zeta_t\,[h_t]^{1+\sigma_L} - K_{w,t} = 0 \tag{III.78}$$

Eq. 7 Relationship between F_w and K_w:

$$K_{w,t} = \frac{\tilde{w}_t F_{w,t}}{\Psi_L} \tag{III.79}$$

Eq. 8 Law of motion of w^*:

$$w_t^* = 1 \tag{III.80}$$

The fact that $w^* = 1$ and $p^* = 1$ impacts these equations:

Eq. 10 Rental rate on capital:

$$r_t^k = \frac{\alpha\varepsilon_t}{[1+\Psi_{k,t}R_t]}\left(\frac{\Upsilon\mu_{z^*,t}L_t}{u_t k_t}\right)^{1-\alpha} s_t \tag{III.81}$$

Eq. 19 Definition of the scaled representation of aggregate output:

$$y_{z,t} = \varepsilon\left(\frac{uk_t}{\mu_{z^*,t}\Upsilon}\right)^{\alpha} h_t^{1-\alpha} - \phi \tag{III.82}$$

Note that $y_{z,t}$ appears in the Resource constraint (Eq.12).

Appendix IV

Parameters of the model and their names in the Dynare code

The parameters that are calibrated are listed first, followed by the parameters that are estimated.

Complete list of calibrated parameters

Parameter in the monetary policy	$\tilde{\alpha}_c$	0	actil_p
Parameter in the monetary policy	$\tilde{\alpha}_d$	0	adptil_p
Power on capital in production function	α	0.40	alpha_p
Parameter in the monetary policy	$\tilde{\alpha}_y$	0	aytil_p
Discount rate in utility	β	0.9987	beta_p
Resources used for state-verification	Θ	0.005	bigtheta_p
Mean value of consumption	c	1.5469	c_p
Depreciation rate on capital	δ	0.025	delta_p
Steady state gov. spending to GDP ratio	η_g	0.20	etag_p
Mean of the process for the technology shock	ε	1	epsil_p
Mean value of gov. spending	g	0.5868	g_p
Mean of the process for the equity shock	γ	0.985	gamma_p
Mean value of investment	i	0.7394	i_p
Mean of the process for the markup shock	λ_f	1.2	lambdaf_p
Mean markup of suppliers of labor	λ_w	1.05	lambdaw_p
Mean of the process for the invest. good shock	μ_Υ	1	muup_p
Mean of the process for the S.S. GDP growth shock	μ_{z^*}	1.0041	muzstar_p
Mean value of inflation	π	1.0061	pi_p
Parameter in $\tilde{\pi}_t$ and $\tilde{\pi}_{w,t}$ (code only and useless)	$\bar{\pi}$	1.0061	pibar_p
Mean value of target inflation	π_t^{target}	1.0061	pitarget_p
Wage bill financing	Ψ_L	0.7705	psiL_p
Mean value of the risk free rate, R_t	R	0.0115	Re_p
Autocorrelation of the equity shock	ρ_γ	0	rhogamma_p
Autocorrelation of the target inflation shock	$\rho_{\pi^{target}}$	0.975	rhopitarget_p
Preference parameter for labor	σ_L	1	sigmaL_p
St. deviation, innovation to the target infl. shock	$\sigma_{\pi^{target}}$	0.0001	stdpitarget_p
Tax rate on consumption	τ^c	0.05	tauc_p
Tax rate on bond	τ^d	0	taud_p
Tax rate on capital income	τ^k	0.32	tauk_p
Tax rate on labor income (wage)	τ^l	0.24	taul_p
Mean of the process for the term structure shock	η	1	term_p
Parameter in Eq. 9,12,17 (equilibrium conditions)	τ^o	1	tauo_p
Trend rate of invest.-specific techno. change	Υ	1.0042	upsil_p
Household lump-sum transfer to entrepreneur	w^e	0.005	we_p
Parameter in Eq. 6	ζ_t	1	zeta_p
Mean of the process for the preference shock	ζ_c	1	zetac_p
Mean of the process for the marg. eff. of invest.	ζ_I	1	zetai_p

Complete list of estimated parameters		
Monetary policy weight on output growth	$\tilde{\alpha}_{\Delta y}$	adytil_p
Monetary policy weight on inflation	$\tilde{\alpha}_{\pi}$	aptil_p
Habit parameter	b	b_p
Steady state probability of default	$F(\bar{\omega})$	Fomegabar_p
Price indexing weight on inflation target	ł	iota_p
Wage indexing weight on inflation target	$ł_w$	iotaw_p
Wage indexing weight on $\mu_{z^*,t}$	$ł_\mu$	iotamu_p
Monitoring cost	μ	mu_p
Autocorrelation, temporary tech. shock	ρ_ε	rhoepsil_p
Autocorrelation, govern. spending shock	ρ_g	rhog_p
Autocorrelation, markup shock shock	ρ_{λ_f}	rholambdaf_p
Autocorrelation, invest. good shock	ρ_{μ_Υ}	rhomuup_p
Autocorrelation, permanent tech. shock	$\rho_{\mu_{z^*}}$	rhomuzstar_p
Autocorrelation, risk shock	ρ_σ	rhosigma_p
Autocorrelation, term structure shock	ρ_η	rhoterm_p
Monetary policy smoothing parameter	$\tilde{\rho}$	rhotil_p
Autocorrelation, marg. eff. of invest.	ρ_{ζ_I}	rhozetac_p
Autocorrelation, preference shock	ρ_{ζ_c}	rhozetac_p
Curvature, invest. adjust. cost	S''	Sdoupr_p
Correlation, signals (anticipated)	$\rho_{\sigma,n}$	signal_corr_p
Curvature, utilization cost	σ_a	sigmaa_p
St. dev., temporary tech. shock	σ_ε	stdepsil_p
St. dev., govern. spending shock	σ_g	stdg_p
St. dev., equity shock	σ_γ	stdgamma_p
St. dev., markup shock shock	σ_{λ_f}	stdlambdaf_p
St. dev., invest. good shock	σ_{μ_Υ}	stdmuup_p
St. dev., permanent tech. shock	$\sigma_{\mu_{z^*}}$	stdmuzstar_p
St. dev., risk shock	$\sigma_{\sigma,0}$	stdsigma1_p
St. dev., signals	$\sigma_{\sigma,n}$	stdsigma2_p
St. dev., term structure shock	σ_η	stdterm_p
St. dev., monetary policy shock	σ_{ε^p}	stdxp_p
St. dev., marg. eff. of invest.	σ_{ζ_I}	stdzetac_p
St. dev., preference shock	σ_{ζ_c}	stdzetac_p
Calvo price rigidity	ξ_p	xip_p
Calvo wage rigidity	ξ_w	xiw_p
Measurement error on networth		

Appendix V

Dynamic responses and Diagnostic of the baseline model after estimation

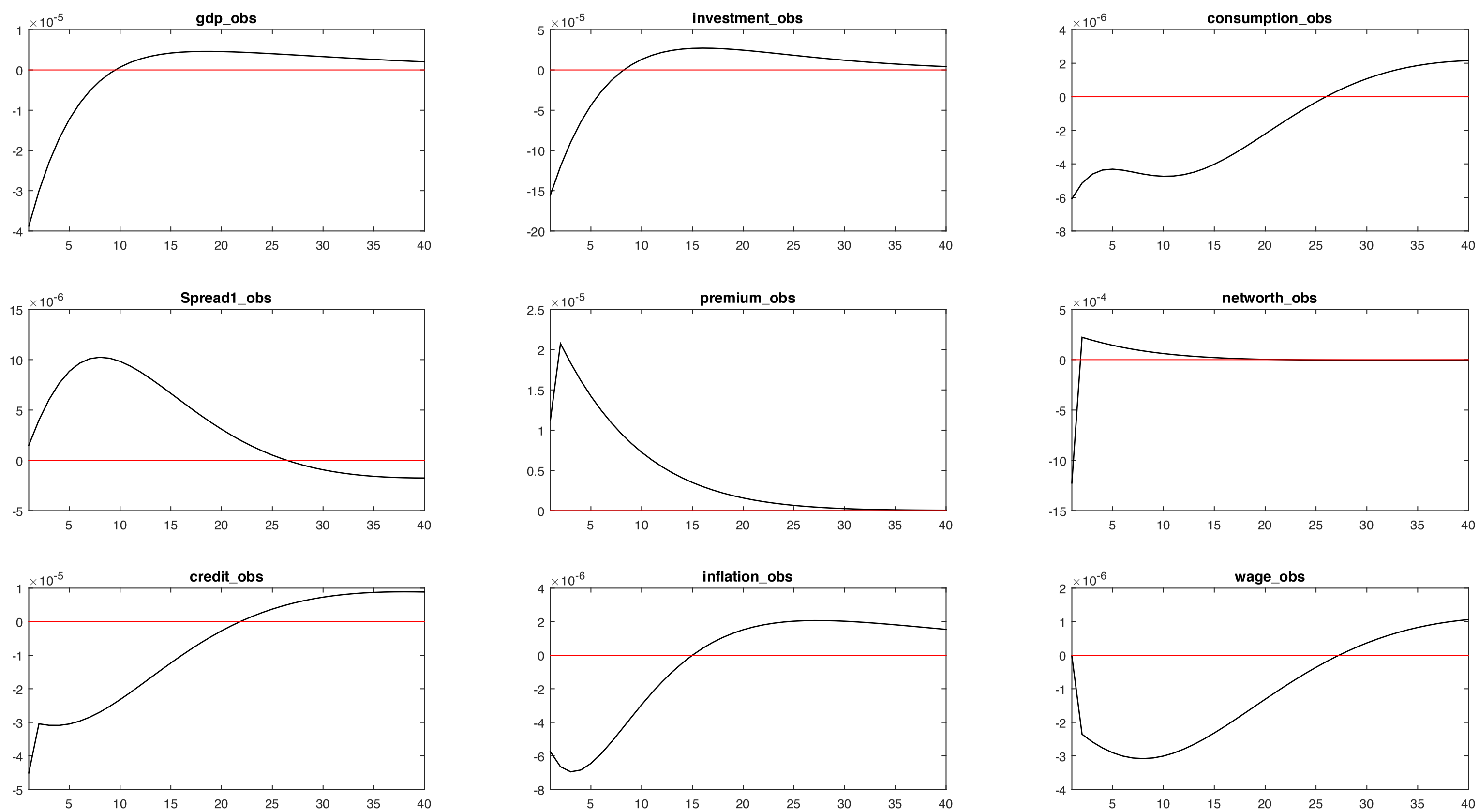

Figure V.1: **Dynamic responses to a negative unanticipated risk shock**

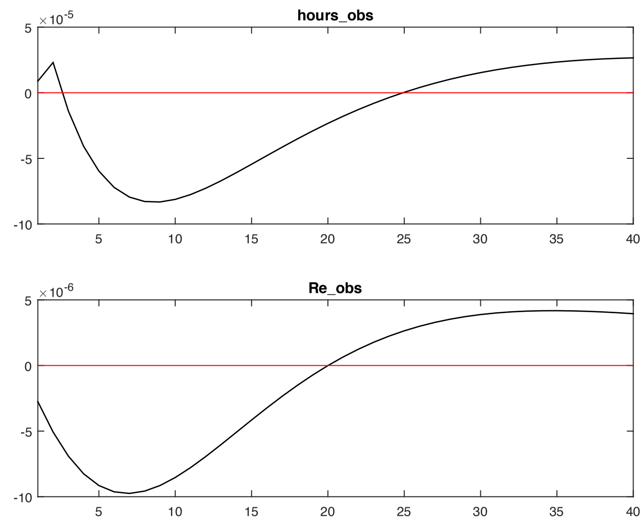

Figure V.2: **Dynamic responses to a negative unanticipated risk shock (continued)**

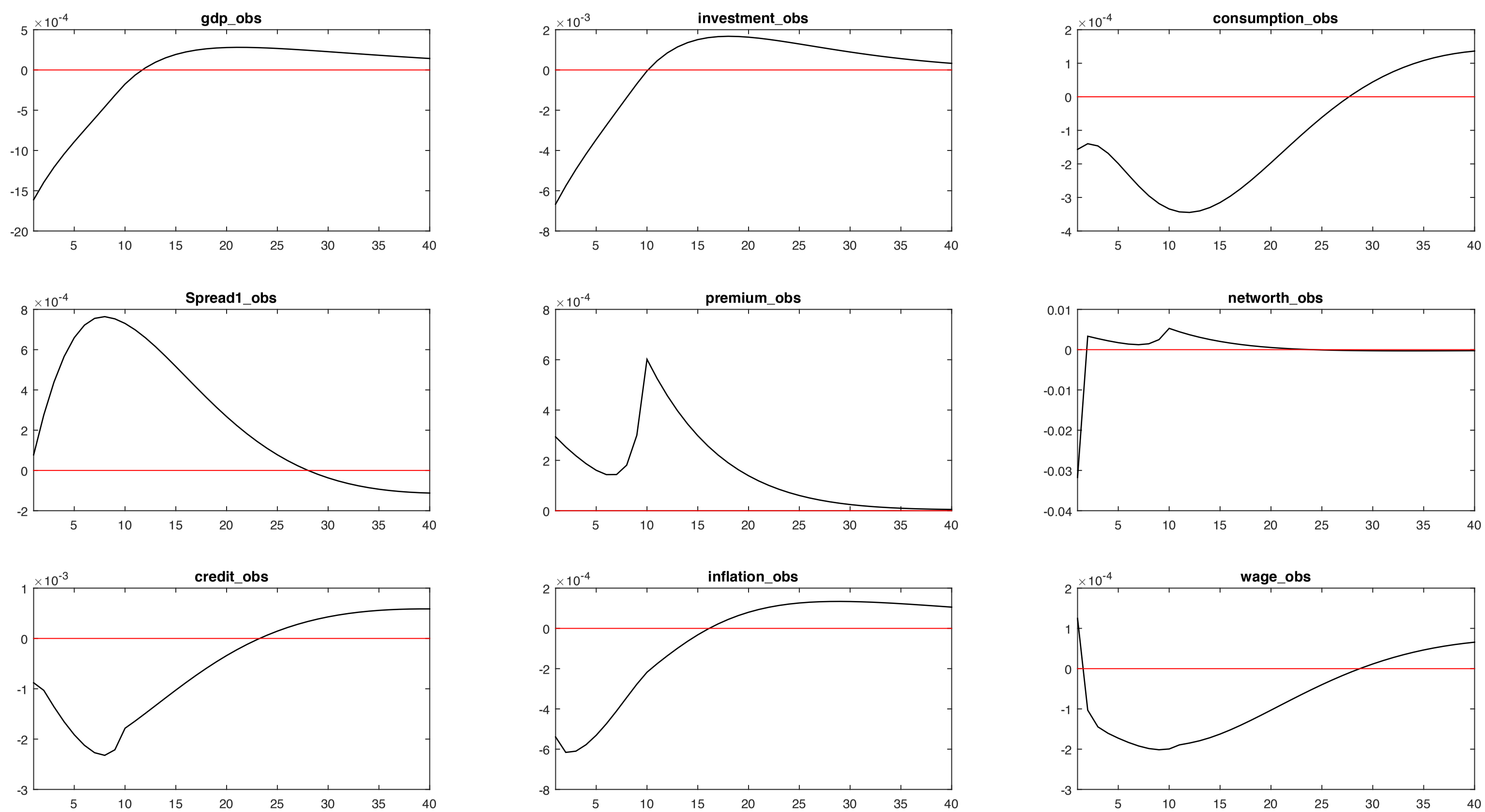

Figure V.3: **Dynamic responses to a negative anticipated risk shock**

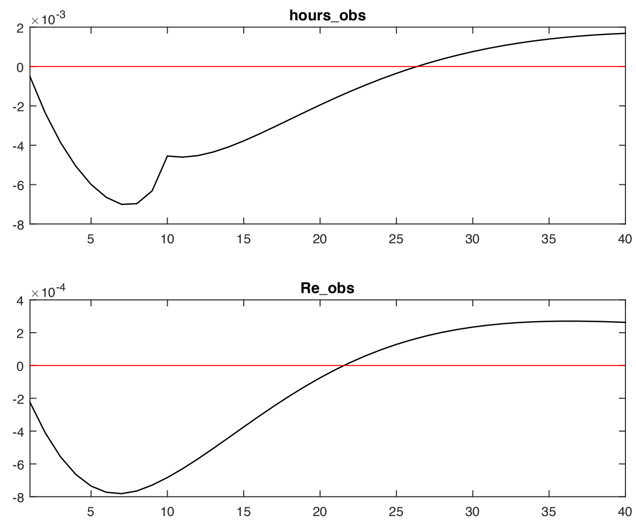

Figure V.4: **Dynamic responses to a negative anticipated risk shock (continued)**

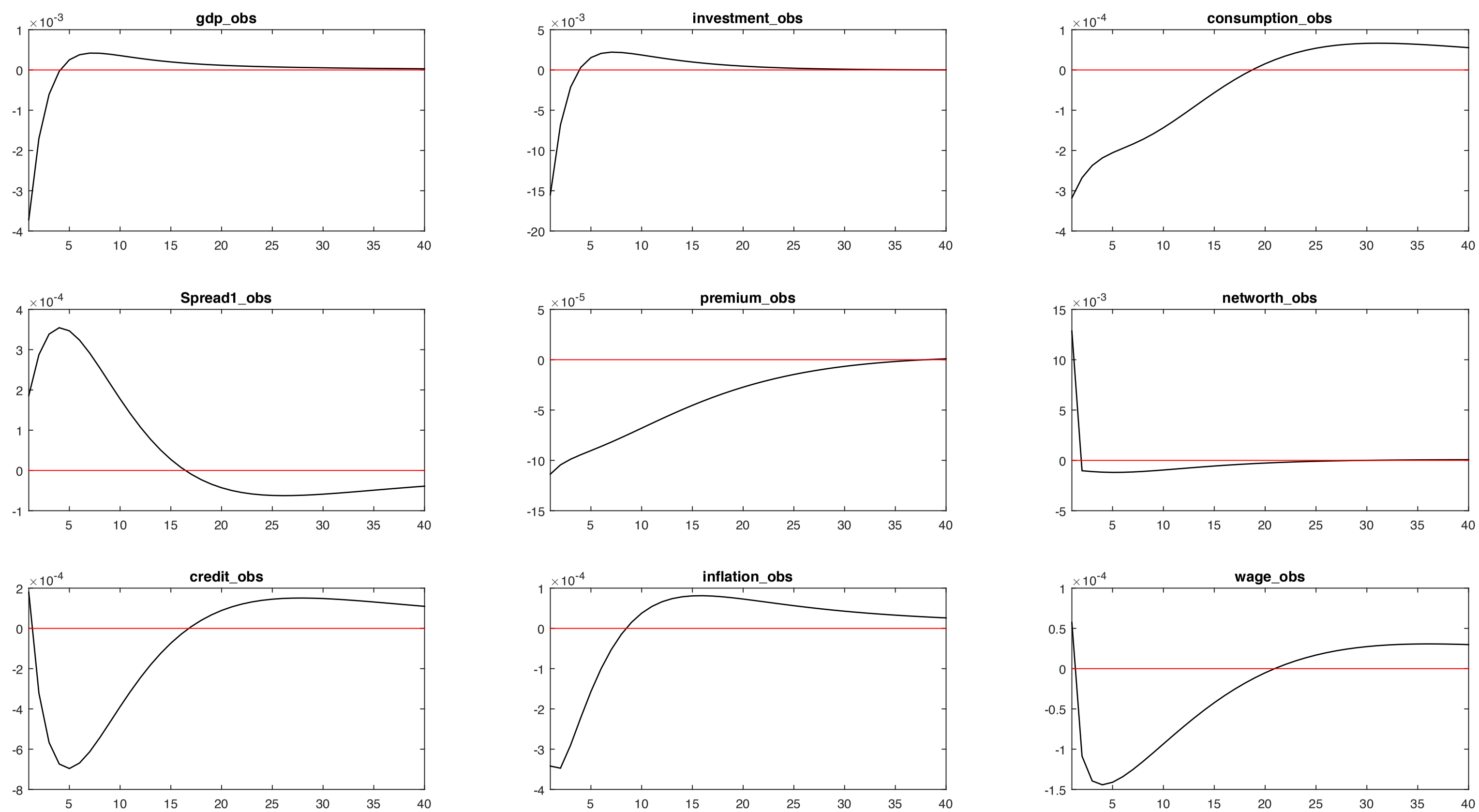

Figure V.5: **Dynamic responses to a negative marginal efficiency of investment shock**

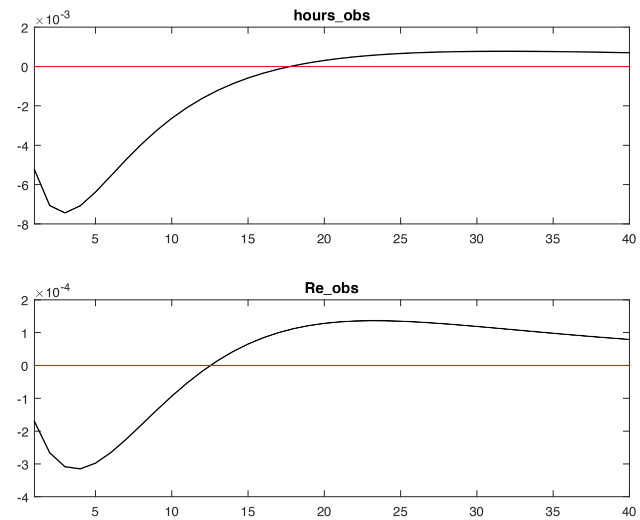

Figure V.6: **Dynamic responses to a negative marginal efficiency of investment shock (continued)**

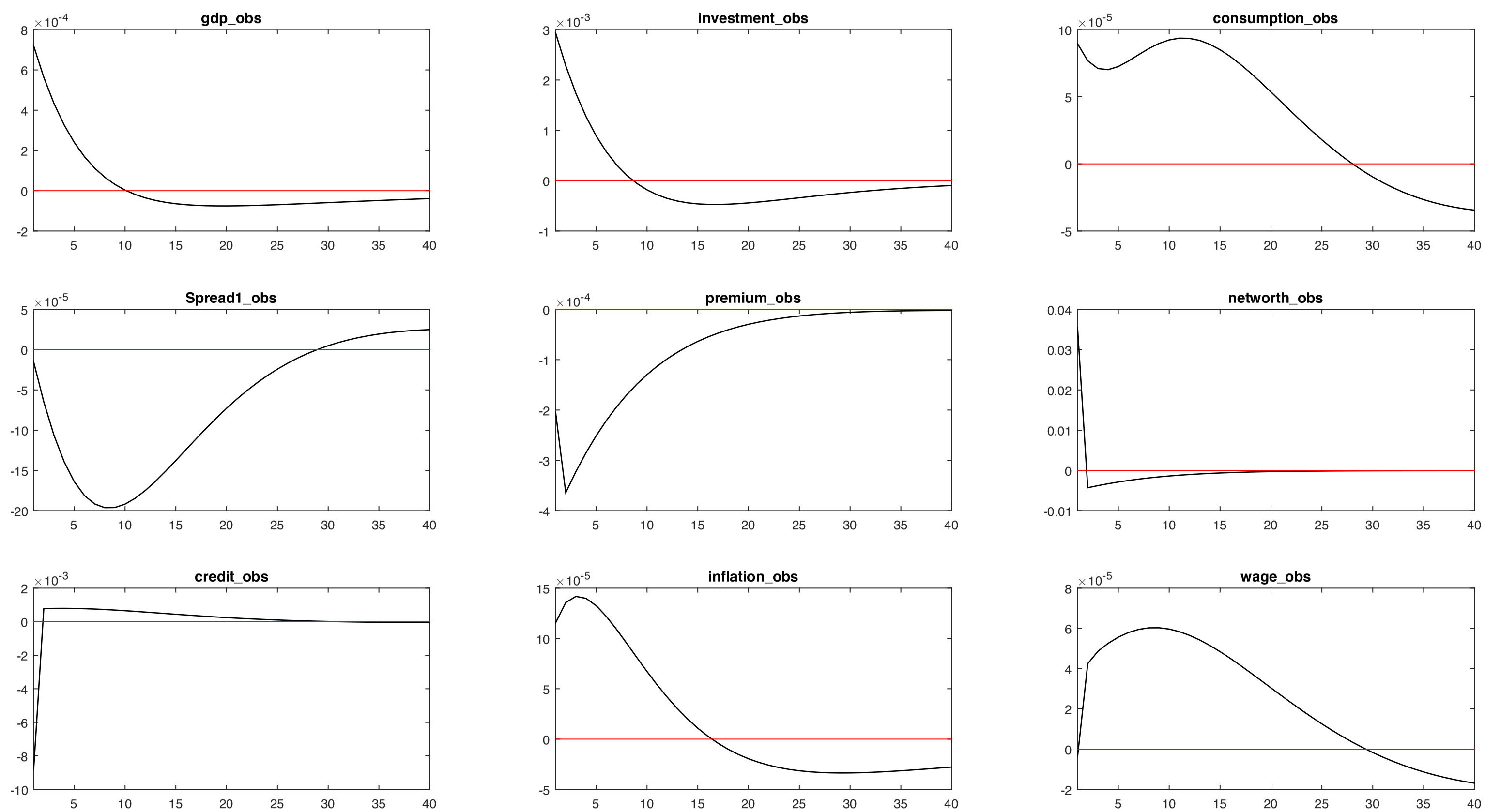

Figure V.7: **Dynamic responses to a positive equity shock**

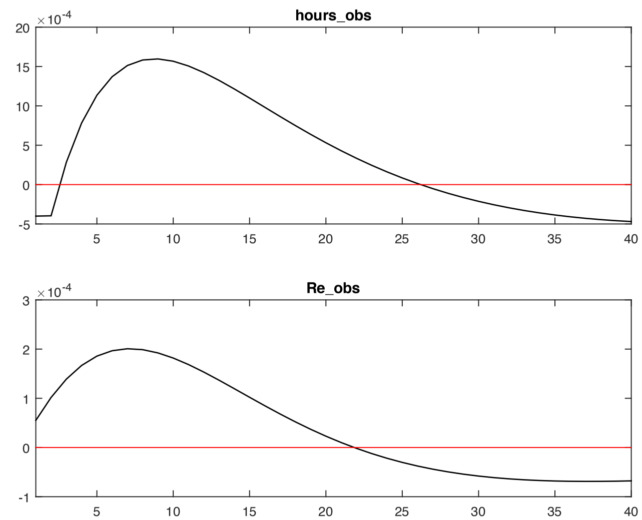

Figure V.8: **Dynamic responses to a positive equity shock (continued)**

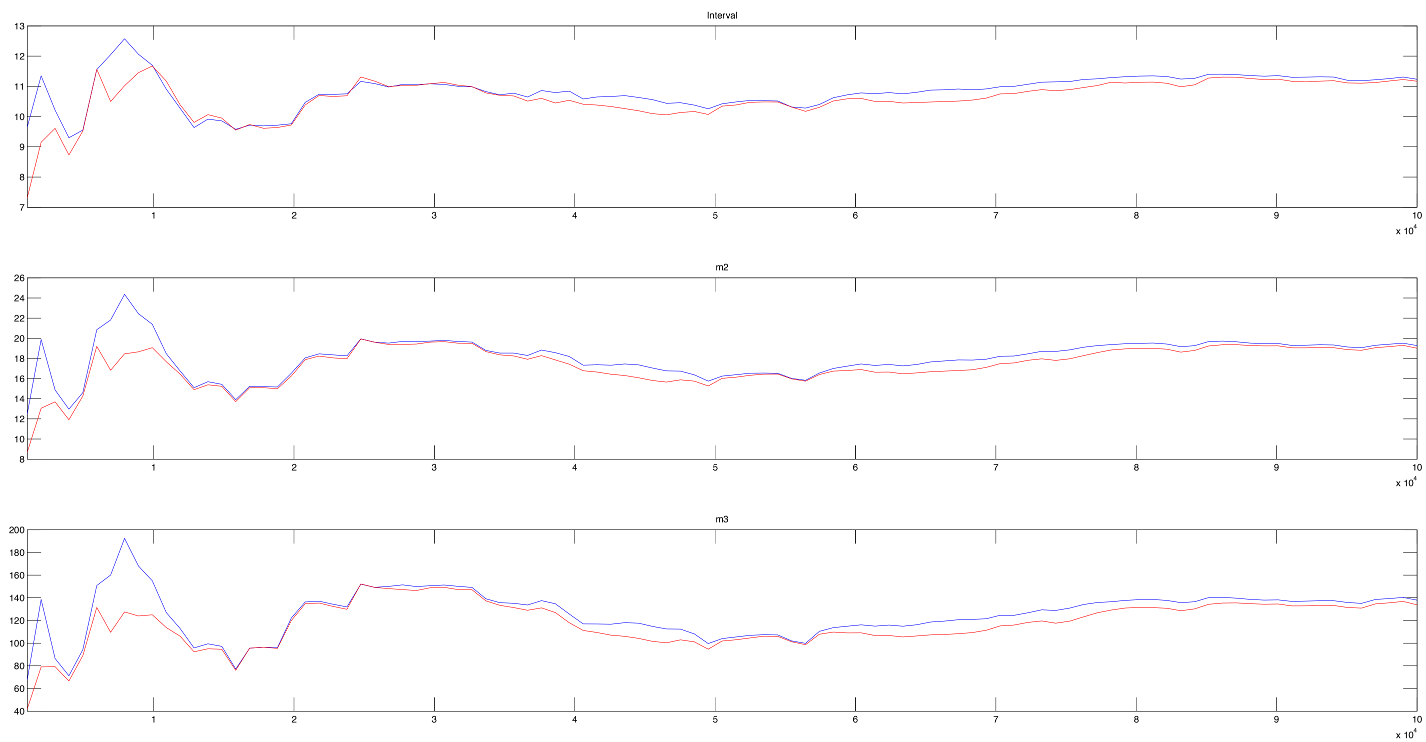

Figure V.9: **Multivariate convergence diagnostic of the Metropolis-Hastings iterations**

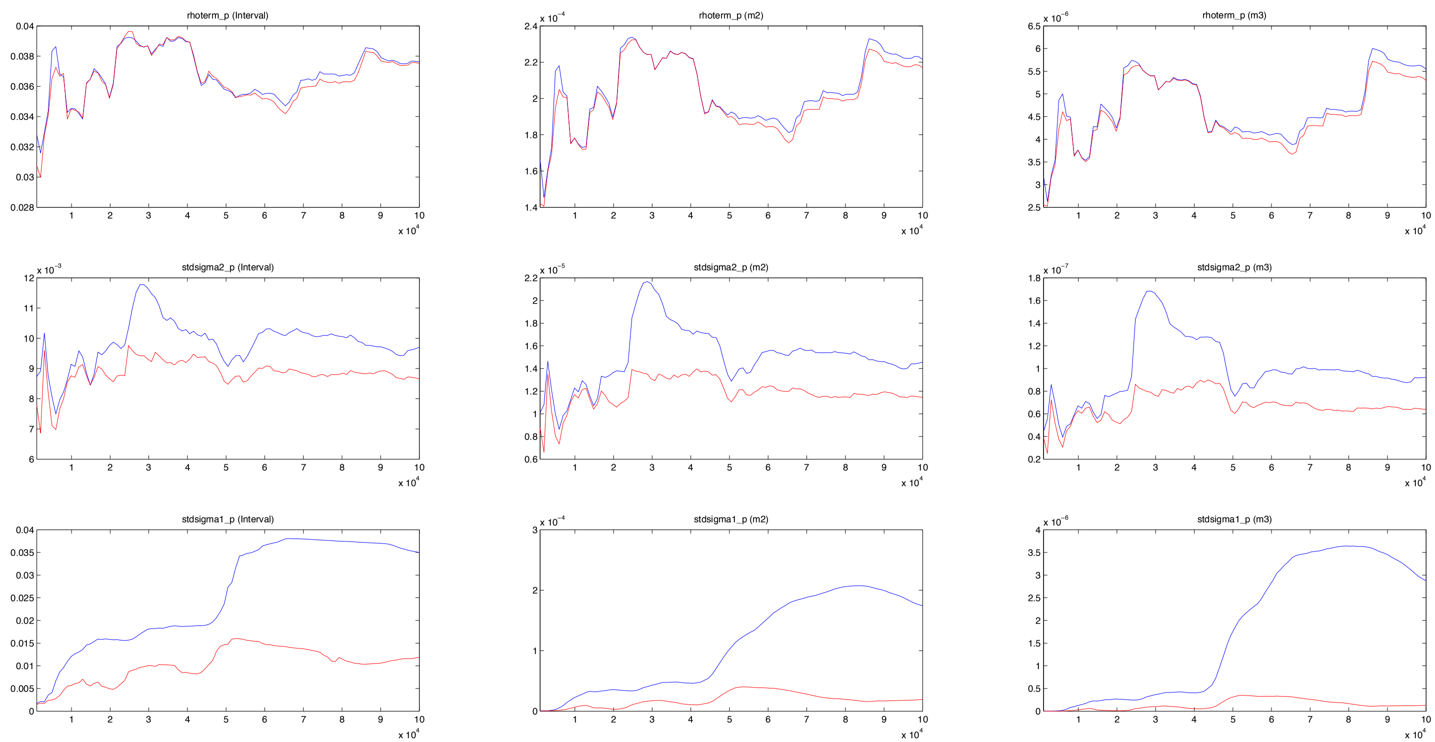

Figure V.10: **Univariate convergence diagnostics of the Metropolis-Hastings iterations**

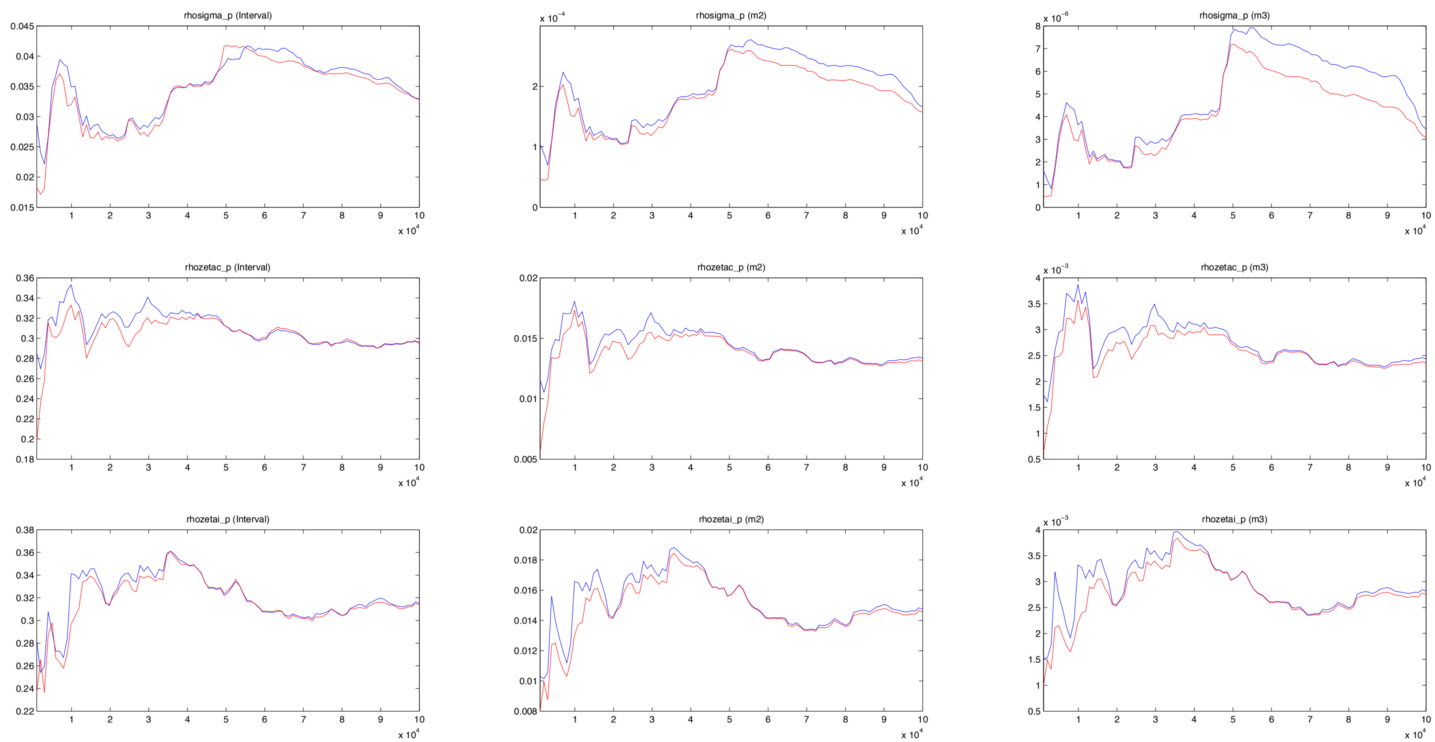

Figure V.11: **Univariate convergence diagnostics of the Metropolis-Hastings iterations (continued)**

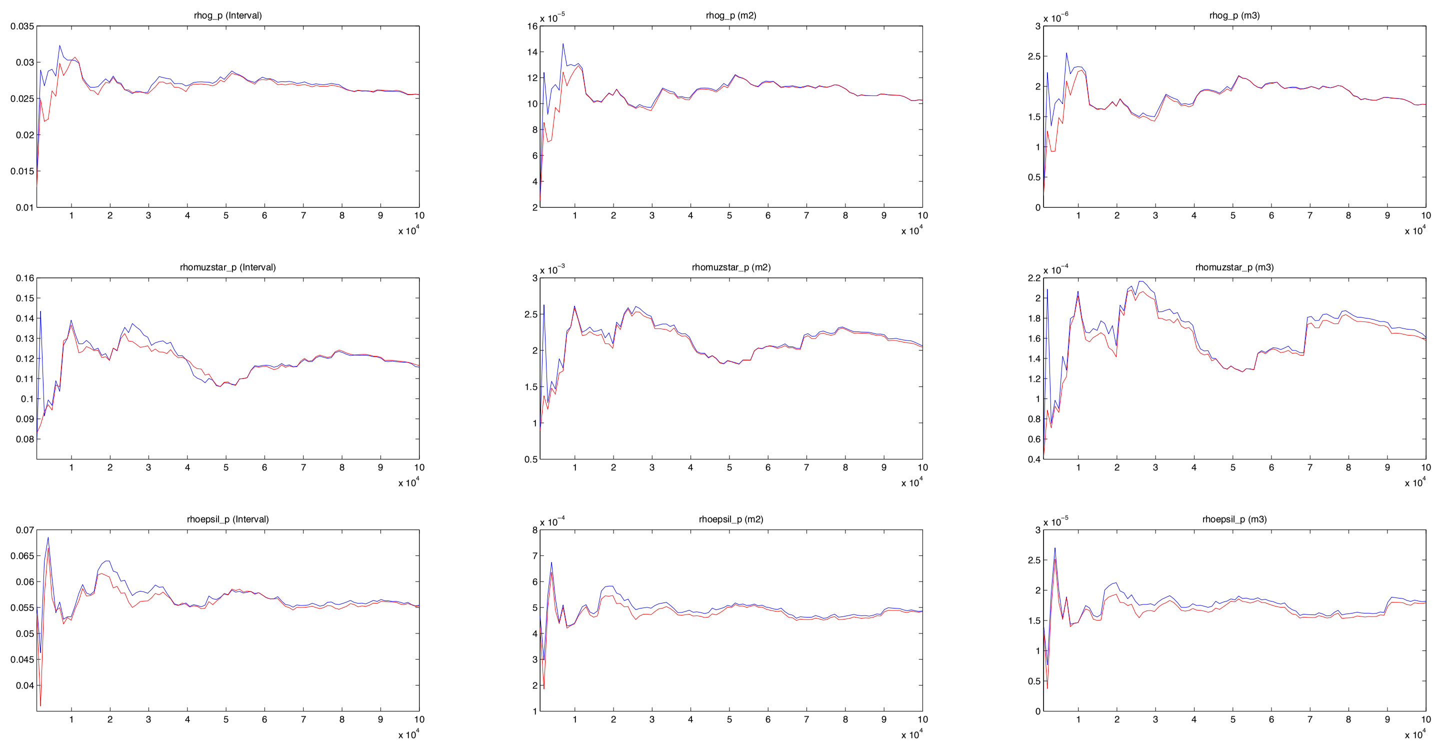

Figure V.12: **Univariate convergence diagnostics of the Metropolis-Hastings iterations (continued)**

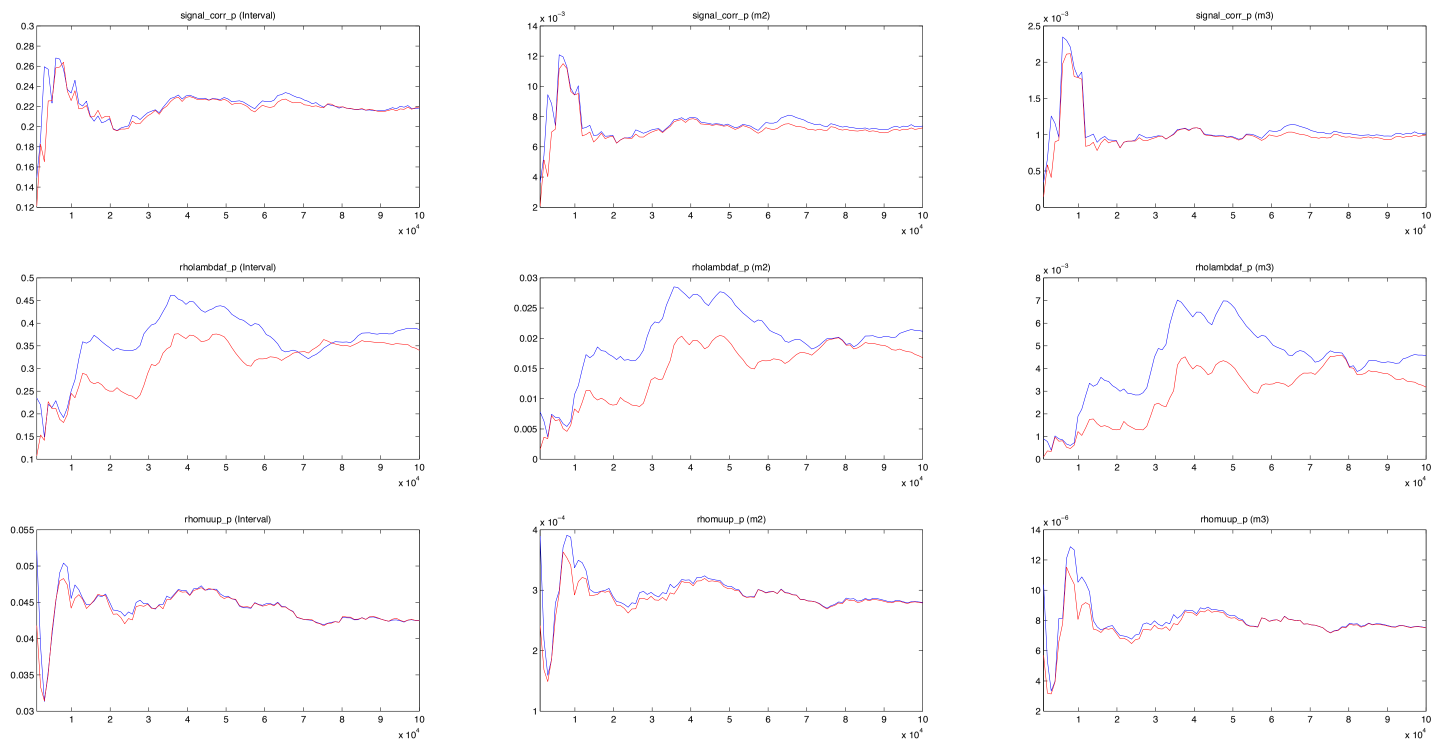

Figure V.13: **Univariate convergence diagnostics of the Metropolis-Hastings iterations (continued)**

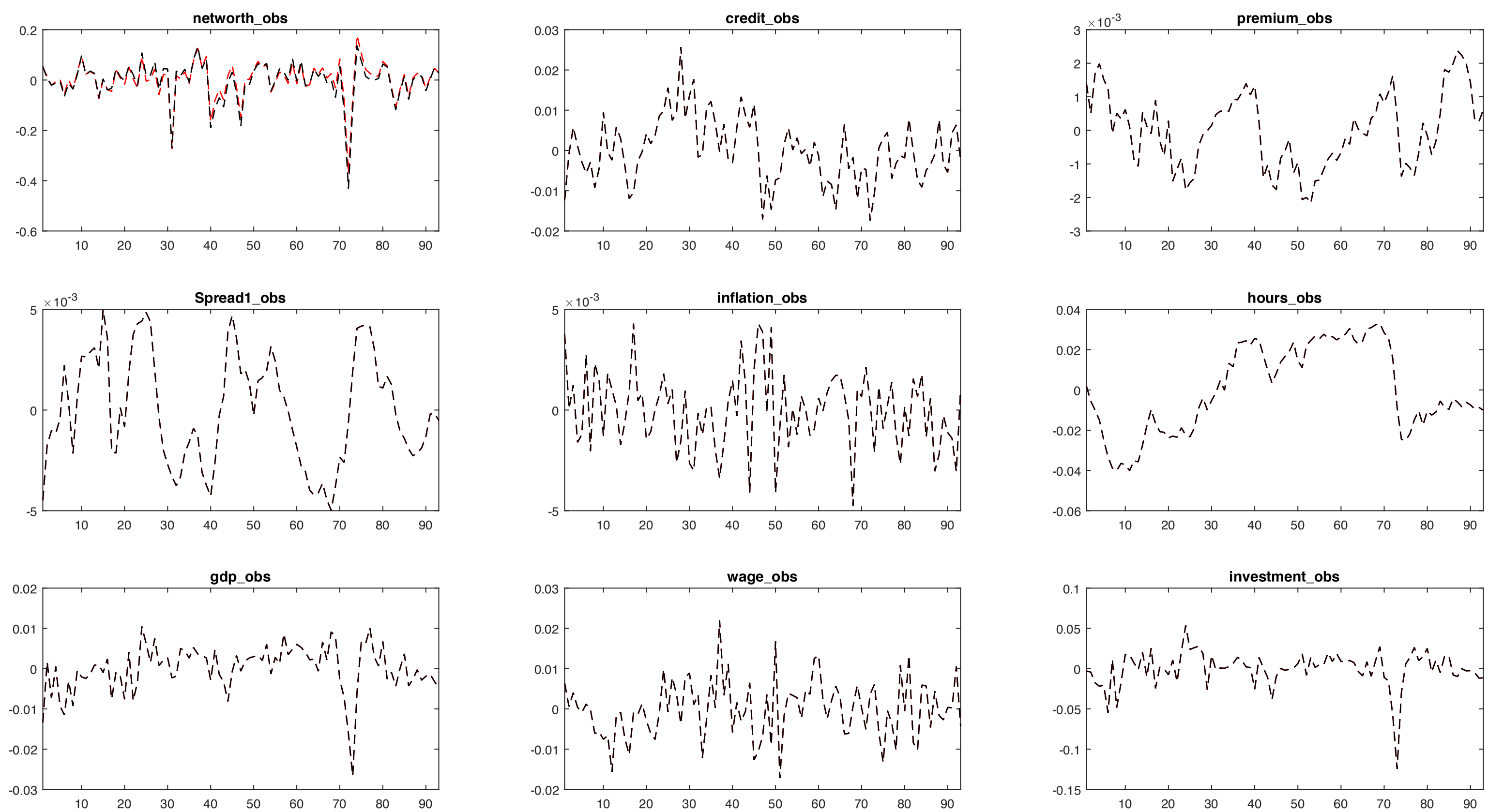

Figure V.14: **Historical (actual) and smoothed (estimated) variables**

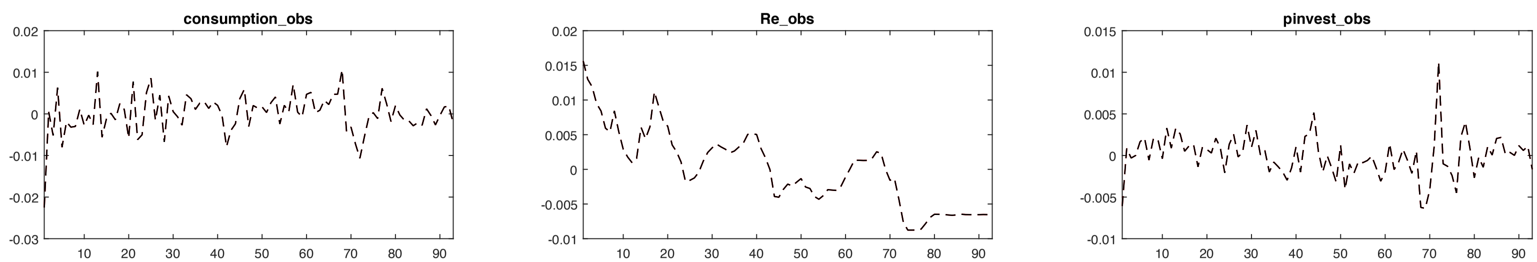

Figure V.15: **Historical (actual) and smoothed (estimated) variables (continued)**

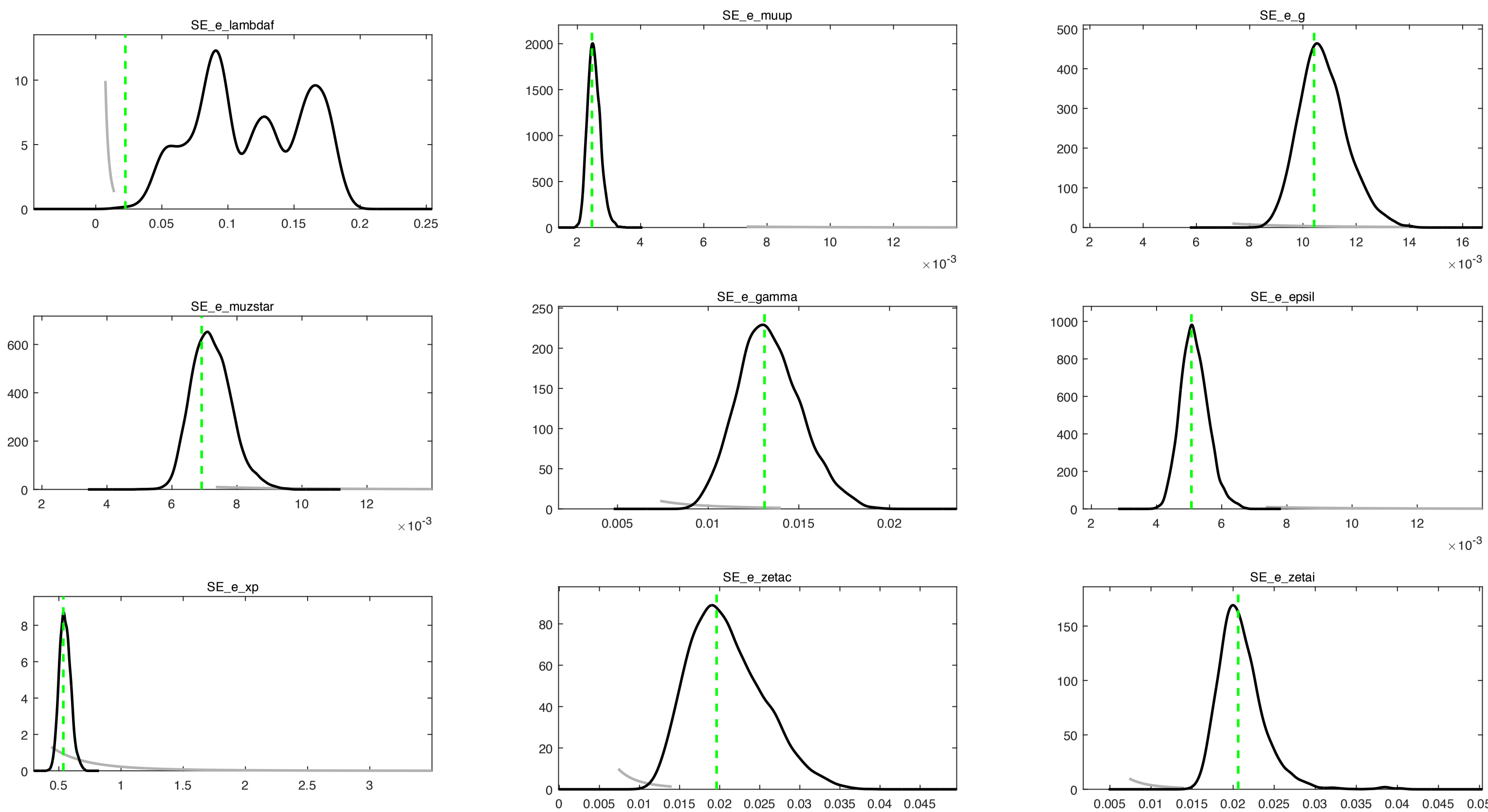

Figure V.16: **Priors and posteriors densities**

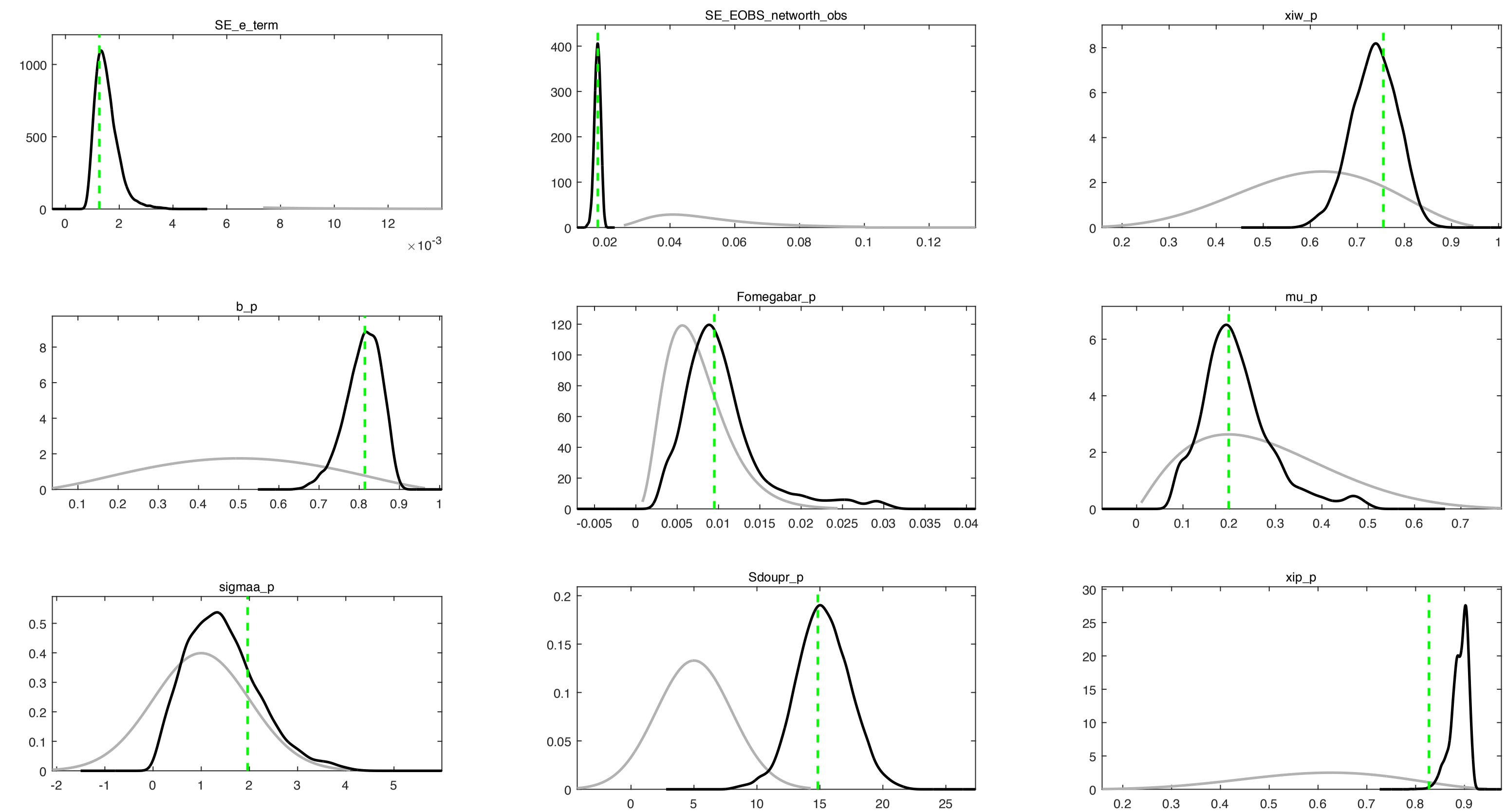

Figure V.17: **Priors and posteriors densities (continued)**

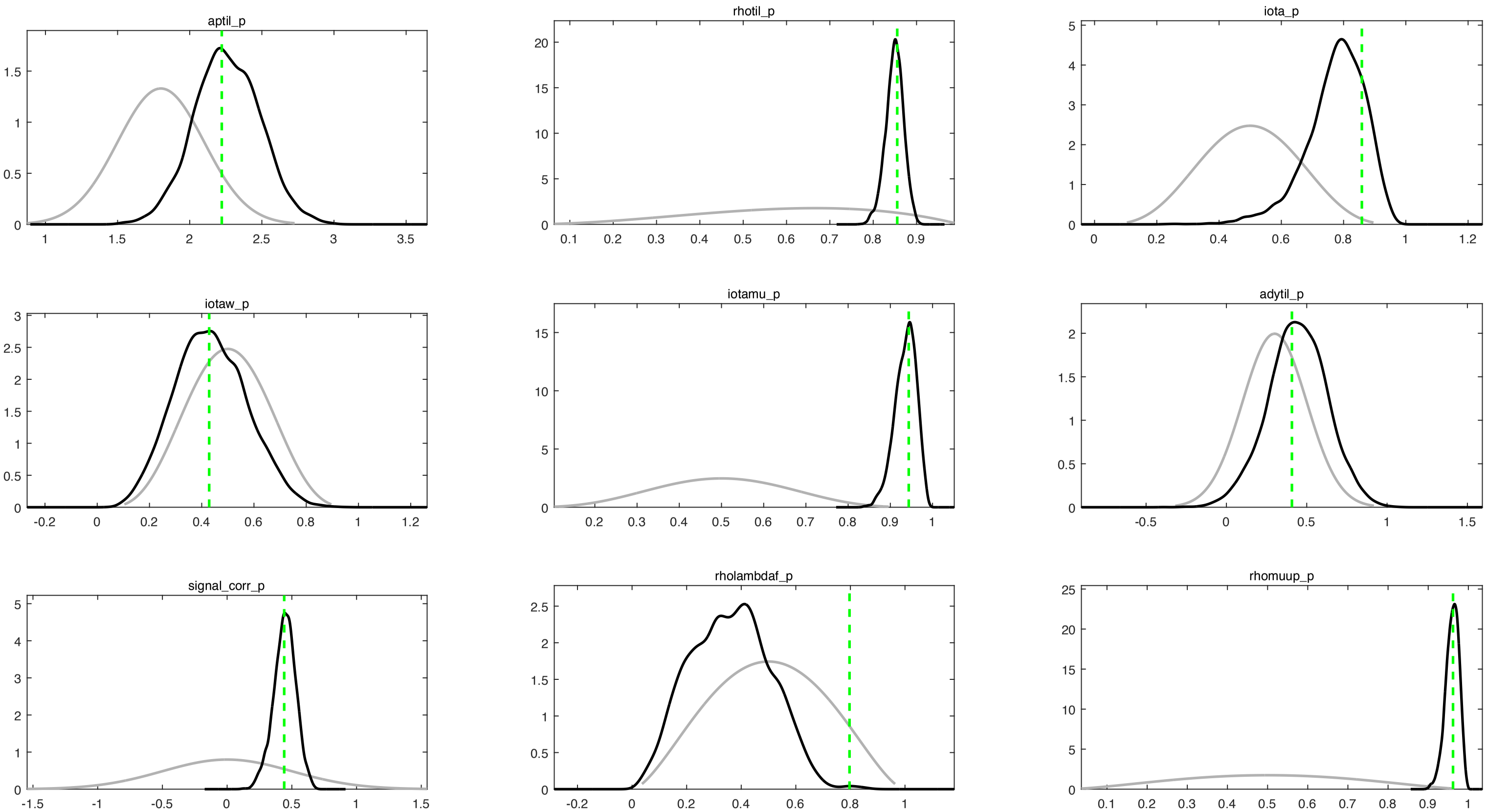

Figure V.18: **Priors and posteriors densities (continued)**

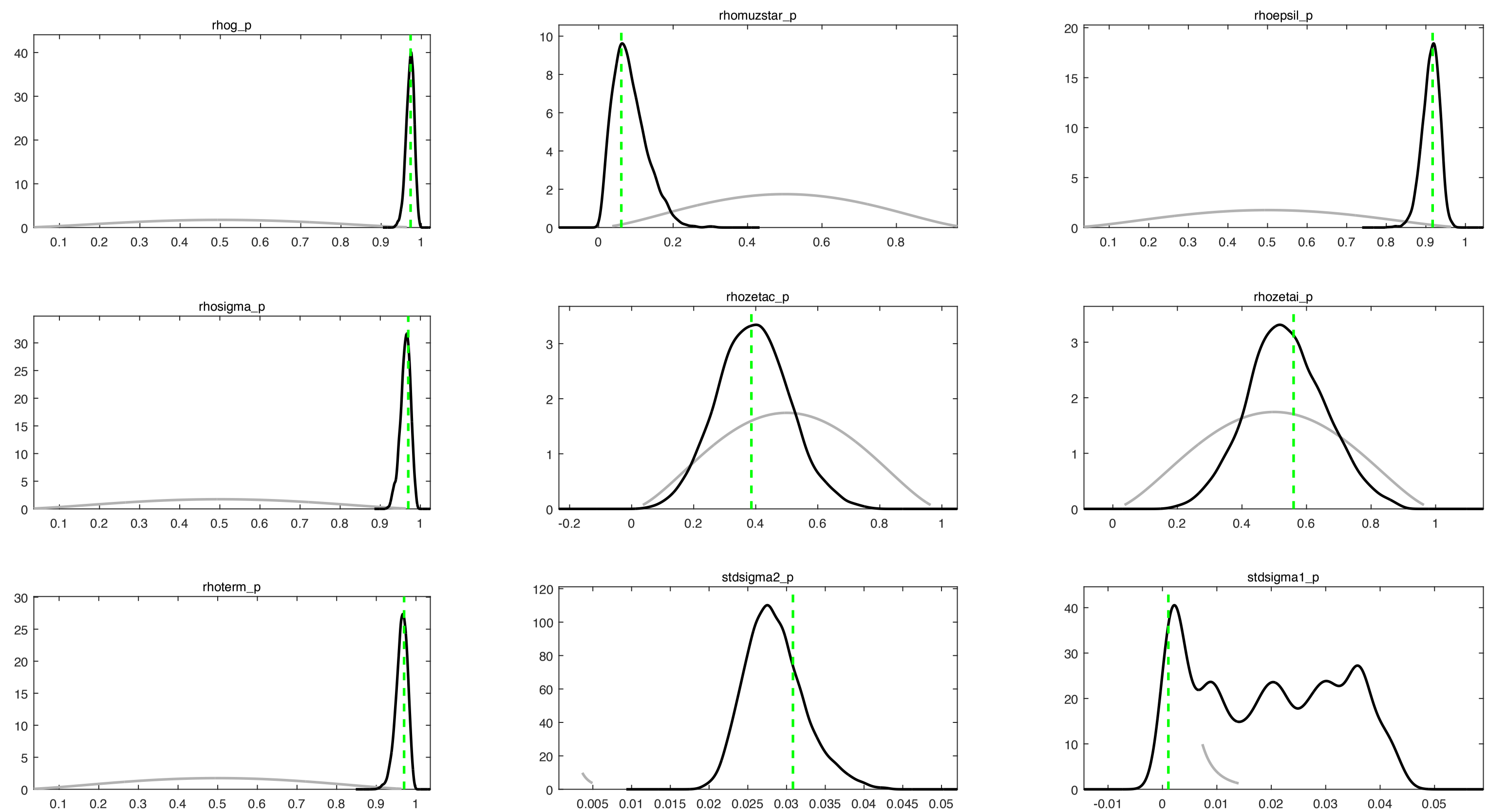

Figure V.19: **Priors and posteriors densities (continued)**