News Shocks under Financial Frictions*

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October 28, 2016

Abstract

We examine the dynamic effects and empirical role of TFP news shocks in the context of frictions in financial markets. We document two new facts using VAR methods. *First*, a (positive) shock to future TFP generates a significant decline in various credit spread indicators considered in the macro-finance literature. The decline in the credit spread indicators is associated with a robust improvement in credit supply indicators, along with a broad based expansion in economic activity. *Second*, it is striking that VAR methods also establish a tight link between TFP news shocks and shocks that explain the majority of un-forecastable movements in credit spread indicators. These two facts provide robust evidence on the importance of movements in credit spreads for the propagation of news shocks. A DSGE model enriched with a financial sector of the Gertler-Kiyotaki-Karadi type generates very similar quantitative dynamics and shows that strong linkages between leveraged equity and excess premiums, which vary inversely with balance sheet conditions, are critical for the amplification of TFP news shocks. The consistent assessment from both methodologies provides support for the traditional 'news view' of aggregate fluctuations.

Keywords: News shocks, Business cycles, DSGE, VAR, Bayesian estimation.
JEL Classification: E2, E3.

*We thank Jesus Fernandez-Villaverde, James Hamilton, Alejandro Justiniano, Lilia Karnizova, Hashmat Khan, Thomas Lubik, Charles Nolan, Giorgio Primiceri, Plutarchos Sakellaris, Frank Schorfheide, Felipe Schwarzman, Stephanie Schmitt-Grohe, Albert Queralto, Harald Uhlig, Mark Watson, Tony Yates and Nadav Ben Zeev for extremely helpful comments and suggestions. We thank seminar and conference participants at the 2016 NBER mid-year DSGE meeting, Richmond Fed, Carleton University, Canadian Economic Association (Ottawa 2016), European Economic Association (Geneva 2016), American Economic Association (Boston 2015), Mid-West Macro Meeting (Missouri 2014), University of Dortmund, DIW Berlin and Universities of Manchester and Sheffield for useful comments. We are grateful to Giorgio Primiceri and Eric Sims for providing computer codes and John Fernald for useful conversations on the construction of the TFP series. All remaining errors are our own. John Tsoukalas and Francesco Zanetti gratefully acknowledge financial support from the Leverhulme Trust Research Project Grant and Christoph Görtz acknowledges financial support from a British Academy/Leverhulme grant. Görtz: University of Birmingham, Department of Economics, Email: c.g.gortz@bham.ac.uk. Tsoukalas: University of Glasgow, Adam Smith Business School/Economics, Email: john.tsoukalas@glasgow.ac.uk. Zanetti: University of Oxford, Department of Economics, Email: francesco.zanetti@economics.ox.ac.uk.

1 Introduction

The news driven business cycle hypothesis formalized in Beaudry and Portier (2004) and restated in Jaimovich and Rebelo (2009) posits that changes in expectations of future fundamentals are an important source of business cycle fluctuations. Movements in financial markets encapsulate changes in expectations about the future and are a powerful mechanism that triggers changes in economic activity. A vast body of research finds that financial markets are characterized by frictions that lead to credit spreads—differences in yields between private debt instruments and government bonds of comparable maturities—whose movements contain important information on the evolution of the real economy and encompass predictive content for future economic activity.[1]

In this paper we quantify the empirical significance and dynamic effects of total factor productivity (TFP) news shocks in light of propagation through frictions in financial intermediation. We investigate the issue using two widely-used methods (VAR and DSGE) that provide complementary readings on the significance and dynamics of news shocks. We use a vector autoregression (VAR) model enriched with credit spread indicators and measures of credit supply conditions to isolate two novel stylized facts.

First, a TFP news shock identified from the VAR model generates an immediate and significant decline of various credit spread indicators along with a broad based increase in economic activity in anticipation of the future improvement in TFP. The decline of the credit spread indicators is a robust finding that holds across alternative specifications of the VAR model and different identification methods.[2] In particular we examine the dynamics of three credit spread indicators, namely, the popular BAA bond spread, the Gilchrist and Zakrajsek (2012) spread (GZ spread), and the Görtz and Tsoukalas (2016) spread and document a strong and significant decline in all indicators conditional on the news shock. We further examine the behavior of the components of the GZ spread, namely the expected default component, and excess bond premium component. We find that the decline in the GZ

[1] See Gilchrist and Zakrajsek (2012) and Philippon (2009).

[2] Our baseline identification scheme follows the approach in Francis et al. (2014). We discuss robustness to alternative identification approaches in section 2.3.

spread is primarily driven by a decline in the excess bond premium, not a fall in the expected default component of the GZ spread, which exhibits an insignificant response. The excess bond premium is interpreted by Gilchrist and Zakrajsek (2012) as an indicator of the capacity of intermediaries to extend loans or more generally the overall credit supply conditions in the economy.

Second, we independently apply an agnostic methodology proposed by Uhlig (2003) to identify a single shock that explains the majority of the unpredictable movements in our credit spread indicators. This exercise reveals a striking fact: the single shock, identified from this procedure, generates dynamics that resemble qualitatively and quantitatively those produced by a TFP news shock. Specifically, it generates a broad based increase in economic activity, a delayed build-up of TFP towards a new permanently higher level, and an immediate and strong decline in any of the credit spread indicators we consider. The shock we recover from this agnostic identification explains at least as much as 50% of the forecast error variance in any of our chosen credit spread indicators. The two novel stylized facts we document provide robust evidence on the importance of movements in credit spread indicators for the propagation of news shocks.

We further investigate the link between credit spread indicators and news shocks using a dynamic stochastic general equilibrium (DSGE) model whose microfoundations enable the underpinning of the theoretical mechanisms for the propagation of news shocks. We enrich a standard DSGE model by embedding financial frictions via leveraged lenders similar to Gertler and Karadi (2011) and Gertler and Kiyotaki (2010) into a two-sector model with nominal and real rigidities. Our approach to introduce frictions in the credit supply is motivated by the joint VAR facts discussed above.[3] We apply the DSGE model directly to post-1990s U.S. real and financial data, estimating its parameters with Bayesian methods. We produce dynamic responses and business cycle statistics that suggest TFP news shocks

[3]An important motivation for considering a two-sector economy is the recent evidence in Basu et al. (2013), which suggests that sector-specific technological changes have different macroeconomic effects. The consumption- and investment-goods-producing sectors are therefore subject to sector-specific TFP technologies, in line with this recent evidence.

are quite important drivers of business cycle fluctuations, accounting for approximately 28% and 40% of the variance in output and hours respectively. The DSGE model provides a compelling structural narrative for the propagation mechanism and the empirical relevance of TFP news shocks. The presence of leveraged financial intermediaries delivers a strong amplification of news shocks due to the feedback loop between leveraged equity and capital prices. Financial intermediaries hold claims to productive capital in their portfolios. When the price of capital increases, their equity value increases and their leverage constraint eases, making the excess premium on holding capital to fall and their balance sheet to expand. This dynamic generates a further rise in the demand for capital and a further rise in the price of capital. The demand for capital is thus amplified by leverage, bidding up the capital price relative to a standard New Keynesian (NK) model without financial frictions. The amplification delivers a strong lending and investment phase and a strong economy-wide boom. By contrast, in the standard DSGE model without financial frictions, amplification is weak. It predicts that TFP news shocks account for a maximum of 12% and 16% of the variance in output and hours worked, respectively, much in line with the existing estimated DSGE literature.

Importantly, the model narrative is consistent with evidence obtained from VAR methods. We additionally examine the response to the VAR identified news shock of (i) the market value of equity of publicly listed U.S. commercial banks, and (ii) the Senior Loan Officers Opinion survey indicator on U.S. bank lending standards for commercial and industrial loans. We find that the market value of equity rises strongly and significantly while lending standards relax significantly following a favorable news shock. Both VAR and DSGE methods thus strongly support the interpretation that variation in the balance sheet conditions of financial intermediaries may be an important transmission channel for news shocks.

To formally assess whether the financial channel conforms the dynamic responses of the variables to TFP news shocks in the DSGE and VAR methods, we perform a Monte Carlo experiment. We compare the impulse responses to an aggregate TFP news shock from the empirical VAR model with those estimated from the same VAR model on artificial data gen-

erated using posterior estimates of the DSGE model. We find that empirical VAR responses of key macroeconomic aggregates (including corporate bond spreads) are qualitatively very similar and in the majority of cases within the confidence intervals of the VAR responses estimated from artificial model data. The experiment shows that accounting for financial frictions leads the two methodologies *independently implemented* to reach similar conclusions on the dynamic effects of TFP news shocks.

To appraise the quantitative relevance of news shocks between the two methods, we undertake a comparison in the shares of the forecast error variance of key macro aggregates. We find those shares to be qualitatively quite similar between methods. For example, at business cycle frequencies (6 to 32 quarters), the VAR model establishes that TFP news shocks account for between 31% to 48% of the variance in output and between 34% to 40% of the variance in hours worked. The DSGE model finds the same shocks account for between 26% to 31% of the variance in output and between 26% to 42% of the variance in hours worked. Taken together, these findings suggest that both methodologies find TFP news shocks an important source of business cycles since the 1990s and hence provide support for the traditional 'news view' of aggregate fluctuations.

Our study is related to the large research agenda on the role of news shocks for macroeconomic fluctuations. The literature shows substantial disagreement over the propagation mechanism and empirical plausibility of TFP news shocks.[4] In the context of the VAR methodology, e.g. Beaudry and Portier (2006), Beaudry and Lucke (2010), and Beaudry et al. (2012) find that TFP news shocks account for a major fraction of macroeconomic fluctuations whereas Barsky and Sims (2011) and Forni et al. (2014) detect a limited role of TFP news shocks to aggregate fluctuations. More recently, Ben Zeev and Khan (2015) identify investment-specific news shocks as a major driver of U.S. business cycles, a finding supportive of the technology news interpretation of aggregate fluctuations. In the context of the DSGE methodology, Schmitt-Grohe and Uribe (2012) estimate a real business cycle model and find that TFP news shocks are unimportant drivers of business cycle fluctuations,

[4]The review article by Beaudry and Portier (2014) provides an extensive discussion on the literature.

but suggest alternative non-structural news shocks, such as wage mark-up news shocks, are important drivers of fluctuations. Fujiwara et al. (2011) and Khan and Tsoukalas (2012) reach a similar conclusion in models with nominal rigidities. Christiano et al. (2014) estimate a DSGE model that emphasizes borrowers' credit frictions and find an empirical role for news shocks in the riskiness of the entrepreneurial sector. Görtz and Tsoukalas (2016) and Theodoridis and Zanetti (2016) find empirical relevance for TFP news shocks highlighting labor frictions and financial frictions, respectively.

Our contribution to this literature is twofold. First, using VAR methods, we document new facts that speak to the relevance and importance of credit supply frictions for the propagation of news shocks. We establish a tight link between TFP news shocks and shocks (identified independently from news shocks) that drive the majority of unpredictable movements in credit spread indicators suggesting the latter are important asset prices that reflect future economic news. Second, our DSGE analysis, using the key amplification mechanism emphasized by Görtz and Tsoukalas (2016), suggests that a model with credit supply frictions is consistent with the VAR narrative and therefore a very good first step in understanding the propagation of news shocks. By focussing on financial frictions our study therefore makes a first step to establish that different methodologies can result in consistent readings and provide a unified view for the macroeconomic effects of TFP news shocks.

The remainder of the paper is organized as follows. Sections 2 and 3 describe the VAR and DSGE analysis, respectively. Section 4 reconciles the differences between the DSGE and the VAR findings and section 5 concludes.

2 VAR analysis

This section describes the VAR model, the data and the methodology used for the estimation and the results from the VAR analysis.

2.1 The VAR model

Consider the following reduced form VAR(p) model,

$$y_t = A(L)u_t, \tag{1}$$

where y_t is an $n \times 1$ vector of variables of interest, $A(L) = I + A_1 L + A_2 L^2 + ... + A_p L^p$ is a lag polynomial, $A_1, A_2, ..., A_p$ are $n \times n$ matrices of coefficients and, finally, u_t is an error term with $n \times n$ covariance matrix Σ. Define a linear mapping between reduced form, u_t, and structural errors, ε_t,

$$u_t = B_0 \varepsilon_t, \tag{2}$$

We can then write the structural moving average representation as

$$y_t = C(L)\varepsilon_t, \tag{3}$$

where $C(L) = A(L)B_0$, $\varepsilon_t = B_0^{-1}u_t$, and the matrix B_0 satisfies $B_0 B_0' = \Sigma$. The B_0 matrix may also be written as $B_0 = \tilde{B}_0 D$, where $\tilde{B}_0$ is any arbitrary orthogonalization of Σ and D is an orthonormal matrix ($DD' = I$).

The h step ahead forecast error is,

$$y_{t+h} - E_{t-1}y_{t+h} = \sum_{\tau=0}^{h} A_\tau \tilde{B}_0 D \varepsilon_{t+h-\tau}. \tag{4}$$

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

$$V_{i,j}(h) = \frac{e_i'\Big(\sum_{\tau=0}^{h} A_\tau \tilde{B}_0 D e_j e_j' D' \tilde{B}_0' A_\tau'\Big) e_i}{e_i'\Big(\sum_{\tau=0}^{h} A_\tau \Sigma A_\tau'\Big) e_i} = \frac{\sum_{\tau=0}^{h} A_{i,\tau} \tilde{B}_0 \gamma\gamma' \tilde{B}_0' A_{i,\tau}'}{\sum_{\tau=0}^{h} A_{i,\tau} \Sigma A_{i,\tau}'}, \tag{5}$$

where e_i denotes selection vectors with one in the i-th position and zeros elsewhere. The e_j vectors pick out the j-th column of D, denoted by γ. $\tilde{B}_0\gamma$ is an $n \times 1$ vector corresponding to the j-th column of a possible orthogonalization and can be interpreted as an impulse response vector. In the following section, we discuss the estimation and identification methodology that yields an estimate for the TFP news shock from the VAR model.

2.2 VAR estimation

We estimate the VAR model using quarterly U.S. data for the period 1990:Q1−2013:Q4. To estimate the VAR model we use four lags with a Minnesota prior and compute confidence bands by drawing from the posterior—details are given in Appendix A.5. A key input is an observable measure of TFP and for this purpose we use the utilization-adjusted aggregate TFP measure provided by John Fernald of the San Francisco Fed. The methodology used to compute the TFP measure is based on the growth accounting methodology in Basu et al. (2006) and corrects for unobserved capacity utilization, described in Fernald (2014).[5] The time series included in the VAR enter in levels, consistent with the treatment in the empirical VAR literature (e.g. Barsky and Sims (2011) and Beaudry and Portier (2004, 2006, 2014)). Details about the data are provided in Appendix B.

To identify the TFP news shock from the VAR model, we adopt the identification scheme of Francis et al. (2014) (referred to as the Max Share method). The Max Share method recovers the news shock by maximizing the variance of TFP at a specific long but finite horizon (we set the horizon to 40 quarters) and imposes a zero impact restriction on TFP conditional on the news shock. We note our results are robust to alternative identification approaches which are described in detail in Appendix A.2. Unless otherwise noted, the Figures display median IRFs along with the confidence bands.

We consider a post 1990s sample for the following reasons.[6] First, following the financial deregulation the importance of the financial sector for the determination of credit and asset prices, which is the main focus of our study, has risen significantly during this period (see e.g. Adrian and Shin (2010) and Jermann and Quadrini (2012)).[7] Second, the sample period roughly corresponds to the Great Moderation era (mid-1980s onwards), which is characterized by a stable structural economic environment (including nature and volatility

[5]Throughout the paper we use the 2015 vintage of TFP which incorporates new updated corrections in the utilization estimates based on Basu et al. (2013).

[6]A further critical consideration to begin in 1990:Q1 is the availability of financial data on sectoral corporate bond spreads used in the application with the DSGE model described below.

[7]A recent study by Gunn and Johri (2013) proposes a news driven interpretation of the financial crisis in that financial innovations during deregulation failed to live to expectations, fuelling a bust in asset prices.

of shocks). For example, Galí and Gambetti (2009), among others, document significant changes in the co-movement properties of important macro-aggregates before and after the mid-1980s. Finally, the corporate bond market–relative to equity markets–which is the source of information for our credit spread indicators has grown tremendously as a source of finance, suggesting that developments in the corporate bond market may more accurately reflect future economic conditions.[8]

2.3 Results from the VAR model

TFP news shock and credit spread indicators. We begin our exploration by estimating VAR specifications that introduce and examine responses to a host of credit spread indicators. Our credit spread indicators include the popular BAA spread (difference between the yield of a BAA rated corporate bond and a ten year Treasury), the GZ spread constructed by Gilchrist and Zakrajsek (2012), and the GT spread constructed by Görtz and Tsoukalas (2016).[9] The GZ and GT spread indicators use firm level information from corporate senior unsecured bonds traded in the secondary market. They both control for the maturity mismatch between corporate and treasuries, not accounted for by the BAA spread. The GZ spread spans the entire spectrum of issuer credit quality (from investment grade to below investment grade), whereas the GT spread focuses on investment grade issues.

VAR specification I. Figure 1 displays IRFs from the first VAR specification featuring aggregate TFP, output, hours, consumption, BAA spread, inflation (log change in GDP deflator), and consumer confidence indicator (E5Y).[10] Several interesting findings emerge. First, TFP rises in a delayed fashion, and it becomes significantly different from zero af-

[8] According to the Securities Industry and Financial Markets Association (SIFMA) over the period 1990 to 2013 the volume of US corporate bonds outstanding more than quantipled from $1.35 trillion to $7.46 trillion. The same body reports that in 2010, total corporate debt was 5.1 times common stock issuance.

[9] We have also examined the Baa minus Aaa spread (difference between the yield of a Baa rated and a Aaa rated corporate bond) and found results that are very similar to the ones reported in the main body of the paper.

[10] The Michigan consumer confidence indicator (E5Y) summarizes responses to the following question: "Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years, or that we'll have periods of widespread unemployment or depression, or what?" The variable is constructed as the percentage giving a favorable answer minus the percentage giving an unfavorable answer plus 100.

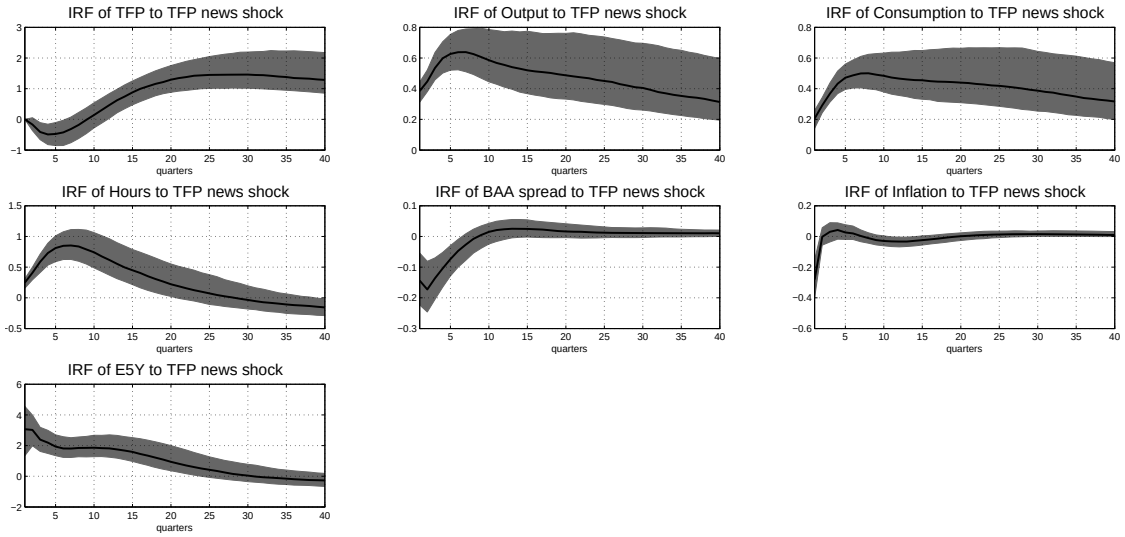

Figure 1: **TFP news shocks, specification I.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

ter approximately three years. This pattern shows that the identification scheme produces empirically plausible news shocks, as discussed in Beaudry and Portier (2014). Second, the VAR-identified TFP news shock creates a boom today: output, consumption, and hours increase significantly on impact, and they display hump-shaped dynamics. Third, the BAA corporate bond spread declines significantly, suggesting that corporate bond markets anticipate movements in future TFP, which is consistent with an economic expansion induced by an increase in lending. The behavior of the BAA spread is a novel stylized fact that, to the best of our knowledge, no previous studies have documented. Further, the confidence indicator also increases in anticipation of the future rise in TFP, consistent with the work by Barsky and Sims (2011) that finds that the indicator retains a strong predicting power of future economic outlook, and finally, the news shocks is associated with a short-lived decline in inflation.

VAR specification II. Recently, Gilchrist and Zakrajsek (2012) construct a credit spread indicator (GZ spread) that is shown to be superior, relative to conventional indicators such as the BAA spread, in terms of forecasting future economic activity. They further decompose the GZ spread into two components: a component capturing cyclical changes

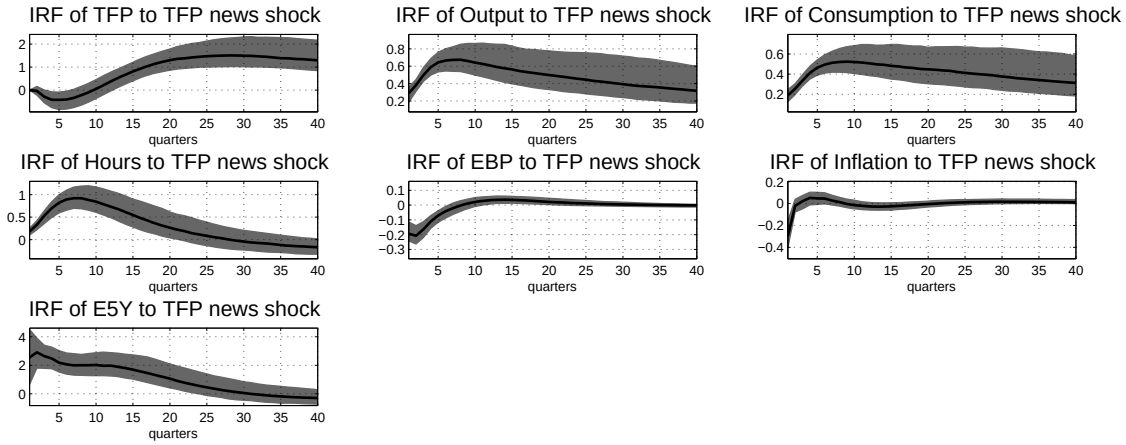

Figure 2: **TFP news shocks, specification II.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

in expected defaults, and a component that measures cyclical changes in the relationship between measured default risk and credit spreads, the 'excess bond premium' (EBP). They suggest, that over the sample 1985-2010, the excess bond premium contains most of the predictive content of the GZ spread for various measures of economic activity. We examine the behaviour of the excess bond premium by replacing the latter in the VAR in place of the BAA spread. Figure 2 displays IRFs from VAR specification II featuring aggregate TFP, output, hours, consumption, excess bond premium, inflation, and consumer confidence indicator. Our novel finding is that the excess bond premium declines significantly on impact and, similarly to the behaviour of the BAA spread, ahead of the future rise in TFP while the economy experiences a broad based boom in activity. Notice that the forecasting ability of the excess bond premium as emphasized by Gilchrist and Zakrajsek (2012) is implicitly reflected in the shape of the IRFs, given the hump shaped dynamics of the real activity variables. Figure 3 displays IRFs from a VAR specification that adds the default risk component of the GZ spread to specification II. The interesting finding is that the default risk component of the GZ spread is not reacting significantly in response to the news shock. The IRFs to the common variables are virtually identical, but measured default risk is not significantly different from zero for ten quarters. It then exhibits a small but significant increase above

zero, which materializes after the peak in economic activity. The fact that the expected default component of the GZ spread is not reacting significantly but the excess bond premium is, shows that the variation in the GZ indicator conditional on the news shock is driven by factors mostly related to credit supply conditions. We provide more evidence for this link below.

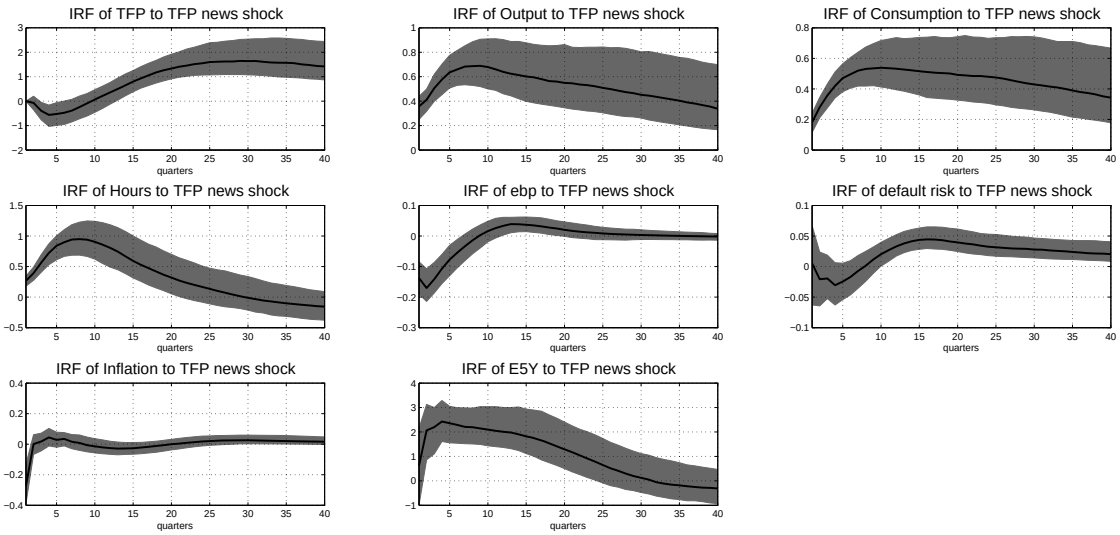

Figure 3: **TFP news shocks, specification II expanded with default risk.** Impulse responses to a TFP news shock from an eight variable VAR estimated with 4 lags. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

VAR specifications with alternative credit spread indicators. Figure 4 displays IRFs of four credit spread indicators, namely, the BAA spread, GZ spread, excess bond premium, and GT spread to an identified TFP news shock. The GT spread is from the study of Görtz and Tsoukalas (2016)—it is constructed as an average spread of firm-level corporate bond yields obtained from investment grade issuers relative to the equivalent maturities government bond yields (details are provided in the data Appendix B). The VAR specification in each case contains the same variables, except that a different credit spread indicator is introduced each time and the VAR is re-estimated.[11] The results suggest a similar and robust dynamic pattern of the four credit spread indicators, namely they portray

[11] We do not show the IRFs to the remaining variables in the VARs in order to conserve space since the IRFs are quantitatively similar to those displayed in figure 1 and figure 2.

a significant decline on impact that precedes the future rise in TFP by several years (not shown in the Figure).

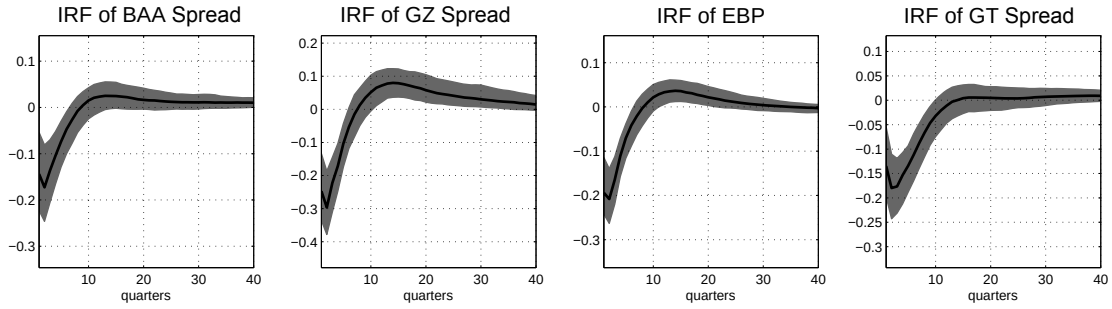

Figure 4: **TFP news shocks and credit spread indicators.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The estimated VARs are based on specification I where we use as the credit spread indicator either the BAA spread, GZ spread, EBP, or the GT spread. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

What are the shocks that move credit spread indicators? The preceding evidence suggests that credit spread indicators may be capturing a transmission mechanism for news shocks that is grounded on credit market frictions. To provide further evidence for the link between news shocks and credit spread indicators we proceed to independently identify shocks that explain the majority of the un-forecastable movements in our credit spread indicators. Consider the BAA spread as our target variable. We proceed to identify, in an agnostic manner, following the methodology proposed by Uhlig (2003), a single shock that maximizes the forecast error variance (FEV) of the BAA spread (we term it the "max FEV BAA shock") at cyclical frequencies (horizons 6 to 32 quarters). It is interesting to note this exercise is similar in spirit to the analysis in Beaudry and Portier (2006) who focus on shocks that explain short run movements in stock prices and then establish a link between those shocks and TFP news shocks. Here the goal is to establish the link, if any, between movements in asset prices from the corporate debt market and news shocks.

Consider VAR specification I featuring the BAA spread, output, hours, consumption, TFP, inflation, and consumer confidence indicator. We find that the max FEV BAA shock identified from this VAR specification, explains between 54% to 58% of the forecast error

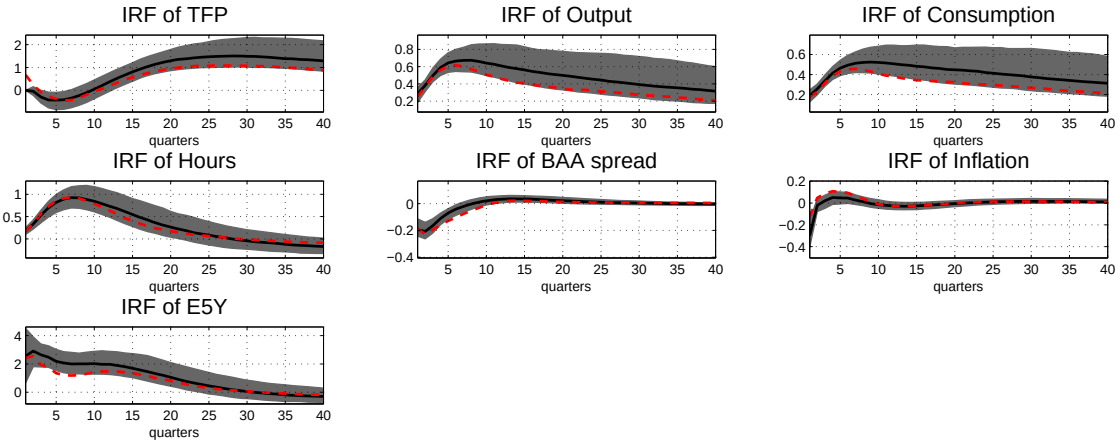

Figure 5: **TFP news shock (solid line) and max FEV BAA shock (dashed line).** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

variance in the BAA spread in forecast horizons from six to thirty-two quarters. We then compare the IRFs induced by the shock that maximizes the FEV of BAA with the IRFs induced by the TFP news shock we have identified from VAR specification I. Figure 5 displays the IRFs. The comparison reveals an striking new finding. The two shocks, independently identified, exhibit very similar dynamic paths. The shock that maximizes the forecast error variance of BAA spread is associated with an immediate increase in economic activity, a rise in the confidence indicator, a short-lived decline in inflation, and a delayed rise in TFP. The initial rise in TFP observed in the case of the max FEV BAA shock is not significantly different from zero.[12] These dynamics are largely shared by the TFP news shock. Moreover, the max FEV BAA shock median IRFs are within the confidence bands of the IRFs obtained from the VAR identified TFP news shock in specification I. Importantly, the max FEV BAA shock is a relevant business cycle shock in a quantitative sense. Briefly, this shock explains more than 50% of the FEV in output and approximately 60% of the FEV in hours. To conserve space the contribution of the max FEV BAA shock to the FEV of all variables included in the VAR is shown in Appendix A.1.

[12]Notice that in VAR with the agnostic identification that seeks for the max FEV BAA shock, there is no zero impact restriction associated with the IRF of TFP, hence TFP can freely move on impact of this shock. Nevertheless, the IRF confidence bands for TFP in this identification suggest that this positive impact response in not significantly different from zero. In fact TFP rises significantly above zero at approximately 20 quarters.

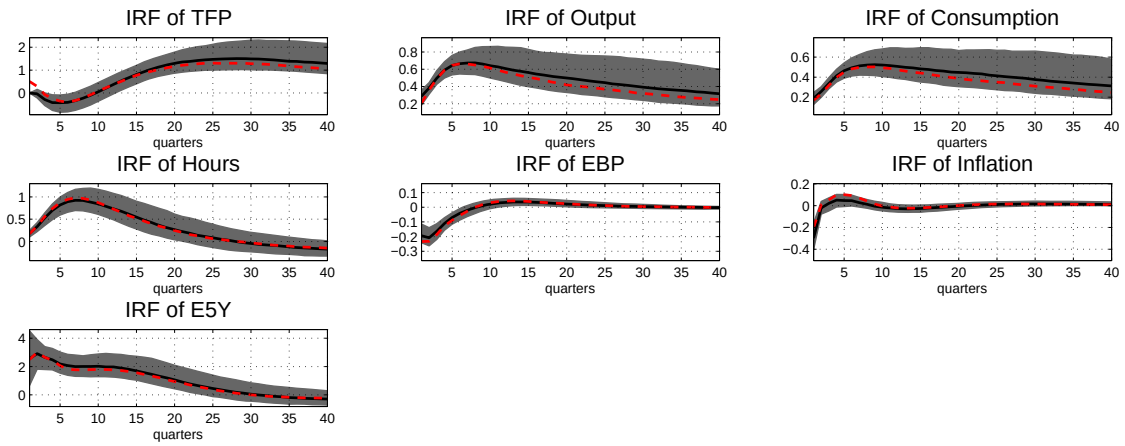

Figure 6: **TFP news shock (solid line) and max FEV EBP shock (dashed line).** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

An alternative VAR specification we use to identify this shock features the EBP, output, hours, consumption, TFP, inflation, and consumer confidence and hence contains the same information set as VAR specification II. The max FEV EBP shock identified from the VAR in this case, explains between 74% to 75% of the forecast error variance in the EBP in forecast horizons from six to thirty-two quarters. We then compare the IRFs induced by this shock with the IRFs induced by the TFP news shock we have identified from VAR specification II. Figure 6 displays the IRFs and the comparison confirms the finding from Figure 5. The two shocks, independently identified, exhibit very similar dynamic paths. Both shocks are associated with an immediate increase in activity, and a countercyclical response of the excess bond premium. The similarity in the dynamics of the excess bond premium across the two independent identification exercises is, we think, an important finding since, according to the arguments and evidence in Gilchrist and Zakrajsek (2012), the excess bond premium captures cyclical variations in credit market supply conditions. Adopting this interpretation, a favourable TFP news shock is associated with a reduction in the excess bond premium and a relaxation of credit market supply conditions that coincides with a boom in activity, leading to the hypothesis we advance in this paper: balance sheet conditions of financial intermediaries matter for the propagation of news shocks. In Appendix A.1 we

perform the same exercise using the GZ spread, and GT spread, as our target variables and demonstrate that the IRFs from the shocks identified using those indicators resemble very closely the IRFs from the TFP news shocks, suggesting a very robust finding. To protect against the possibility that our results are not driven by the financial crisis years (which were characterized by large, albeit short-lived, swings in credit spreads) or the "Great Recession" more generally we have repeated the VAR analysis excluding this part of the sample, and we also repeated the analysis for an extended sample that begins in 1985. It is interesting to examine robustness in the extended sample since deregulation took place in phases beginning in the late 1970s to early 1980s and the corporate bond market has already been developing quite strongly since the start of the decade. Moreover, Gilchrist and Zakrajsek (2012) argue that the forecasting power of credit spread indicators has been stronger post 1985 relative to earlier periods. The results are reported in Appendix A.3 and suggest that all of our VAR findings are robust considering these two alternative sample periods.[13]

VAR specifications with bank equity and lending standards. To study the role of balance sheet conditions of intermediaries for the propagation of news shocks we examine the behaviour of the market value of U.S. commercial banks equity, a key indicator to assess balance sheet conditions. The market value of equity is aggregated from all publicly listed financial institutions provided by the Center for Research in Securities Prices (CRSP)(Appendix B provides details on the data). We also examine the behaviour of lending standards using the Senior Loan Officer Opinion Survey of Bank Lending Practices (SLOOS). Specifically, we focus on the survey that asks participating banks to report changes in lending standards for commercial and industrial loans.[14] We first examine the response of the market value

[13]Our decomposition leaves some room for other shocks to explain movements in credit spread indicators and consequently have real economic consequences. Our approach seeks to isolate a single shock that explains the majority of movements in the credit spread indicators. For example in the case of the BAA spread, the agnostic approach discussed above suggests that slightly less than half of the variance of the BAA spread remains un-accounted for by this single shock, in horizons between six to thirty-two quarters. The fraction of variance that remains unaccounted for by this shock is however considerably less when the GZ, GT spread or EBP are the target variables.

[14]The SLOOS measures the net percentage of domestic respondents tightening standards for commercial and industry loans. We use the net percentage applicable for loans to medium and large firms. Specifically the net percentage measures the fraction of banks that reported having tightened ("tightened considerably" or "tightened somewhat") minus the fraction of banks that reported having eased ("eased considerably" or

of equity to a TFP news shock, by expanding VAR specification II to include the market equity variable and re-estimating the VAR. The IRFs in Figure 7 suggest an immediate, strong and significant positive response of market equity along with a decline in the excess bond premium, whereas the same dynamic pattern is obtained for the activity variables as in specification II. The response of market equity is consistent with the notion that it reflects increased profitability and/or valuation of the asset side of the balance sheet of the intermediaries.

We also examine the response of the lending standards indicator to a TFP news shock, by expanding VAR specification II to include the SLOOS and re-estimating the VAR. Figure 8 displays the IRFs to the identified TFP news shock. The IRFs to the variables common to the specification considered above are qualitatively and quantitatively similar. The response of the SLOOS variable suggests an immediate and significant relaxation of lending standards, a relaxation that persists for about two years. Both sets of findings related to the joint response of the excess bond premium, market equity and lending standards are consistent with the evidence reported in Gilchrist and Zakrajsek (2012), where higher profitability of the U.S. financial corporate sector is associated with a reduction in the excess bond premium. Taken together, these findings support the hypothesis that balance sheet and more generally credit supply conditions are an important transmission channel for TFP news shocks.

VAR specification III. Before we conclude with the VAR evidence, we briefly discuss a few additional results obtained from a VAR specification that incorporates other important macro variables. Figure 9 displays IRF from VAR specification III that features TFP, output, investment, hours, S&P 500 index, inflation, and consumer confidence. First, note that the IRFs for the variables that are common in VAR specifications described above are qualitatively and quantitatively similar to each other. The response of investment is consistent with the overall broad-based rise in activity, and it rises significantly in response to good news about future TFP, anticipating the realization of improved productivity. The S&P 500 index also rises significantly in anticipation of the future rise in TFP, consistent with the

"eased somewhat").

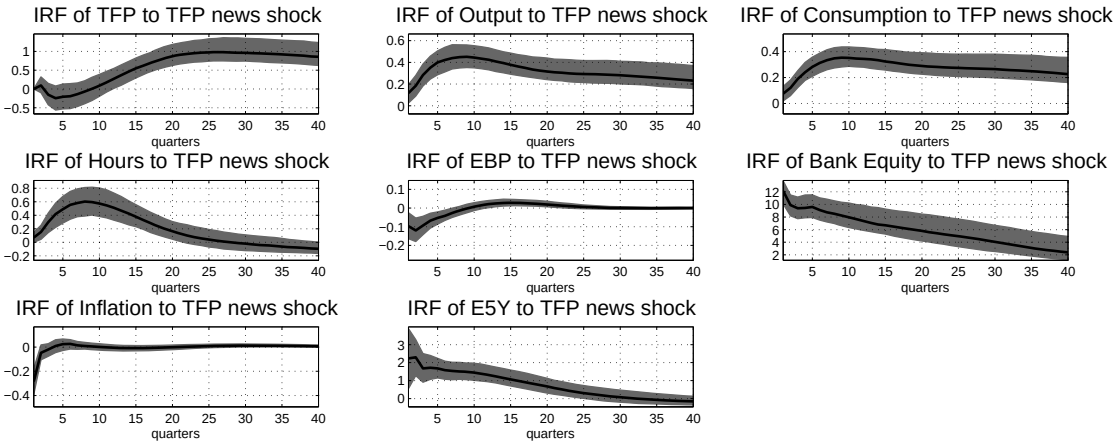

Figure 7: **TFP news shocks. Specification II expanded with bank equity.** Impulse responses to a TFP news shock from an eight variable VAR estimated with 4 lags.The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

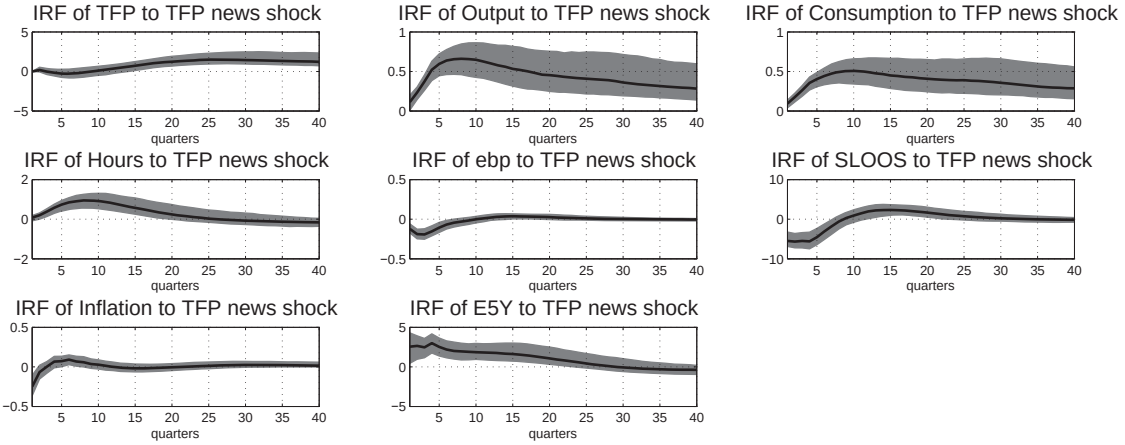

Figure 8: **TFP news shocks. Specification II expanded with SLOOS** Impulse responses to a TFP news shock from an eight variable VAR estimated with 4 lags. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

evidence reported in Beaudry and Portier (2006) that equity prices incorporate news about future fundamentals.

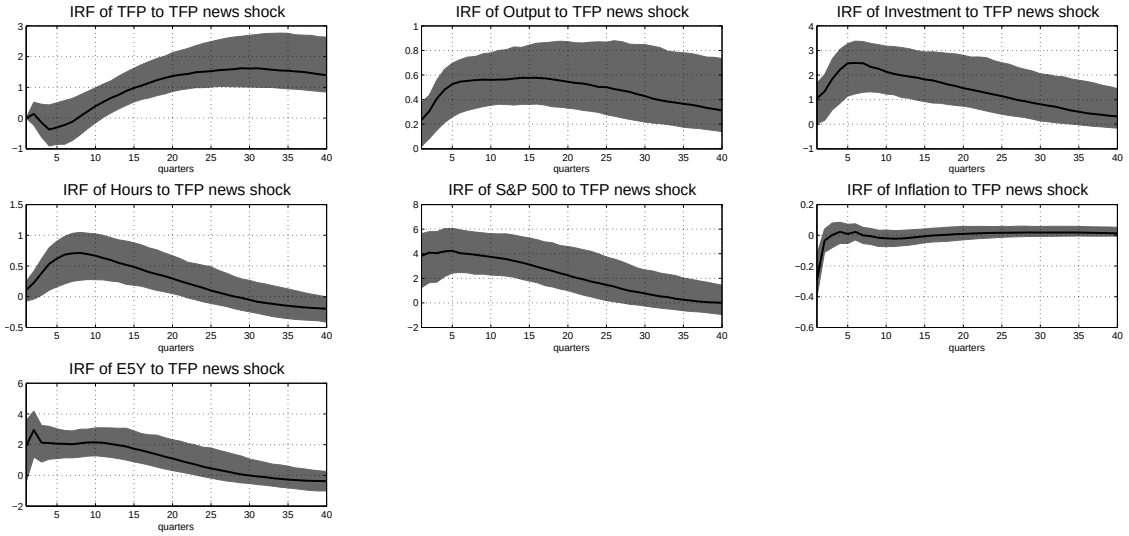

Figure 9: **TFP news shocks, specification III.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

3 DSGE analysis

This section provides an overview of the DSGE model, it discusses the data, the methodology used for the estimation and the results from the DSGE analysis.

3.1 Overview of the DSGE model

We employ a two-sector DSGE model that most closely resembles those developed by Ireland and Schuh (2008) and Görtz and Tsoukalas (2016). The model introduces a financial sector similar to Gertler and Karadi (2011), where banks lend capital to consumption- and investment-goods-producing sectors, to interact with sectoral news shocks. Below, we describe the parts of the model related to the goods-producing sectors, the financial sector, the exogenous disturbances, and the arrival of information. Appendix C provides a description of the complete model.

Our choice to use a two sector model is three-fold. First, the methodology to measure aggregate TFP described in Fernald (2014) is based on sectoral TFP data. The equation is

$$dTFP_{agg,t} = w_{i,t} dTFP_{i,t} + (1 - w_{i,t}) dTFP_{c,t}, \tag{6}$$

where the variables $dTFP_{agg}$, $dTFP_i$, and $dTFP_c$ denote (utilization-adjusted) TFP growth rates in aggregate, investment- and consumption-specific sectors, respectively, and the coefficient w_i denotes the share of the investment sector, expressed in value added. Equation (6) shows that the aggregate TFP growth rate is an expenditure share-weighted average of sectoral TFP growth rates. The correlation between $dTFP_i$ and $dTFP_c$ is equal to 0.31, pointing to a weak co-movement between the two series and therefore suggesting that changes in aggregate TFP cannot be interpreted as a single homogeneous technological indicator. In our sample, average w_i is equal to 0.24. Therefore, by construction, the growth rate of the consumption-specific TFP holds a larger contribution to the growth rate of aggregate TFP. In addition, the aggregate TFP growth rate co-moves more closely with the growth rate of consumption-specific TFP (correlation coefficient equal to 0.88) than the growth rate of investment-specific TFP (correlation coefficient equal to 0.72), further suggesting that movements in the growth rate of aggregate TFP are largely influenced by the growth rate in consumption-specific TFP. It is therefore important from a model perspective to tease out separate sector specific technologies and use the same methodology as in Fernald (2014) to produce an aggregate TFP series when we compare results from the two methodologies. Second, a two sector model allows a more precise decomposition of the data variation into shocks, compared to a one sector model.[15] Last, Görtz and Tsoukalas (2016) show that a two sector model, has a better fit with the data compared to a one sector model.

[15] To illustrate, consider the relative price of investment (RPI) in the two sector model, given as:

$$\frac{P_{I,t}}{P_{C,t}} = \frac{\text{mark up}_{I,t}}{\text{mark up}_{C,t}} \frac{1 - a_c}{1 - a_i} \frac{A_t}{V_t} \left(\frac{K_{I,t}}{L_{I,t}}\right)^{-a_i} \left(\frac{K_{C,t}}{L_{C,t}}\right)^{a_c}$$

where a_c and a_i are capital shares in consumption and investment sector, respectively; V_t and A_t, are TFP in the investment and consumption sector, respectively; and $\frac{K_{x,t}}{L_{x,t}}, x = I, C$ is the capital-labor ratio in sector x. mark up$_{x,t}$ is the price mark-up, or inverse of the real marginal cost, in sector x. In one sector models the investment specific technology, V, is identified one-for-one from the variation in the RPI alone. Moreover, in our sample the cyclical component of the RPI is procyclical rendering this restriction inappropriate, because investment specific V shocks predict a countercyclical RPI response.

The model comprises two sectors that manufacture consumption and investment goods. Investment goods are used as capital input in the production process of each sector, and consumption goods provide utility to the households. Households consume, save in interest-bearing deposits with financial intermediaries, and supply labor input in a monopolistically competitive labor market where wages are set with Calvo contracts. A continuum of sector-specific intermediate goods producers use labor and capital services to manufacture distinct investment and consumption goods subject to sector-specific Calvo contracts. Capital producers use investment goods and existing capital to manufacture new sector-specific capital goods. Leveraged constrained financial intermediaries acquire capital and collect deposits from households. The monetary authority sets the nominal interest rate, according to a Taylor rule. The model is closely related to Görtz and Tsoukalas (2016), one of the few existing DSGE models that can generate empirical relevance of TFP news shocks when taken to the data. There are two notable differences. First, we entertain a richer shock structure that compete with news shocks in the estimation, and second we use the relative price of investment among the set of observables. Both of these departures allow for a more precise comparison with state-of-the-art estimated DSGE models and previous findings in the literature on the sources of business cycles.

3.1.1 Intermediate and final goods production

A monopolist produces consumption and investment-specific intermediate goods according to the production technologies

$$C_t(i) = \max\left[a_{lt}A_t(L_{C,t}(i))^{1-a_c}(K_{C,t}(i))^{a_c} - A_t V_t^{\frac{a_c}{1-a_i}} F_C, 0\right]$$

and

$$I_t(i) = \max\left[v_{lt}V_t(L_{I,t}(i))^{1-a_i}(K_{I,t}(i))^{a_i} - V_t^{\frac{1}{1-a_i}} F_I, 0\right],$$

respectively. The variables $K_{x,t}(i)$ and $L_{x,t}(i)$ denote the amount of capital and labor services rented by firm i in sector $x = C, I$, and the parameters $(a_c, a_i) \in (0, 1)$ denote capital shares

in production.[16] The variables A_t and V_t denote the (non-stationary) level of TFP in the consumption and investment sector, respectively, and the variables $z_t = ln(A_t/A_{t-1})$ and $v_t = ln(V_t/V_{t-1})$ denote (stationary) stochastic growth rates of TFP in the consumption and investment sector, respectively. The variables a_{lt}, v_{lt}, denote the stationary level of TFP in the consumption and investment sector, respectively. To facilitate the exposition, subsection 3.1.5 describes the processes for the exogenous disturbances. Intermediate goods producers set prices according to Calvo (1983) contracts.

Perfectly competitive firms manufacture final goods, C_t and I_t, in the consumption and investment sector by combining a continuum of intermediate goods in each sector, $C_t(i)$ and $I_t(i)$, respectively, according to the production technologies

$$C_t = \left[\int_0^1 (C_t(i))^{\frac{1}{1+\lambda^C_{p,t}}} di\right]^{1+\lambda^C_{p,t}} \quad \text{and} \quad I_t = \left[\int_0^1 (I_t(i))^{\frac{1}{1+\lambda^I_{p,t}}} di\right]^{1+\lambda^I_{p,t}},$$

where the exogenous elasticities $\lambda^C_{p,t}$ and $\lambda^I_{p,t}$ across intermediate goods in each sector determine the (sectoral) price markup over marginal cost. Similar to the standard NK framework, prices of final goods in each sector ($P_{C,t}$ and $P_{I,t}$) are CES aggregates of intermediate goods prices. Appendix C provides details on price-setting decisions of the intermediate goods producers.

3.1.2 Households

As in Gertler and Karadi (2011), households comprise two types of members, workers of size $1-f$ and bankers of size f. Each workers j supplies diversified labor in return for a wage while each bankers f manages a financial intermediary. Effectively, households own the intermediaries managed by bankers, but they do not own the deposits held by the financial intermediaries. Perfect risk sharing exists within each household. The proportion of workers and bankers remains constant over time. However, members of the households are allowed to switch occupations to avoid bankers having to fund investments from their own capital

[16] As in Christiano et al. (2005), the presence of fixed costs in production in both sectors (i.e. $F_C > 0$ and $F_I > 0$) leads to zero profits along the non-stochastic balanced growth path thereby the analysis abstracts from entry and exit of intermediate good producers. Fixed costs grow at the same rate of sectoral output to retain relevance for the firms' profit decisions.

without having to access credit. Bankers become workers in the next period with probability $(1-\theta_B)$ and transfer the retained earnings to households. Household supply start-up funds to workers who become bankers. Each household maximizes the utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t b_t \left[\ln(C_t - hC_{t-1}) - \varphi \frac{(L_{C,t}(j) + L_{I,t}(j))^{1+\nu}}{1+\nu} \right],$$

where E_0 is the conditional expectation operator at the beginning of period 0, $\beta \in (0,1)$ is the discount factor, and $h \in (0,1)$ is the degree of external habit formation. The inverse Frisch labor supply elasticity is denoted by $\nu > 0$, and the parameter $\varphi > 0$ enables the model to replicate the steady state level of total labor supply in the data.[17] The variable b_t denotes an intertemporal preference shock. Each household faces the following budget constraint expressed in consumption units

$$C_t + \frac{B_t}{P_{C,t}} \leq \frac{W_t(j)}{P_{C,t}}(L_{C,t}(j) + L_{I,t}(j)) + R_{t-1}\frac{B_{t-1}}{P_{C,t}} - \frac{T_t}{P_{C,t}} + \frac{\Psi_t(j)}{P_{C,t}} + \frac{\Pi_t}{P_{C,t}}, \tag{7}$$

where the variable B_t denotes holdings of risk-free bank deposits, Ψ_t is the net cash flow from the household's portfolio of state contingent securities, T_t is lump-sum taxes, R_t, is the (gross) nominal interest rate paid on deposits, and Π_t is the net profit accruing to households from ownership of all firms. The wage rate, W_t, is identical across sectors due to perfect labor mobility. As in Erceg et al. (2000), each household sets the wage according to Calvo contracts. The desired markup of wages over the household's marginal rate of substitution (or wage mark-up), $\lambda_{w,t}$, follows an exogenous stochastic process.

3.1.3 Production of capital goods

Production of physical capital. We assume that significant reallocation costs between sectors lead to immobile sector-specific capital.[18] Capital producers in each sector $x = C, I$

[17] Note that consumption is not indexed by (j) because perfect risk sharing leads to similar asset holding across members of the household.

[18] Ramey and Shapiro (2001) find strong evidence of large reallocation costs between sectors. Boldrin et al. (2001), Ireland and Schuh (2008), Huffman and Wynne (1999) and Papanikolaou (2011) establish that constrained factor mobility improves the performance of theoretical models of the business cycle to replicate

manufacture capital goods using a fraction of investment goods from final-goods producers and undepreciated capital from capital-services producers, subject to investment adjustment costs (IAC), similar to Christiano et al. (2005). Solving the optimization problem of capital producers yields the standard capital accumulation equation

$$\bar{K}_{x,t} = (1-\delta_x)\bar{K}_{x,t-1} + \mu_t\left(1 - S\Big(\frac{I_{x,t}}{I_{x,t-1}}\Big)\right)I_{x,t}, \tag{8}$$

for $x = C, I$. The parameter δ_x denotes the sectoral depreciation rate, the function $S(I_{x,t}/I_{x,t-1})$ captures IAC and has standard properties—i.e. $S(\cdot)$ satisfies the following conditions: $S(1) = S'(1) = 0$ and $S''(1) = \kappa > 0$. Finally, the variable μ_t denotes the marginal efficiency of investment (MEI) shock, as in Justiniano et al. (2010).

Production of capital services. The producers of physical capital use funds from financial intermediaries to purchase capital from physical capital producers and choose the utilization rate to convert it into capital services. They rent capital services to intermediate-goods producers that operate in a perfectly competitive market for a rental rate equal to $R^K_{x,t}/P_{C,t}$ per unit of capital. At the end of period $t+1$, they sell the undepreciated portion of capital to physical capital producers.[19] The utilization rate, $u_{x,t}$, transforms physical capital into capital services according to

$$K_{x,t} = u_{x,t}\bar{K}_{x,t-1},$$

for $x = C, I$ and subjects to a cost $a_x(u_{x,t})$ per unit of capital. The function $a_x(u_{x,t})$ has standard properties—i.e. in steady state, $u = 1$, $a_x(1) = 0$ and $\chi_x \equiv (a''_x(1)/a'_x(1))$ denotes the cost elasticity. The producers of capital services choose the utilization rate to maximize their profits

$$\max_{u_{x,t+1}}\left[\frac{R^K_{x,t+1}}{P_{C,t+1}}u_{x,t+1}\bar{K}_{x,t} - a_x(u_{x,t+1})\bar{K}_{x,t}A_{t+1}V_{t+1}^{\frac{a_c-1}{1-a_i}}\right],$$

for $x = C, I$. The total income for the producers of capital services in period $t+1$ is equal

movements in aggregate fluctuations.

[19] It is worth noting that the price of capital, equivalent to Tobin's marginal Q, is equal to $Q_{x,t} = \Phi_{x,t}/\Lambda_t$, where Λ_t and $\Phi_{x,t}$ are the Lagrange multipliers on the households' budget constraint (7) and capital accumulation constraint (8), respectively.

to $R^B_{x,t+1}Q_{x,t}\bar{K}_{x,t}$, with

$$R^B_{x,t+1} = \frac{\frac{R^K_{x,t+1}}{P_{x,t+1}}u_{x,t+1} + Q_{x,t+1}(1-\delta_x) - a_x(u_{x,t+1})A_{t+1}V_{t+1}^{\frac{a_c-1}{1-a_i}}}{Q_{x,t}}, \tag{9}$$

where $R^B_{x,t+1}$ denotes the real return from capital. As in Gertler and Karadi (2011), producers of capital services finance the purchase of capital at the end of each period with funds from financial intermediaries, as described in the next subsection. Thus, $R^B_{x,t+1}$ also represents the return earned by financial intermediaries (see Appendix C for details).

3.1.4 Financial sector

Financial intermediaries fund the acquisitions of physical capital from capital-services producers using their own equity capital and deposits from households. They lend in specific islands (sectors) and cannot switch between them.[20] The financial sector in the model follows closely Gertler and Karadi (2011), and we therefore limit the exposition to the key equations and Appendix C provides the complete set of equations. Three equations encapsulate the key dynamics in the financial sector: the balance sheet identity, the demand for assets that links equity capital with the value of physical capital (i.e. the leverage constraint) and the evolution of equity capital. We describe each of them in turn.

The nominal **balance sheet identity** of a branch that lends to sector $x = C, I$ is,

$$Q_{x,t}P_{C,t}S_{x,t} = N_{x,t}P_{C,t} + B_{x,t}, \tag{10}$$

where the variable $S_{x,t}$ denotes the quantity of financial claims on capital services that the producers held by the intermediary, and $Q_{x,t}$ denotes the price per unit of claim. The variable $N_{x,t}$ denotes equity capital (i.e. wealth) at the end of period t, $B_{x,t}$ are households deposits, and $P_{C,t}$ is the price level in the consumption sector.

Financial intermediaries maximize the discounted sum of future equity capital (i.e. the expected terminal wealth). Bankers may abduct funds and transfer them to the household.

[20] Alternatively we can interpret the financial sector as a single intermediary with two branches, each specializing in providing financing to one sector only, where the probability of lending specialization is equal across sectors and independent across time. Each branch maximizes equity from financing the specific sector. For example, within an intermediary, there are divisions specializing in consumer or corporate finance. The financial sector can be interpreted as a special case of Gertler and Kiyotaki (2010).

This moral hazard/costly enforcement problem limits the capacity of financial intermediaries to borrow funds from the households and generates an endogenous **leverage constraint** that limits the bank's ability to acquire assets. Thus, the equation for the demand of assets is

$$Q_{x,t}S_{x,t} = \varrho_{x,t}N_{x,t}, \tag{11}$$

where the value of assets that the intermediary acquires ($Q_{x,t}S_{x,t}$) depends on equity capital, $N_{x,t}$, and the leverage ratio, $\varrho_{x,t}$.[21] Note that when $\varrho_{x,t} > 1$, the leverage constraint (11) magnifies the changes in equity capital on the demand for assets. For instance, higher demand for capital goods, which raises the price of capital, increases equity capital (through the balance sheet identity), which in turn generates further changes in the demand for assets by intermediaries pushing the price of capital. This amplification turns out to be the critical mechanism to attach an important role to news shocks in the estimated model.

The **evolution of equity capital** is described by the law of motion,

$$N_{x,t+1} = \left(\theta_B[(R^B_{x,t+1}\pi_{C,t} - R_t)\varrho_{x,t} + R_t]\frac{N_{x,t}}{\pi_{C,t+1}} + \varpi Q_{x,t+1}S_{x,t+1}\right), \tag{12}$$

where θ_B is the survival rate of bankers, ϖ denotes the fraction of assets transferred to new bankers, and $\pi_{C,t+1}$ denotes the gross inflation rate in the consumption sector. Equation (12) shows that equity capital is a function of the excess (leveraged) real returns earned on equity capital of surviving bankers and the value of assets owned by news bankers. Banks earn expected (nominal) returns on assets (i.e. the risk premium) equal to

$$R^S_{x,t} = R^B_{x,t+1}\pi_{C,t+1} - R_t, \tag{13}$$

for $x = C, I$. The leverage constraint (11) entails non-negative excess returns that vary over time with movements in the equity capital of intermediaries.

Producers of capital services finance capital acquisition ($Q_{x,t}\bar{K}_{x,t}$) by issuing financial claims against the value of acquired physical capital ($Q_{x,t}S_{x,t}$), such that the following constraint holds

$$Q_{x,t}\bar{K}_{x,t} = Q_{x,t}S_{x,t}. \tag{14}$$

[21] As shown in Appendix C, the leverage ratio (i.e. the bank's intermediated assets-to-equity ratio) is a function of the marginal gains of increasing assets (holding equity constant), increasing equity (holding assets constant), and the gain from diverting assets.

As in Gertler and Karadi (2011), there are no frictions in the process of intermediation between nonfinancial firms, and banks and therefore we can interpret the financial claims as one-period, state-contingent bonds in order to interpret the excess returns in equation (13) as a corporate bond spread.

3.1.5 Exogenous disturbances and arrival of information

The model embeds the following exogenous disturbances: sectoral shocks to the growth rate of TFP (z_t, v_t), sectoral shocks to the level of TFP (a_{lt}, v_{lt}), sectoral price mark-up shocks ($\lambda^C_{p,t}$, $\lambda^I_{p,t}$), wage mark-up shock ($\lambda_{w,t}$), preference shock (b_t), monetary policy shock ($\eta_{mp,t}$), government spending shock (g_t), and MEI (μ_t) shock. Each exogenous disturbance is expressed in log deviations from the steady state as a first-order autoregressive (AR(1)) process whose stochastic innovation is uncorrelated with other shocks, has a zero-mean, and is normally distributed. For the monetary policy shock ($\eta_{mp,t}$), the first order autoregressive parameter is set equal to zero. Appendix C provides details on the exogenous disturbances.

The model embeds news shocks to sectoral productivity growth. The productivity growth processes in the consumption and investment sector follow the law of motions

$$z_t = (1-\rho_z)g_a + \rho_z z_{t-1} + \varepsilon^z_t, \qquad \text{and} \qquad v_t = (1-\rho_v)g_v + \rho_v v_{t-1} + \varepsilon^v_t, \tag{15}$$

where the parameters g_a and g_v are the steady-state growth rates of the two TFP processes above, and $\rho_z, \rho_v \in (0,1)$ determine their persistence.

The representation of news shocks is standard and follows, for example, Schmitt-Grohe and Uribe (2012), and Khan and Tsoukalas (2012). The stochastic innovations in the exogenous disturbances in (15) are defined as

$$\varepsilon^z_t = \varepsilon^z_{t,0} + \varepsilon^z_{t-4,4} + \varepsilon^z_{t-8,8} + \varepsilon^z_{t-12,12}, \quad \text{and} \quad \varepsilon^v_t = \varepsilon^v_{t,0} + \varepsilon^v_{t-4,4} + \varepsilon^v_{t-8,8} + +\varepsilon^v_{t-12,12},$$

where the first component, $\varepsilon^x_{t,0}$, is unanticipated (with $x = z, v$) whereas the components $\varepsilon^x_{t-4,4}$, $\varepsilon^x_{t-8,8}$, and $\varepsilon^x_{t-12,12}$ are anticipated and represent news about period t that arrives four, eight and twelve quarters ahead, respectively. As conventional in the literature, the anticipated and unanticipated components for sector $x = C, I$ and horizon $h = 0, 1, \ldots, H$

are *i.i.d.* with distributions $N(0, \sigma^2_{z,t-h})$ and $N(0, \sigma^2_{v,t-h})$ that are uncorrelated across sector, horizon and time. Our choice to consider four, eight, and twelve quarter ahead sector-specific TFP news is guided by the desire to limit the size of the state space of the model while being flexible enough to allow the news processes to accommodate revisions in expectations.

3.2 DSGE estimation

We estimate the DSGE model using quarterly U.S. data for the period 1990:Q1−2013:Q4, the same sample period as for the VAR model. We estimate the model using the following vector of observables: $\left[\Delta \log Y_t, \Delta \log C_t, \Delta \log I_t, \Delta \log W_t, \pi_{C,t}, \Delta(\frac{P^I}{P^C}), \log L_t, R_t, R^C_t, R^I_t, \Delta \log N_t\right]$, which comprises output (Y_t), consumption (C_t), investment (I_t), real wage (W_t), consumption sector inflation ($\pi_{C,t}$), relative price of investment ($\frac{P^I}{P^C}$), hours worked (L_t), nominal interest rate (R_t), consumption sector corporate bond spread (R^C_t), investment sector corporate bond spread (R^I_t), and bank equity, respectively (N_t), and the term Δ denotes the first-difference operator. Variables for aggregate quantities are expressed in real, per-capita terms using civilian noninstitutional population. We demean the data prior to estimation.[22] We use these variables to keep the analysis as close as possible to related studies such as Smets and Wouters (2007), Justiniano et al. (2010) and Khan and Tsoukalas (2012) while incorporating important financial variables. Appendix B provides a detailed description of data sources. The financial variables consist of separate sectoral corporate bond spreads (the GT spread referred to in section 2.3 is an average of the sectoral series) and a publicly available measure of intermediaries' equity capital reported by the Federal Financial Institutions Examination Council.[23] The latter refers to total equity of all insured U.S. commercial banks, expressed in real per capita terms. It is important to note that the measure of equity

[22]Removing sample means from the data prevents the possibility that counterfactual implications of the model for the low frequencies may distort inference on business cycle dynamics. For example, in the sample, consumption has grown by approximately 0.32% on average per quarter, while output has grown by 0.20% on average per quarter respectively. However, the model predicts that they grow at the same rate. Thus, if we hardwire a counterfactual common trend growth rate in the two series, we may distort inference on business cycle implications that is of interest to us.

[23]In constructing spreads, we consider only nonfinancial corporations and only bonds traded in the secondary market. Appendix B describes how we map individual companies to the consumption and investment sector using the input-output tables.

we use in the DSGE estimation is referred to as book equity which is different to the market value of equity used in section 2.3. We have chosen to estimate the model with the book value rather than the market value equity since the former refers to the whole of the U.S. commercial bank sector. Importantly, and motivated by the VAR evidence above, we inform the estimation with the corporate bond spreads which are very likely to contain information about news shocks. Philippon (2009) argues that corporate bond spreads may contain news about future corporate fundamentals and provides evidence that information extracted from corporate bond markets, in contrast to the stock market, is informative for U.S. business fixed investment.

In the DSGE model, TFP news shocks compete with other shocks to account for the variation in the data. The cross equation restrictions implied by the equilibrium conditions of the model identify the different shocks. We estimate a subset of parameters using Bayesian methods and calibrate the remaining parameters with the standard values described in Table 6 of Appendix A.6. The prior distributions conform to the assumptions in Justiniano et al. (2010) and Khan and Tsoukalas (2012), as reported in Table 1.[24]

Table 1 reports information on the posterior distribution of parameters. In the interest of space, we do not discuss the posterior means of the estimated parameters in detail. Posterior means are broadly in line with estimates from earlier work: Khan and Tsoukalas (2012), and Justiniano et al. (2010).

3.3 Results from the DSGE model

In this section we discuss key findings from the DSGE model on the empirical significance and the dynamic propagation of news shocks. We also provide a comparison with findings from standard models in the literature that abstract from financial frictions.

Table 2 reports the variance decomposition of the estimated DSGE model for each news shock and the sum of the unanticipated shocks. The entries show that the estimation assigns

[24]The prior means assumed for the TFP news components are in line with these studies and imply that the sum of the variance of news components is, evaluated at prior means, at most one half of the variance of the corresponding unanticipated component.

Table 1: Prior and Posterior Distributions

Parameter	Description	Prior Distribution			Posterior Distribution		
		Distribution	Mean	Std. dev.	Mean	10%	90%
h	Consumption habit	Beta	0.50	0.10	0.51	0.45	0.58
ν	Inverse labour supply elasticity	Gamma	2.00	0.75	0.20	0.11	0.33
ξ_w	Wage Calvo probability	Beta	0.66	0.10	0.59	0.54	0.63
ξ_C	C-sector price Calvo probability	Beta	0.66	0.10	0.83	0.81	0.85
ξ_I	I-sector price Calvo probability	Beta	0.66	0.10	0.83	0.79	0.87
ι_w	Wage indexation	Beta	0.50	0.15	0.17	0.08	0.27
ι_{p_C}	C-sector price indexation	Beta	0.50	0.15	0.07	0.04	0.10
ι_{p_I}	I-sector price indexation	Beta	0.50	0.15	0.61	0.43	0.78
χI	I-sector utilization	Gamma	5.00	1.00	4.32	3.12	5.62
χC	C-sector utilization	Gamma	5.00	1.00	4.52	3.26	5.84
κ	Investment adj. cost	Gamma	4.00	1.00	2.29	1.87	2.74
ϕ_π	Taylor rule inflation	Normal	1.70	0.30	1.57	1.45	1.70
ρ_R	Taylor rule inertia	Beta	0.60	0.20	0.82	0.79	0.85
ϕ_{dX}	Taylor rule output growth	Normal	0.125	0.10	0.74	0.64	0.83
	Shocks: Persistence						
ρ_z	C-sector TFP growth	Beta	0.40	0.20	0.72	0.67	0.77
ρ_v	I-sector TFP growth	Beta	0.40	0.20	0.38	0.27	0.47
ρ_b	Preference	Beta	0.60	0.20	0.90	0.87	0.92
ρ_μ	Marginal efficiency of investment	Beta	0.60	0.20	0.90	0.87	0.93
ρ_g	Government spending	Beta	0.60	0.20	0.97	0.96	0.99
$\rho_{\lambda_p^C}$	C-sector price markup	Beta	0.60	0.20	0.06	0.03	0.10
$\rho_{\lambda_p^I}$	I-sector price markup	Beta	0.60	0.20	0.84	0.78	0.89
ρ_{λ_w}	Wage markup	Beta	0.60	0.20	0.08	0.03	0.13
ρ_{a_l}	C-sector stationary TFP	Beta	0.60	0.20	0.83	0.41	0.98
ρ_{v_l}	I-sector stationary TFP	Beta	0.60	0.20	0.95	0.93	0.96
	Shocks: Volatilities						
σ_z	C-sector TFP	Inv Gamma	0.50	2	0.17	0.14	0.21
σ_{z4}	C-sector TFP. 4Q ahead news	Inv Gamma	$0.5/\sqrt{3}$	2	0.09	0.07	0.11
σ_{z8}	C-sector TFP. 8Q ahead news	Inv Gamma	$0.5/\sqrt{3}$	2	0.14	0.10	0.18
σ_{z12}	C-sector TFP. 12Q ahead news	Inv Gamma	$0.5/\sqrt{3}$	2	0.22	0.18	0.26
σ_v	I-sector TFP	Inv Gamma	0.50	2	0.26	0.19	0.34
σ_{v4}	I-sector TFP. 4Q ahead news	Inv Gamma	$0.5/\sqrt{3}$	2	0.20	0.14	0.26
σ_{v8}	I-sector TFP. 8Q ahead news	Inv Gamma	$0.5/\sqrt{3}$	2	0.13	0.09	0.17
σ_{v12}	I-sector TFP. 12Q ahead news	Inv Gamma	$0.5/\sqrt{3}$	2	0.24	0.17	0.30
σ_b	Preference	Inv Gamma	0.10	2	1.11	0.95	1.28
σ_μ	Marginal efficiency of investment	Inv Gamma	0.50	2	1.62	1.37	1.89
σ_g	Government spending	Inv Gamma	0.50	2	0.46	0.42	0.50
σ_{mp}	Monetary policy	Inv Gamma	0.10	2	0.12	0.11	0.14
$\sigma_{\lambda_p^C}$	C-sector price markup	Inv Gamma	0.10	2	0.50	0.46	0.55
$\sigma_{\lambda_p^I}$	I-sector price markup	Inv Gamma	0.10	2	0.09	0.06	0.11
σ_{λ_w}	Wage markup	Inv Gamma	0.10	2	0.81	0.69	0.93
σ_{a_l}	C-sector stationary TFP	Inv Gamma	0.50	2	0.34	0.25	0.44
σ_{v_l}	I-sector stationary TFP	Inv Gamma	0.50	2	1.57	1.29	1.83

Notes. The posterior distribution of parameters is evaluated numerically using the random walk Metropolis-Hastings algorithm. We simulate the posterior using a sample of 500,000 draws and discard the first 100,000 of the draws.

significant importance to TFP news shocks as a source of fluctuations. In their totality, TFP news shocks account for 27.6%, 28.6%, 30.4%, 39.5% of the variance in output, consumption, investment and hours worked, respectively, in business cycle frequencies. Consumption-specific news shocks play a major role in this total, accounting for 24.6%, 27.7%, 26.2%, 37.1% of the variance in the same macro aggregates. The estimation finds strong links between financial variables and real aggregates as sectoral news shocks explain a sizable share of the variance in the sectoral bond spreads. These links help to quantify the amplification of TFP news shocks which, as discussed below, results from the presence of leveraged intermediaries.[25]

[25]The propagation of news shocks and the co-movement of aggregate variables hinge on the countercyclical markups, as outlined in Görtz and Tsoukalas (2016) in the context of a two-sector model with nominal rigidities and news shocks. In the aftermath of a positive news shock, countercyclical markups move labour demand and supply curves rightwards offsetting the negative wealth effect on labour supply, thereby generating co-movement in aggregate variables.

Table 2: Variance decomposition at posterior estimates—business cycle frequencies (6-32 quarters)

	z	z^4	z^8	z^{12}	v	v^4	v^8	v^{12}	a_l	v_l	μ	all other shocks	Sum of TFP shock contribution: unanticipated cols. 1, 5	all news cols. 2-4 , 6-8	z news cols. 2-4	v news cols. 6-8
Output	16.0	3.8	8.7	12.2	1.0	0.6	0.3	2.0	0.8	7.8	18.0	28.8	25.6	27.6	24.6	3.0
Consumption	24.4	5.1	9.0	13.6	0.1	0.1	0.1	0.6	5.5	4.2	5.1	31.8	34.2	28.6	27.7	0.8
Investment	3.7	2.1	8.2	16.0	1.7	1.0	0.5	2.7	0.1	13.9	13.6	36.6	19.4	30.4	26.2	4.2
Total Hours	4.9	3.7	13.2	20.2	0.8	0.5	0.3	1.6	0.2	6.4	12.7	35.4	12.4	39.5	37.1	2.4
Real Wage	20.5	3.8	4.6	4.7	0.1	0.6	0.3	1.5	3.9	2.3	3.3	54.2	26.8	15.4	13.1	2.3
Nominal Interest Rate	3.6	3.3	17.0	40.6	0.4	0.1	0.1	0.4	0.2	4.4	9.5	20.6	8.6	61.6	60.9	0.6
C-Sector Inflation	1.3	1.6	11.6	35.7	0.3	0.1	0.0	0.2	1.7	1.0	2.4	44.2	4.2	49.3	48.9	0.3
C-Sector Spread	8.0	3.8	13.5	24.2	0.3	0.3	0.3	2.0	0.9	6.5	13.9	26.1	15.7	44.2	41.6	2.6
I-Sector Spread	9.7	4.0	13.4	23.5	0.8	0.2	0.0	0.1	0.9	4.2	9.6	33.5	15.6	41.3	40.9	0.4
Equity	16.0	3.1	11.1	29.4	0.4	0.1	0.0	0.5	0.1	6.3	11.0	21.8	22.8	44.2	43.6	0.6
Rel. Price of Investment	15.3	2.8	2.7	1.3	3.2	1.8	0.5	1.8	1.1	22.2	6.8	39.9	41.8	11.0	6.8	4.2

z = TFP growth shock in consumption sector, $z^x = x$ quarters ahead consumption sector TFP growth news shock, v = TFP growth shock in investment sector, $v^x = x$ quarters ahead investment sector TFP growth news shock, a_l and v_l = stationary (level) TFP shocks in the consumption and investment sector, μ = marginal efficiency of investment shock. Business cycle frequencies considered in the decomposition correspond to periodic components with cycles between 6 and 32 quarters. The decomposition is performed using the spectrum of the DSGE model and an inverse first difference filter to reconstruct the levels for output, consumption, total investment, the real wage, equity, and the relative price of investment. The spectral density is computed from the state space representation of the model with 500 bins for frequencies covering the range of periodicities. We report median shares.

TFP news shocks account for a share of approximately 41% and 44% of the variance of bond spreads in the investment and consumption sector, respectively. TFP news shocks are also quantitatively important for the variation in the nominal interest rate and consumption inflation rate, accounting for approximately 49% and 61% of their variance, respectively. Appendix A.4 examines and verifies the robustness of our findings regarding the empirical significance of news shocks to two considerations. First, excluding observations from the Great Recession, addressing a mis-specification concern regarding the policy rule due to a binding zero lower bound (ZLB) constraint. Second introducing measurement wedges in corporate bond spreads in the mapping between model and data concepts, partly addressing a concern that default risk, which is absent from the model, may contribute to variation in credit spreads (though the VAR evidence of section 2.3 suggests the variation in credit spreads is not driven by default risk).

These findings are in sharp contrast to the results in DSGE models that abstract from financial frictions. To isolate the contribution of the financial channel in our model, we estimate two restricted versions of the model that abstract from financial frictions: a one-sector model, similar to one described in Fujiwara et al. (2011), Khan and Tsoukalas (2012), and Justiniano et al. (2010) as well as a variant of our two-sector model.[26] Table 3 compares the variance decomposition across the different models and shows that one- and two-sector versions of the model that abstract from financial frictions find a limited empirical role to news shocks. In these constrained versions of the baseline model, the totality of TFP news shocks account for approximately 10% and 11% of the variation in output. This finding is consistent with related results in the DSGE literature that attribute a limited role to TFP news shocks (see, for example, Fujiwara et al. (2011), Khan and Tsoukalas (2012) and Schmitt-Grohe and Uribe (2012), among others).

[26]Both models turn off the financial channel, i.e. the balance sheet identity (10), the leverage constraint (11), the evolution of equity capital (12), and the financial constraint (14) that describe the financial sector. The one-sector model can be written as a special case of the two-sector model. It imposes a perfectly competitive investment sector and perfect capital mobility.

Table 3: Variance decomposition – business cycle frequencies (6-32 quarters)

	Baseline model with financial frictions				Two sector model without financial frictions				One sector model without financial frictions			
	all TFP unanticipated	all TFP news	MEI (μ)	all other shocks	all TFP unanticipated	all TFP news	MEI (μ)	all other shocks	all TFP unanticipated	all TFP news	MEI (μ)	all other shocks
Output	25.6	27.6	18.0	28.8	10.1	8.7	41.5	39.6	11.5	11.2	30.5	46.9
Consumption	34.2	28.6	5.1	31.8	8.2	6.1	5.0	79.5	8.1	5.1	29.0	57.8
Investment	19.4	30.4	13.6	36.6	18.7	11.8	53.4	15.7	9.4	12.8	39.1	38.7
Total Hours	12.4	39.5	12.7	35.4	8.3	13.1	37.1	40.7	2.8	12.4	33.1	51.7
Real Wage	26.8	15.4	3.3	54.2	7.8	13.9	35.8	41.7	21.8	17.6	3.6	57.0
Nominal Interest Rate	8.6	61.6	9.5	20.6	5.1	7.7	32.9	54.4	2.8	6.7	75.4	15.2
C-Sector Inflation	4.2	49.3	2.4	44.2	0.8	0.2	0.0	98.9	6.0	4.7	51.0	38.3
C-Sector Spread	15.7	44.2	13.9	26.1	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
I-Sector Spread	15.6	41.3	9.6	33.5	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Equity	22.8	44.2	11.0	21.8	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Rel. Price of Investment	41.8	11.0	6.8	39.9	27.5	6.6	29.9	35.0	81.0	19.0	0.0	0.0

Business cycle frequencies considered in the decomposition correspond to periodic components with cycles between 6 and 32 quarters. The decomposition is performed using the spectrum of the DSGE model and an inverse first difference filter to reconstruct the levels for output, consumption, total investment, the real wage and the relative price of investment. The spectral density is computed from the state space representation of the model with 500 bins for frequencies covering the range of periodicities. We report median shares.

We examine IRFs in order to gain intuition on the propagation of TFP news shocks and isolate the mechanism that enhances their empirical relevance in the baseline model with financial frictions. Figure 10 plots the response of selected variables to a three-year ahead consumption-specific TFP news shock in the two-sector model with financial channel (solid line) together with those for the two-sector model without the financial channel (dashed line). We normalize the shock to be of equal size across simulations. The amplification of the news shock is significantly stronger in the model with the financial channel.

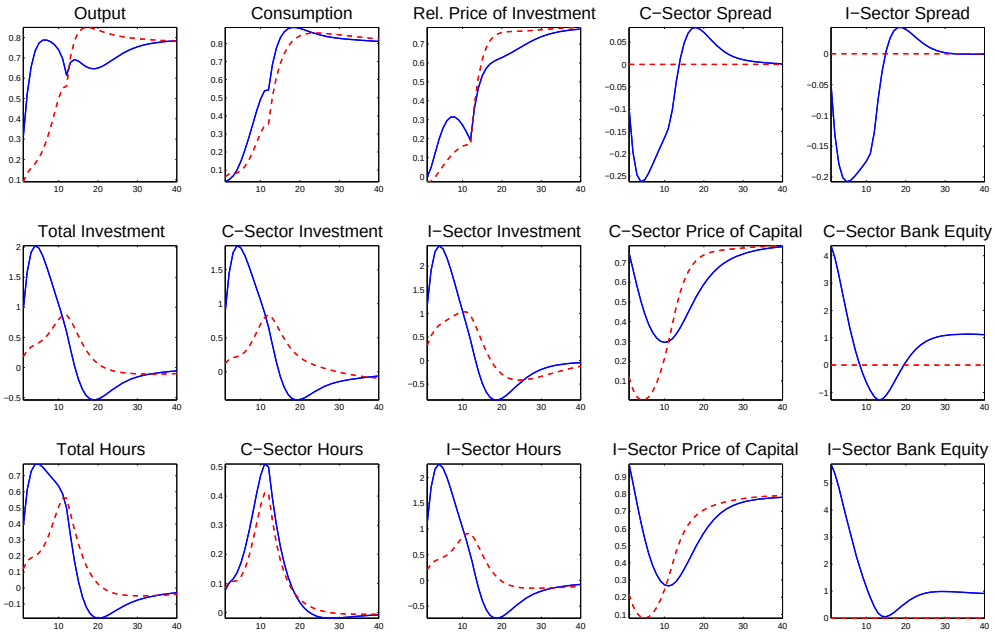

Figure 10: Responses to a one std. deviation TFP news shock (anticipated 12-quarters ahead) in the consumption sector. Baseline model with financial intermediation (blue solid line), and model without financial intermediation (red dashed line) at baseline estimates. The horizontal axes refer to quarters and the units of the vertical axes are percentage deviations.

In the model with financial frictions, the impact of the consumption-specific news shock is amplified by the effect of capital prices on intermediaries' equity. A positive news shock raises capital prices, which in turn boost bank equity. Better capitalized banks expand demand for capital assets, and the process further increases capital prices, leading to a strong investment boom and a decline in the excess premiums on holding the assets, noted as C-Sector spread and I-Sector spread in the figure. Although in equilibrium there is no default of intermediaries, higher equity implies that depositors are better protected from

the costly enforcement/inefficient liquidation problem and hence they are willing to place deposits in banks that earn a lower excess premium. The response of the excess bond premium we have documented in section 2.3 is hence consistent with the narrative from the model. Figure 10 shows that the responses of capital prices are qualitatively different between the two models. In both models, capital prices increase in anticipation of the future rise in productivity. However, in the baseline model with financial frictions, capital prices rise sharply (approximately seven times more compared to the model without financial frictions) due to the amplification effect of financial intermediaries on the demand for capital. As the stock of capital increases and accumulates, agents expect capital prices and returns from capital to decline. Other things equal, the surge in capital prices creates a strong incentive to build new capital before the improvement in technology materializes, which in turn stimulates a strong rise in current hours worked and output. By contrast, in the model without financial frictions, capital prices increase moderately on impact and rise further in the future, which suppresses—relative to the baseline—current investment spending in anticipation of future increase in the returns to capital.

Our study provides relevant insights on the significance of the marginal efficiency of investment (MEI) shock, which recent studies that estimate DSGE models with and without news shocks (Khan and Tsoukalas (2012) and Justiniano et al. (2010), respectively), find considerably more important than TFP shocks to explain business cycles fluctuations.[27] We corroborate these findings in the estimated versions of the model that abstracts from the financial channel, namely, the one-sector and two-sector model without financial frictions (see Table 3). For instance, in the two-sector model without financial frictions, MEI shocks explain the bulk of movements in the variance of output (41%), investment (53%), and hours worked (37%). By contrast, in the baseline model with the financial sector, MEI shocks account for approximately, 18%, 14%, and 13% in the variance of the same set of

[27] We include the MEI shock in the estimation for comparison purposes with the literature. The MEI shock differs from the investment-specific shock in that the latter is a permanent shock and affects only the productivity of the investment sector. By contrast, the MEI impacts the transformation of investment goods to installed capital and affects both sectors.

macroeconomic aggregates. The key reason for the reduced role of MEI shocks in the presence of financial frictions is related to the fact that an exogenous increase in MEI generates a fall in the price of installed capital by increasing the transformation rate of investment goods to installed capital. The decline in capital prices severs the financial channel that stimulates equity capital gains for the financial intermediaries in response to an increase in investment demand and capital prices. Thus, a decline in capital prices induces a fall in equity and restricts the facilitation of lending and investment spending. The same logic operates in the case of investment-specific shocks of the unanticipated or anticipated type.

4 Reconciling DSGE and VAR results

4.1 The DSGE as the data generating process

In this section, we compare the dynamics to TFP news shocks across the DSGE and VAR analysis. We perform a Monte Carlo experiment and generate 1,000 samples of artificial data from the DSGE model, drawing parameter values from the posterior distribution. We compare the empirical IRF from the VAR model (specification I, excluding the confidence indicator) against those estimated with identical VAR specifications (along with posterior bands) on the artificial data samples.[28] Following the methodology in Fernald (2014), we extract a model-based aggregate TFP measure by weighting (using GDP shares) together the two model-based sectoral TFP growth components as in equation (6) referred to in section 3. Figure 11 compares the IRF from the VAR model in specification I (solid line) with those from the Monte Carlo experiment (line with crosses). Qualitatively, the dynamic responses from the model-based VAR are similar to the responses from the empirical VAR. It is perhaps striking, that for most of the variables, the empirical median response estimated from the VAR model is, in the vast majority of periods, inside the posterior confidence bands of the

[28] We have simulated the model over 1,096 periods. We construct the level of the resulting time series and discard all but the last 96 periods (the same sample size as the data) to minimize the impact of initial values. We have used a simple average of the sectoral spreads to estimate the VAR on the simulated model samples consistent with the GT VAR analysis in section 2.

VAR estimated on the artificial model data. A noticeable exception is the impact response of inflation, which is positive in the DSGE model but negative in the VAR model. The intuition for this difference is as follows: In the baseline DSGE model with financial frictions, the rise in the price of capital in response to the TFP news shock generates a strong increase in the rental rate of capital (driven by a strong increase in utilization rates), which amplifies the increase in the marginal cost of production and therefore leads to an increase in inflation. Another notable difference is the response of the aggregate TFP, as the long-run increase is

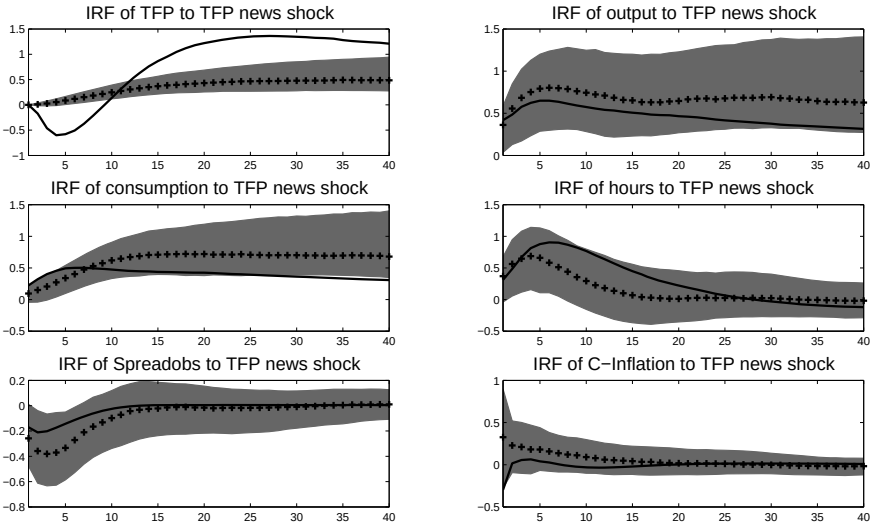

Figure 11: **TFP news shock.** The solid line is the impulse response to TFP news shock from a six variable VAR featuring aggregate TFP, corporate bond spread (GT spread), consumption, output, hours, CPI inflation, estimated with 4 lags. The line with crosses (grey shaded areas) is the median (16%, 84% confidence bands) impulse response to an aggregate TFP news shock estimated from a VAR on 1,000 samples, generated from the model. The horizontal axes refer to forecast horizons (quarters) and the units of the vertical axes are percentage deviations.

relatively higher in the empirical responses compared to the responses with artificial data. The intuition for this difference comes from the fact that (utilization-adjusted) measured TFP growth in the investment sector is significantly higher on average compared to the corresponding TFP measure in the consumption sector and, by virtue of equation (6), the aggregate measure. We note however that the estimation of the DSGE model does not include a measure of TFP among the observables to produce an estimate of the TFP news shock. In this respect, we follow the majority of studies that use DSGE models to infer

technology shocks without using TFP as an observable.[29]

4.2 A quantitative evaluation

To evaluate the quantitative differences between the VAR and DSGE methods, we compare the forecast error variance decompositions (FEVD) for the totality of TFP news shocks obtained from the VAR and DSGE models at business cycle frequencies (6-32 quarters). Table 4 shows the FEVD of the common variables in the VAR model (top panel), the baseline DSGE model with financial frictions (center panel), and the DSGE model without financial frictions (bottom panel). Table 4 shows that in general the median shares of the FEVD accounted for by TFP news shocks in the DSGE model with financial frictions are close and, in the vast majority of cases, fall within the posterior bands of the median shares predicted by the VAR model. The model that abstracts from financial frictions predicts instead a considerably smaller role that news shocks play in explaining movements in macroeconomic variables. An obvious shortcoming of the model without financial frictions, relative to the baseline model, is its inability to account for the variance in the corporate bond spread indicators. While useful as an informal test of the model's ability to close the gap with VAR-based estimates, the comparison is meant to be suggestive and qualitative. The DSGE model uses different data moments and identifies many more shocks compared to the VAR. For example, the variance of the TFP news shocks estimated by the DSGE model is a fraction of the variance estimated by the VAR news shock, putting the DSGE model at a disadvantage relative to the VAR model. The comparison is nevertheless informative as it shows that, in principle, both methodologies imply a significant empirical relevance of news shocks.

[29] We refrain from using the utilization adjusted TFP measure in the DSGE estimation since it lacks corrections for imperfect competition and potential mark-up variation as well as factor reallocation that are only available with annual data. Thus, short-run movements in quarterly TFP series may potentially reflect non-technology factors and therefore a noisy measure of the true underlying technological process. This is problematic since the DSGE estimation would force the model-implied TFP to exactly replicate the imperfect measure of TFP.

Table 4: Share of variance explained by TFP news shocks

	Horizon (quarters)				
	6	12	20	24	32
VAR (medians, 16% and 84% confidence bands in brackets.)					
Output*	31	38	43	44	48
	[7 58]	[8 64]	[9 70]	[10 72]	[13 76]
Consumption*	27	34	40	43	46
	[5 50]	[7 58]	[9 66]	[10 70]	[13 74]
Investment*	33	37	39	41	43
	[6 59]	[7 63]	[8 68]	[9 70]	[11 73]
Total Hours*	34	39	40	40	40
	[6 62]	[8 67]	[9 69]	[9 69]	[11 68]
BAA spread$^{\flat}$	27	27	28	28	29
	[7 53]	[8 51]	[10 52]	[10 52]	[10 53]
GZ spread†	42	42	44	45	45
	[18 63]	[20 61]	[22 63]	[22 64]	[23 65]
Excess bond premium‡	21	21	22	22	22
	[6 43]	[7 41]	[8 42]	[8 43]	[8 44]
GT spread*	22	24	25	25	25
	[6 48]	[8 50]	[9 48]	[10 49]	[10 48]
Bank (market) equity‡	76	80	81	82	82
	[60 86]	[65 89]	[67 91]	[68 91]	[68 91]
Bank (book) equity*	22	26	28	30	34
	[2 65]	[4 62]	[7 55]	[10 53]	[16 55]
S&P 500§	38	47	53	53	52
	[12 65]	[21 70]	[27 73]	[28 73]	[29 72]
C-Sector Inflation*	14	14	17	18	18
	[6 24]	[7 24]	[8 27]	[9 28]	[10 30]
DSGE model with financial frictions (medians)					
Output	31	29	29	28	26
Consumption	14	4	19	28	39
Investment	33	26	32	32	29
Total Hours	26	25	39	42	42
C-Sector Spread	17	24	44	47	48
I-Sector Spread	12	21	42	44	45
GT Spread	14	23	43	46	47
Bank equity	51	53	53	46	30
C-Sector Price of Capital	49	49	56	54	45
I-Sector Price of Capital	49	46	50	50	42
Average Price of Capital	49	48	53	52	44
C-Sector Inflation	8	22	51	57	62
DSGE model without financial frictions (medians)					
Output	6	6	6	8	12
Consumption	17	16	6	5	7
Investment	3	4	10	12	16
Total Hours	5	7	12	14	16
C-Sector Price of Capital	7	11	18	18	17
I-Sector Price of Capital	13	13	28	30	30
Average Price of Capital	10	12	23	24	24
C-Sector Inflation	0	0	0	0	0

The FEV of variables denoted with a $*$ are obtained from a 10 variable VAR specification with an information set that comes as close as possible to the information set used in the DSGE, namely, aggregate TFP, consumption, output, hours, investment, GT spread, RPI, Bank (book) equity, real wage. The FEV of variables denoted with a $\flat$ are obtained from VAR specification IA. The FEV of variables denoted with a $\dagger$ are obtained from VAR specification IA, but where the GZ spread replaces the BAA spread and otherwise identical. The FEV of variables denoted with a $\ddagger$ are obtained from VAR specification IB. The FEV of variables denoted with a $\S$ are obtained from VAR specification II.

5 Conclusion

This paper examines the empirical significance and dynamic effects of TFP news shocks in the context of financial frictions using complementary VAR and DSGE methods. The VAR model identifies two robust stylized facts. *First*, a shock to future TFP is associated with a significant decline of several, widely used, credit spread indicators, along with a broad-based expansion in activity. These indicators include, the BAA spread, the GZ spread and excess bond premium (Gilchrist and Zakrajsek (2012)), among others. The decline in credit spread indicators is associated with an improvement in the balance sheet conditions of financial intermediaries, suggesting that credit supply conditions are critical for the propagation of news shocks. *Second*, we independently identify a single shock that seeks to explain as much as possible of the un-forecastable movements in our credit spread indicators. This single shock explains between 50% to 65% in the forecast error variance of our credit spread indicators. Importantly, the dynamic macro effects generated by this shock are qualitatively and quantitatively very similar to the macro effects generated by the TFP news shock. This finding provides strong support for the notion that movements in a host of financial indicators are tightly linked with news shocks.

We employ a DSGE model with financial frictions of the Gertler-Kiyotaki-Karadi type and suggest it is a useful structural framework to understand the propagation of news shocks through the lens of credit supply frictions. The model analysis shows that the critical mechanism for the strong macro effects of news shocks relies on the linkages between leveraged equity, capital prices, and excess premiums which vary inversely with the balance sheet condition of intermediaries, consistent with the VAR evidence. Moreover, the estimated model generates dynamic responses and quantitative estimates of TFP news shocks very similar to those obtained from the VAR model. The consistent assessment of news shocks across methods provides support for the traditional 'news view' of business cycles.

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Appendix with supplementary material (Not for publication)

A Supporting details and results

A.1 Robustness to max FEV credit spread shock indicator

Figure 12 displays the variance shares explained by the max FEV BAA shock discussed in the main body, section 2.

Figures 13, and 14 display the IRFs to the (i) the single shock that maximizes the FEV of the GZ spread over forecast horizons six to thirty-two quarters and (ii), the single shock that maximizes the FEV of the GT spread over forecast horizons six to thirty-two quarters. In (i) the VAR specification features, the GZ spread, output, consumption, hours, TFP, Inflation and E5Y, in (ii) the VAR specification features the EBP, output, consumption, hours, TFP, Inflation and E5Y, and in (iii) the VAR specification features the GT spread, output, consumption, hours, TFP, Inflation and E5Y. In both cases the IRFs are qualitatively and quantitatively very similar to the IRFs due to the TFP news shock, estimated in each case by an identical VAR specification.

A.2 Robustness to VAR methodology

The results in the main body of the paper are generated using the Francis et al. (2014) identification approach (referred to as Max share method). This section reports VAR findings using three alternative approaches. First, the identification scheme in Barsky and Sims (2011) that recovers the news shock by maximizing the variance of TFP over the horizons zero to 40 quarters, and the restriction that the news shock does not move TFP on impact. Second, the identification scheme in Kurmann and Sims (2016), that recovers the news shock by maximizing the FEV of TFP at a very long horizon (80 quarters) without however

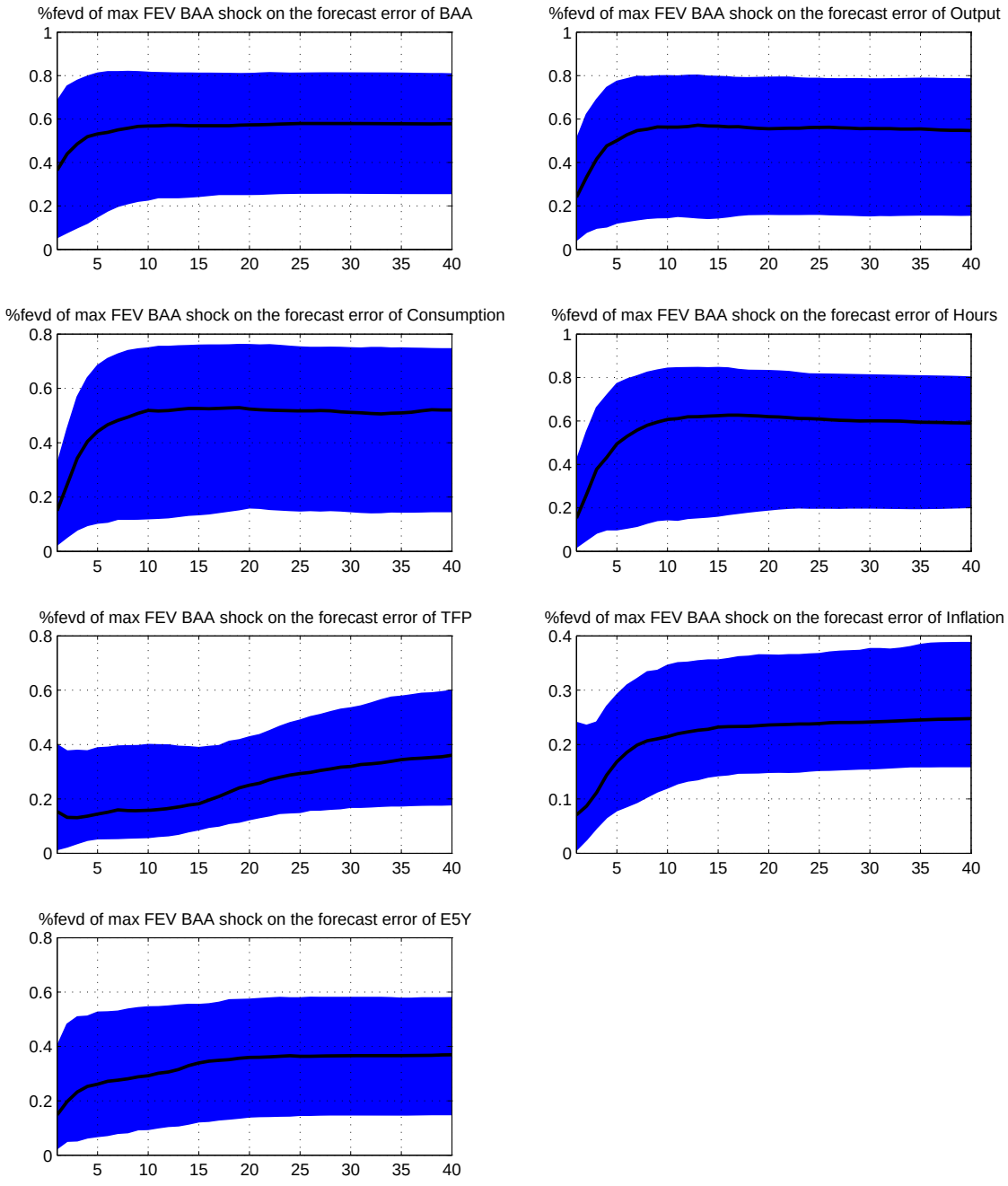

Figure 12: **FEV of variable 'x' of the max FEV BAA shock (median – solid line).** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters.

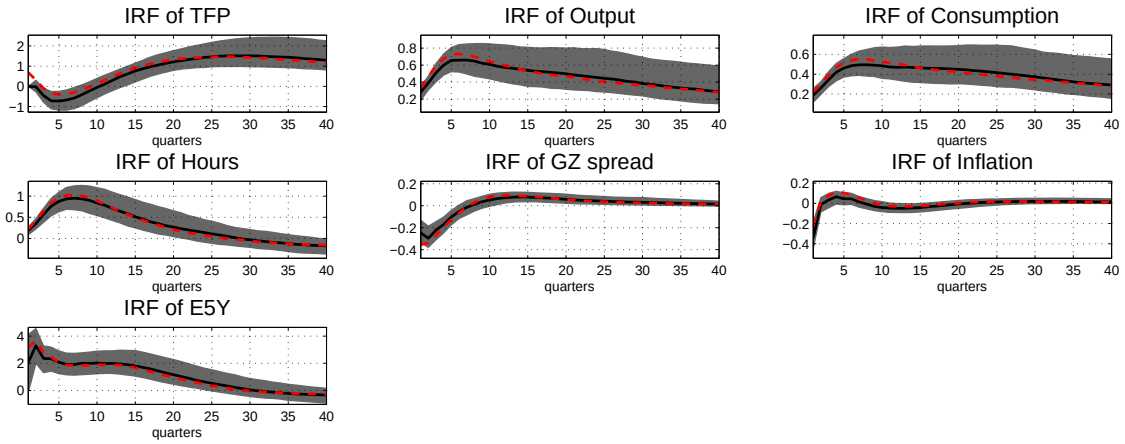

Figure 13: **TFP news shock (solid line) and max FEV GZ shock (dashed line).** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

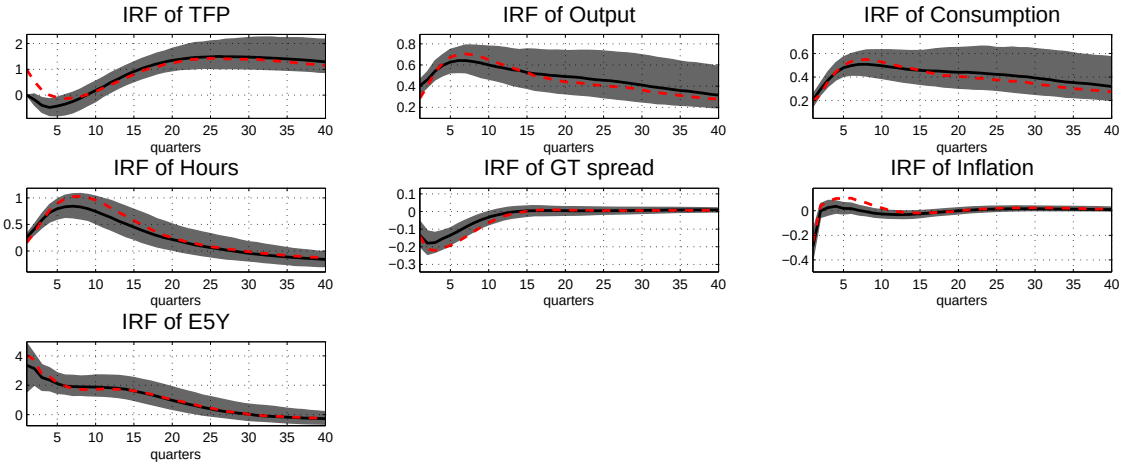

Figure 14: **TFP news shock (solid line) and max FEV GT shock (dashed line).** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

imposing the zero impact restriction on TFP conditional on the news shock.[30] Third, the Forni et al. (2014) long-run identification scheme which is similar in spirit to the Max Share method and has been used in an application with news shocks. The latter method identifies the news shock by imposing the zero impact restriction on TFP, and seeks to maximise the impact of the news shock on TFP in the long run.

We compare IRFs using the three different methods above for identifying TFP news shocks, along with IRFs displayed in the main body of the paper. For illustration, Figures 15, 16, 17, and 18 show the responses obtained from the different methods for VAR specifications I and III. The IRFs are qualitatively and quantitatively very similar to each other. In fact they are virtually identical across the Max share, Barsky and Sims (2011), and Forni et al. (2014) methods. The only noticeable difference in the IRFs across these methods is in the short run response to TFP when the Kurmann and Sims (2016) method is used. This method allows the TFP to jump on impact following a news shock, and TFP does increase on impact (though the response is not significant different from zero). Qualitatively however, all methods suggest that TFP rises significantly above zero only with a significant delay. Importantly, the results suggest that the identified news shocks from the four methods are qualitatively and in the majority of cases quantitatively very similar to each other. The same holds for specification II which is not shown for space considerations, but IRFs are available upon request.

A.3 Robustness of VAR results to alternative samples

In addition to the results reported in the main body of the paper for the sample 1990Q1-2013Q4, we also report results for two additional samples. We consider our sample without the Great Recession period (1990Q1-2007Q3) and an extended sample (1985Q1-2013Q4). We consider this extended sample since deregulation took place in phases beginning in the late 1970s to early 1980s and the corporate bond market has already been developing quite

[30] These authors argue that allowing TFP to jump freely on impact, conditional on a news shock, produces robust inference to cyclical measurement error in the construction of TFP.

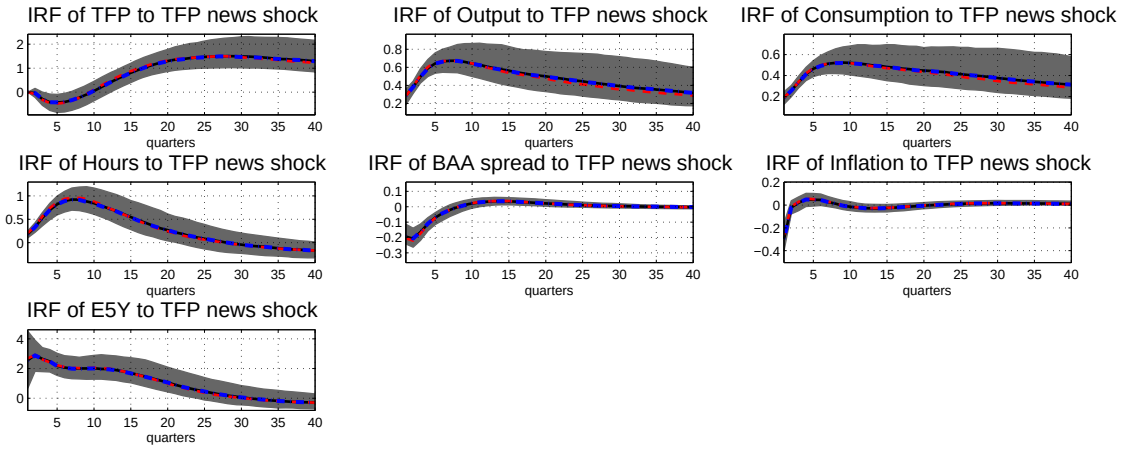

Figure 15: **TFP news shocks. VAR Specification I.** The lines display impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The solid line is the Max Share news identification, the dashed line is the long-run restriction method as in Forni et al. (2014) and the dash-dotted line is the Barsky-Sims identification. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The horizontal axes refer to forecast horizons (quarters) and the units of the vertical axes are percentage deviations.

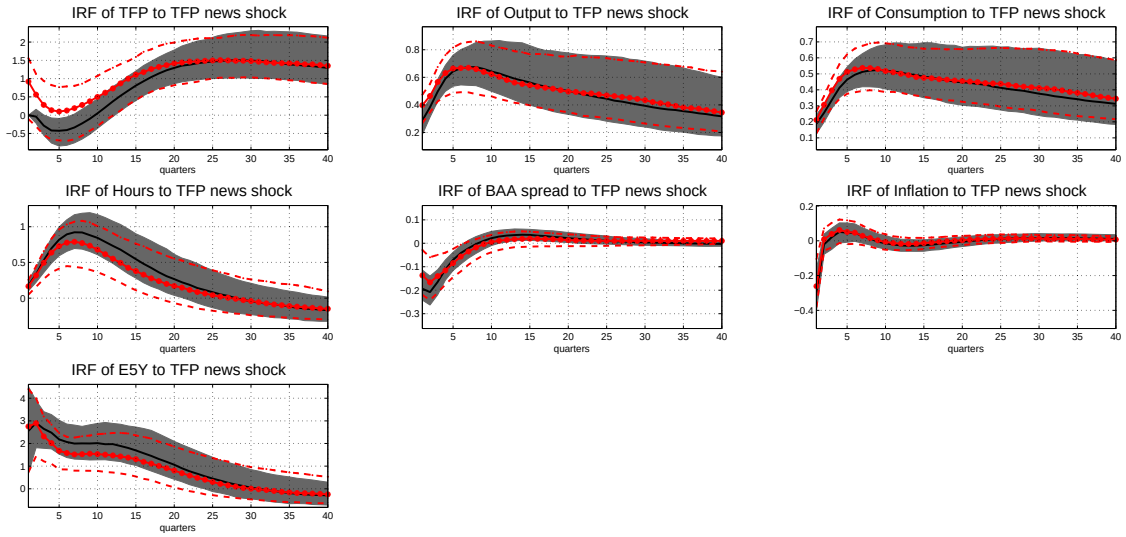

Figure 16: **TFP news shocks. VAR Specification I.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The solid line (shaded gray areas) is the median (16% and 84% posterior bands) from the Max Share method. The line with circles (dashed lines) is the median (16% and 84% posterior bands) from the Kurmann-Sims method. The posterior bands are generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

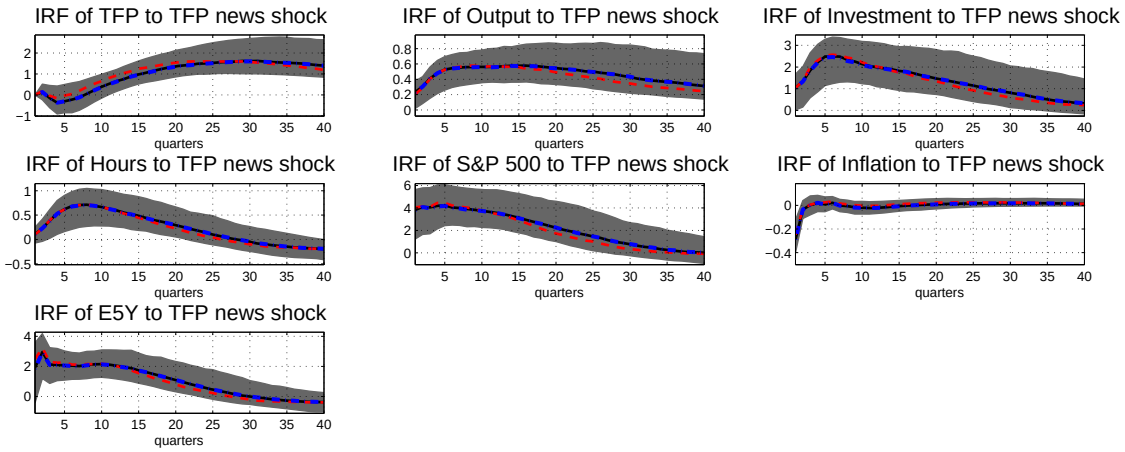

Figure 17: **TFP news shocks. VAR specification III.** The lines display impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The solid line is the Max Share news identification, the dashed line is the long-run restriction method as in Forni et al. (2014) and the dash-dotted line is the Barsky-Sims identification. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The horizontal axes refer to forecast horizons (quarters) and the units of the vertical axes are percentage deviations.

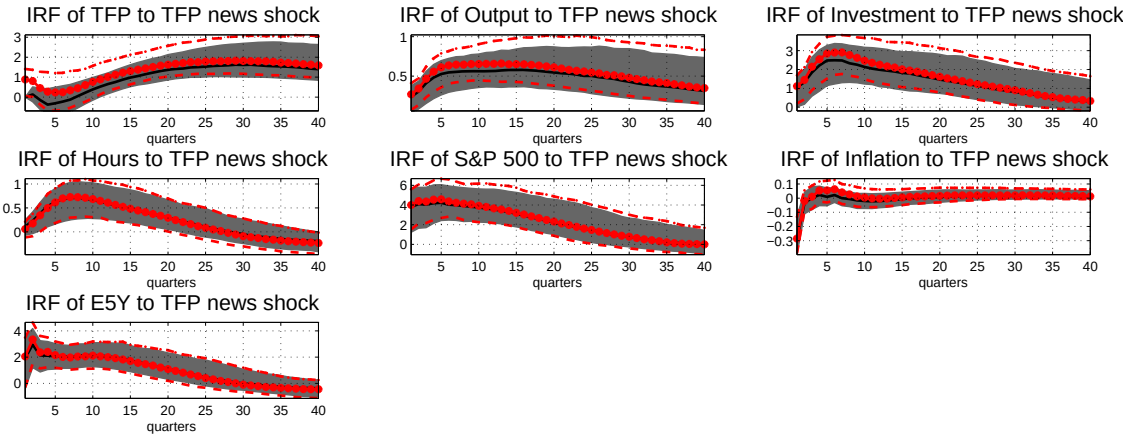

Figure 18: **TFP news shocks. VAR Specification III.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The solid line (shaded gray areas) is the median (16% and 84% posterior bands) from the Max Share method. The line with circles (dashed lines) is the median (16% and 84% posterior bands) from the Kurmann-Sims method. The posterior bands are generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

strongly since the start of the decade. Moreover, Gilchrist and Zakrajsek (2012) argue that the forecasting power of credit spread indicators has been stronger post 1985 relative to earlier periods. Figures 19 and 20 show responses from seven variable VARs estimated with 4 lags similar to specification I. The only difference is that each VAR includes a different credit spread indicator, namely, the BAA spread, the GZ spread, the excess bond premium, and the GT spread (the GT spread is available only from 1990Q1 and hence not included in the extended sample) one at a time. We only display IRFs for the credit spread indicators to conserve space since the responses of the remaining variables are quantitatively very similar to those reported for specification I in Figure 1. Figures 19 and 20 suggest that the significant decline of the credit spread indicators documented for our baseline sample is robust also when excluding the Great Recession or considering an extended sample that begins in the mid-1980s.

We also regenerate the results that speak to the link between TFP news shocks and shocks that explain the majority of un-forecastable movements in our credit spread indicators shown for the baseline sample in Figure 5 for the shorter sample without the Great Recession (1990Q1-2007Q3), and the extended sample (1985Q1-2013Q4), using sequentially one at a time, the BAA spread, the GZ spread, the excess bond premium, and the GT spread. In particular, using the agnostic approach in Uhlig (2003), we identify the single shock that maximizes the forecast error variance in each one of these four credit spread indicators at cyclical frequencies, and compare it to the TFP news shock identified from an identical specification (using the respective credit spread indicator). These independently identified shocks still account for a very sizable fraction of FEV in our credit spread indicators. For example, in the sample without the Great Recession (extended sample), and, in forecast horizons six to thirty-two quarters, they account for between 44% to 60% (between 58% to 62%) of the FEV in the BAA spread, 34% to 55% (between 60% to 64%) in the FEV of the GZ spread, 37% to 50% (between 68% to 69%) in the FEV of the excess bond premium, and 68% to 72% in the GT spread. The IRFs in response to the two independently identified shocks are displayed in Figures 21-27. Similar to our baseline sample, the two shocks, namely

the TFP news shock and the shock that explains as much as possible of the FEV in our credit spread indicators, trigger very similar dynamic responses.

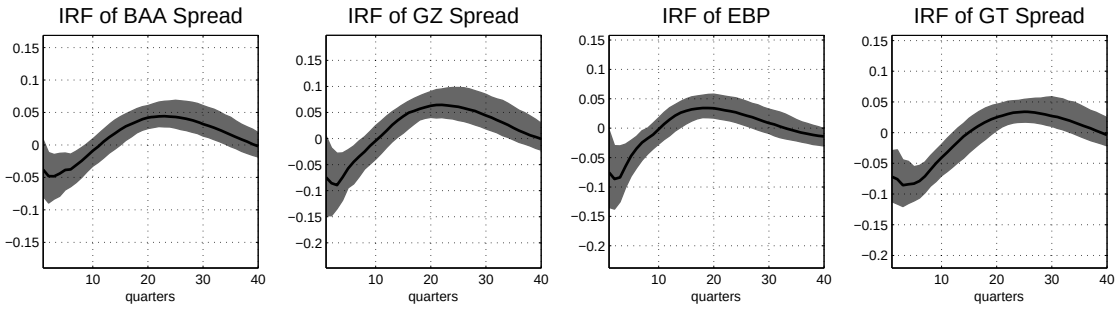

Figure 19: **TFP news shocks and credit spread indicators. Sample without Great Recession, 1990Q1-2007Q3** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The estimated VARs are based on specification I where we use as the credit spread indicator either the BAA spread, GZ spread, EBP or the GT spread. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

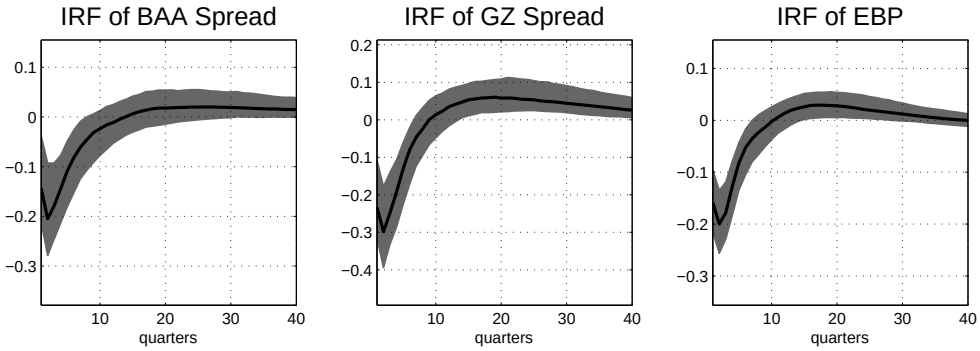

Figure 20: **TFP news shocks and credit spread indicators. Extended sample, 1985Q1-2013Q4.** Impulse responses to a TFP news shock from a seven variable VAR estimated with 4 lags. The estimated VARs are based on specification I where we use as the credit spread indicator either the BAA spread, GZ spread or the EBP. The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

A.4 Robustness of DSGE model results

We scrutinise our baseline DSGE model results in two dimensions. First, we extend our baseline DSGE model by incorporating a wedge between the model implied sectoral spreads

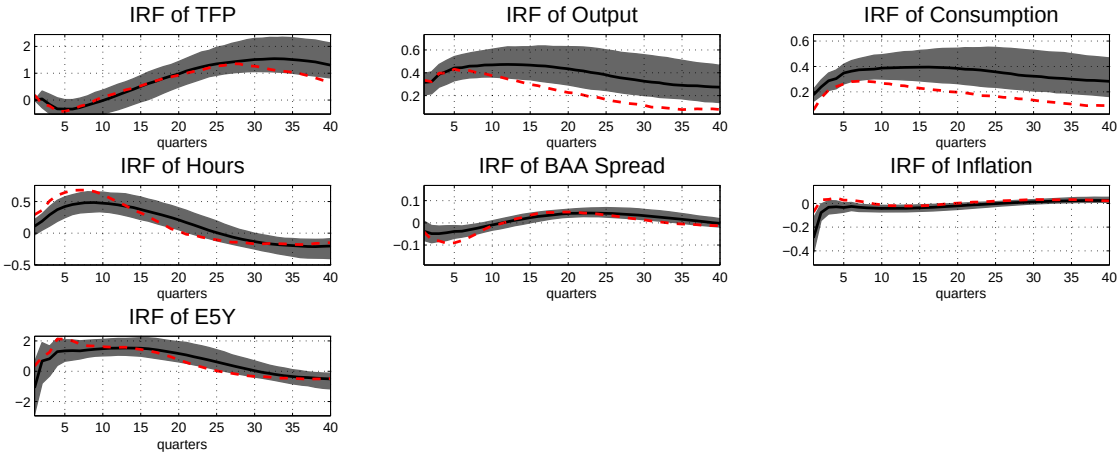

Figure 21: **TFP news shock (solid line) and max FEV BAA shock (dashed line). Sample without Great Recession, 1990Q1-2007Q3.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

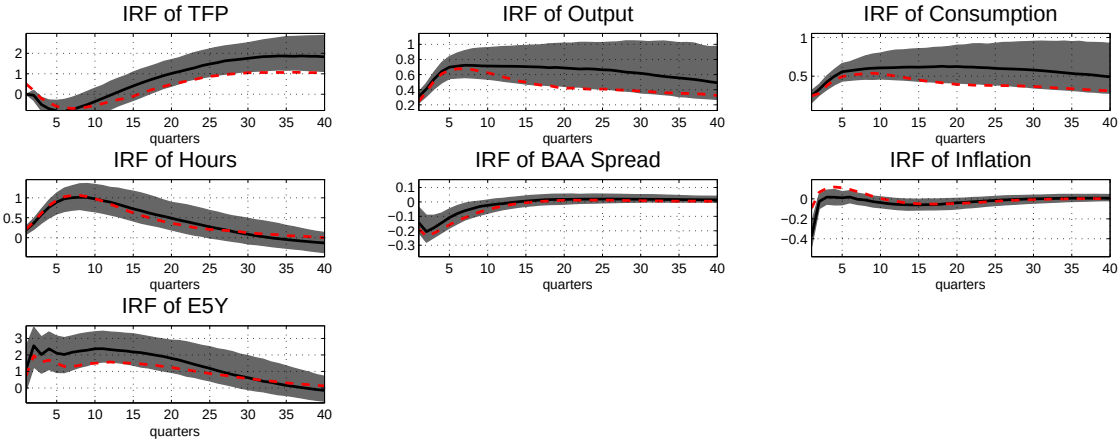

Figure 22: **TFP news shock (solid line) and max FEV BAA shock (dashed line). Extended sample, 1985Q1-2013Q4.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

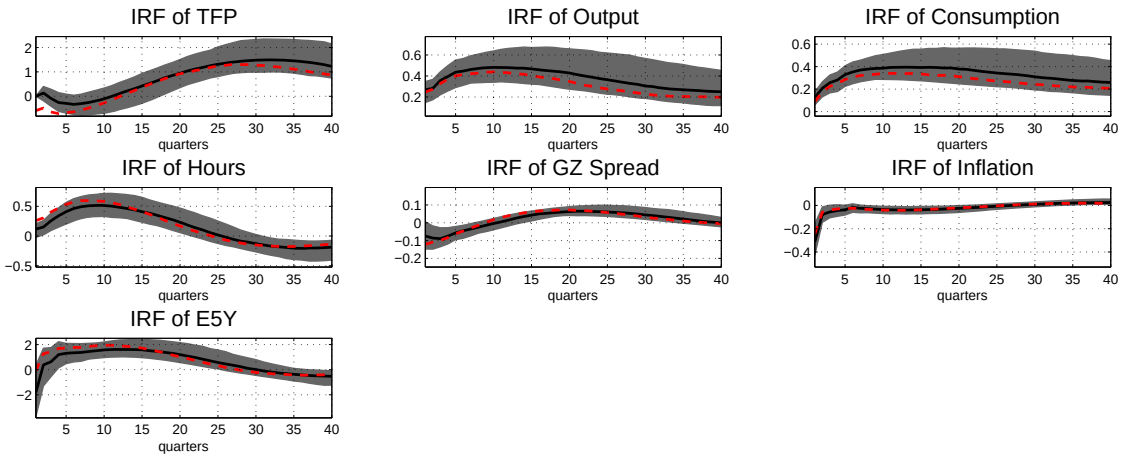

Figure 23: **TFP news shock (solid line) and max FEV GZ shock (dashed line). Sample without Great Recession, 1990Q1-2007Q3.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

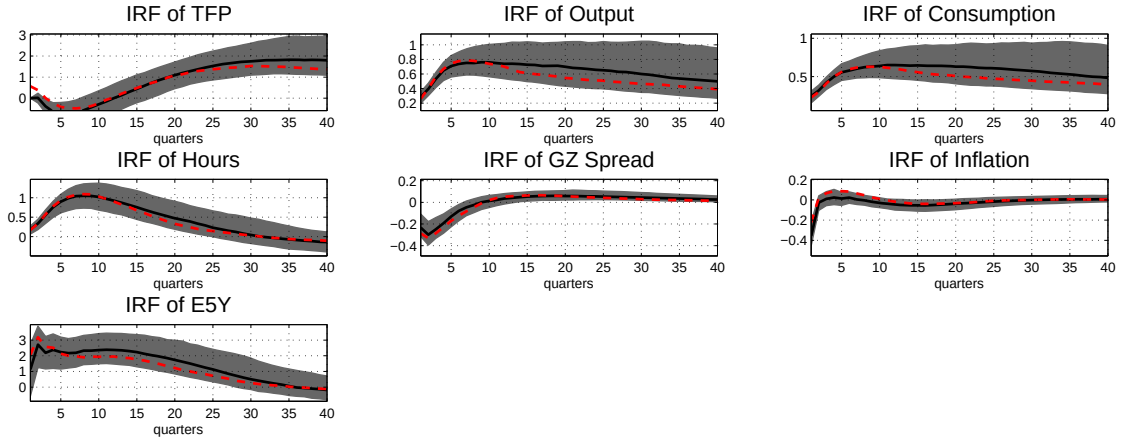

Figure 24: **TFP news shock (solid line) and max FEV GZ shock (dashed line). Extended sample, 1985Q1-2013Q4.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

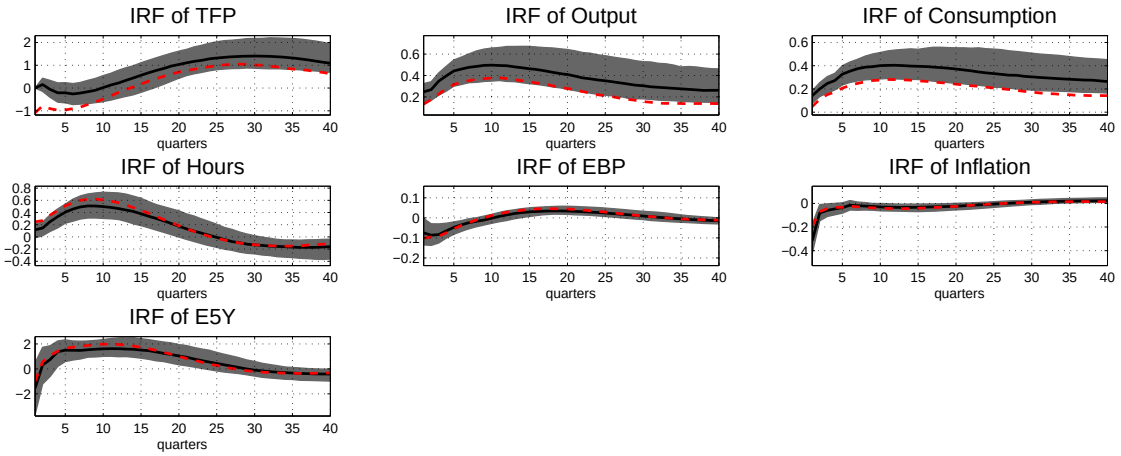

Figure 25: **TFP news shock (solid line) and max FEV EBP shock (dashed line). Sample without Great Recession, 1990Q1-2007Q3.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

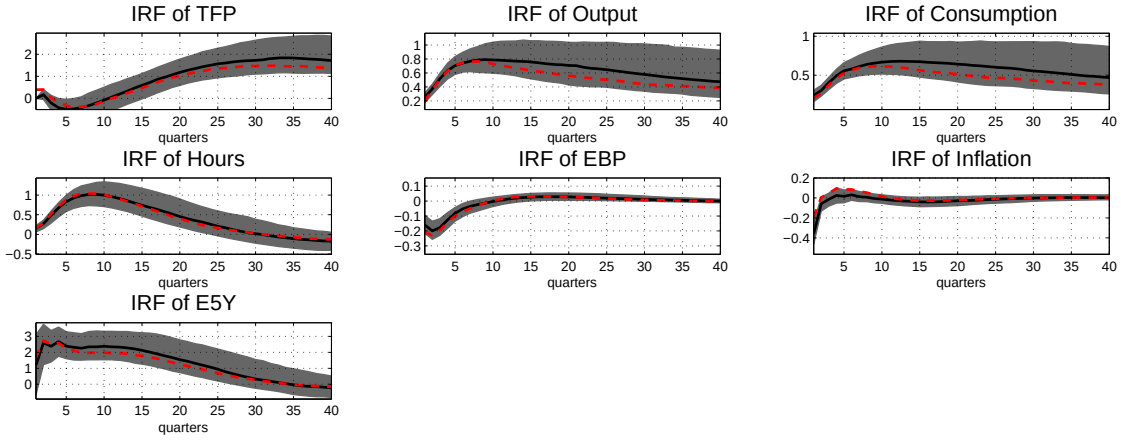

Figure 26: **TFP news shock (solid line) and max FEV EBP shock (dashed line). Extended sample, 1985Q1-2013Q4.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

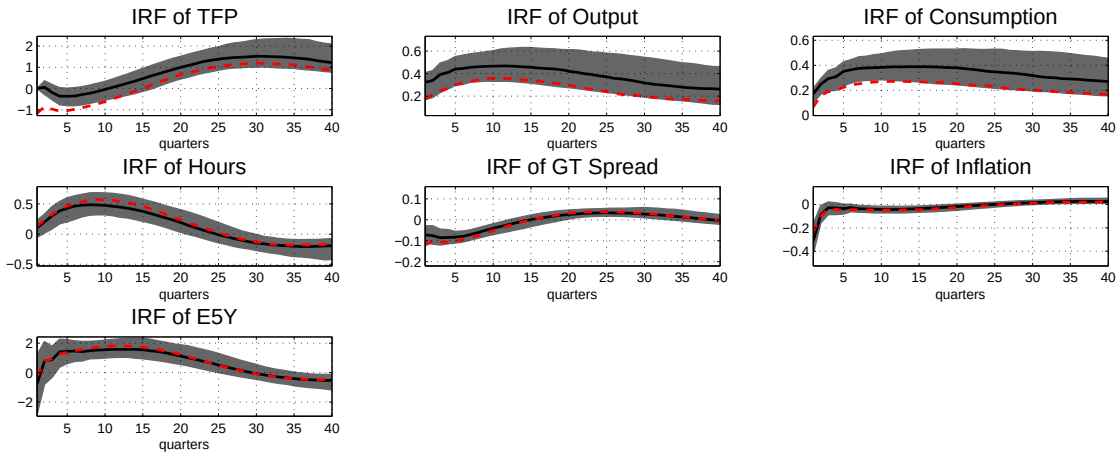

Figure 27: **TFP news shock (solid line) and max FEV GT shock (dashed line). Sample without Great Recession, 1990Q1-2007Q3.** The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters corresponding to the TFP news shock. The units of the vertical axes are percentage deviations.

and the corresponding corporate spread concepts in the data. The wedges follow the process

$$wedge_{x,t} = \rho_{wedge_x} wedge_{x,t-1} + \varepsilon_{wedge_x,t}, \qquad x = C, I,$$

where $\rho_{wedge_x} \in (0,1)$ and $\varepsilon_{wedge_x,t}$ is $i.i.d.$ $N(0, \sigma^2_{wedge_x})$. The wedges are introduced as an reduced form way to account for variation in spreads that could reflect factors we do not model, such as agents' default risk (although our VAR findings do not suggest this is a major consideration) or other non-fundamental factors in the pricing of corporate bond as recently argued by Gilchrist and Zakrajsek (2012). We report the variance decomposition at business cycle frequencies for our baseline model and the extended model with measurement error in the corporate spread equations in Table 5. Results are consistent across the two model specifications in the way that they point towards a quantitatively important role of TFP news shocks.

Second, we estimate the baseline model using a sample that excludes the Great Recession (1990Q1-2007Q3), addressing concerns about misspecification of the monetary policy rule when the policy rate approaches the zero lower bound, as well as concerns that high volatility in corporate bond spreads and disruptions in financial markets may, at least partly, drive the

important role of TFP news shocks. It is evident from the variance decomposition provided in Table 5 that the DSGE model's prediction on the quantitative importance of TFP news shocks as drivers of aggregate fluctuations is robust to excluding the Great Recession from the sample.

Table 5: Variance Decomposition at Business Cycle Frequencies

	Baseline model			Model with measurement error in spread eqs.			Baseline without Great Recession		
	all TFP unanticipated	all TFP news	all other shocks	all TFP unanticipated	all TFP news	all other shocks	all TFP unanticipated	all TFP news	all other shocks
Output	0.256	0.276	0.468	0.208	0.200	0.592	0.261	0.270	0.469
Consumption	0.342	0.286	0.372	0.327	0.182	0.491	0.344	0.283	0.373
Investment	0.194	0.304	0.502	0.166	0.180	0.653	0.199	0.297	0.504
Total Hours	0.124	0.395	0.481	0.105	0.260	0.635	0.127	0.388	0.485
Real Wage	0.268	0.154	0.578	0.204	0.098	0.698	0.267	0.152	0.580
Nominal Interest Rate	0.086	0.616	0.299	0.084	0.462	0.455	0.088	0.609	0.303
C-Sector Inflation	0.042	0.493	0.465	0.079	0.325	0.596	0.043	0.486	0.471
C-Sector Spread	0.157	0.442	0.401	0.160	0.341	0.499	0.161	0.434	0.405
I-Sector Spread	0.156	0.413	0.432	0.120	0.305	0.576	0.158	0.409	0.433
Equity	0.228	0.442	0.330	0.155	0.363	0.481	0.230	0.436	0.334
Rel. Price of Investment	0.418	0.110	0.472	0.299	0.067	0.634	0.421	0.107	0.472

Business cycle frequencies considered in the decomposition correspond to periodic components with cycles between 6 and 32 quarters. The decomposition is performed using the spectrum of the DSGE models and an inverse first difference filter to reconstruct the levels for output, consumption, total investment, the real wage and the relative price of investment. The spectral density is computed from the state space representation of the model with 500 bins for frequencies covering the range of periodicities.

A.5 Specification for the Minnesota prior in the VAR

The prior for the VAR coefficients A is of the form

$$vec\,(A) \sim N\left(\underline{\beta}, \underline{V}\right),$$

where $\underline{\beta}$ is one for variables which are in log-levels, and zero for the corporate bond spread as well as inflation. The prior variance $\underline{V}$ is diagonal with elements,

$$\underline{V}_{i,jj} = \begin{cases} \frac{\underline{a}_1}{p^2} \text{ for coefficients on own lags} \\ \frac{\underline{a}_2 \sigma_{ii}}{p^2 \sigma_{jj}} \text{ for coefficients on lags of variable } j \neq i \\ \underline{a}_3 \sigma_{ii} \text{ for intercepts} \end{cases} . \tag{A.1}$$

where, p denotes the number of lags. Here σ_{ii} is the residual variance from the unrestricted p-lag univariate autoregression for variable i. The degree of shrinkage depends on the hyperparameters $\underline{a}_1, \underline{a}_2, \underline{a}_3$. We set $\underline{a}_3 = 100$ and we select $\underline{a}_1, \underline{a}_2$ by searching on a grid and selecting the prior that maximizes the in-sample fit of the VAR, as measured by the Bayesian Information Criterion.[31]

A.6 Calibration and estimation

Calibration. Table 6 describes the calibrated parameters referred to in section 3.2. We set the quarterly depreciation rate to be equal across sectors, $\delta_C = \delta_I = 0.025$. From the steady state restriction $\beta = \pi_C / R$, we set $\beta = 0.9974$. The shares of capital in the production functions, a_C and a_I, are assumed equal across sectors and fixed at 0.3. The steady state values for the ratios of nominal investment to consumption and government spending to output are calibrated to be consistent with the average values in the data.

The steady state sectoral inflation rates are set to the sample averages and the sectoral steady state mark-ups are assumed to be equal to 15%. We also calibrate the steady state (deterministic) growth of TFP in the consumption/investment sectors in line with the sample

[31] The grid of values we use is:
$\underline{a}_1$ = (1e-5,2e-5,3e-5,4e-5,5e-5,6e-5,7e-5,8e-5,9e-5, 1e-4,2e-4,3e-4,4e-4,5e-4,6e-4,7e-4,8e-4,9e-4, 0.001,0.002,0.003,0.004,0.005,0.006,0.007,0.008,0.009, 0.01,0.02,0.03,0.04,0.05,0.06,0.07,0.08,0.09, 0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9, 1,2,3,4,5,6,7,8,9,10),
$\underline{a}_2$ = (0.01,0.02,0.03,0.04,0.05,0.06,0.07,0.08,0.09, 0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,2,3,4,5,6,7,8,910).
We take all possible pairs of $\underline{a}_1$ and $\underline{a}_2$ in the above grids, so we end up estimating 1540 models.

Table 6: Calibrated Parameters

Parameter	Value	Description
δ_C	0.025	Consumption sector capital depreciation
δ_I	0.025	Investment sector capital depreciation
a_c	0.3	Consumption sector share of capital
a_I	0.3	Investment sector share of capital
β	0.9974	Discount factor
$\pi_C - 1$	0.642	Steady state consumption sector net inflation rate (percent quarterly)
$\pi_I - 1$	0.080	Steady state investment sector net inflation rate (percent quarterly)
λ_p	0.15	Steady state price markup
λ_w	0.15	Steady state wage markup
g_a	0.097	Steady state C-sector TFP growth (percent quarterly)
g_v	0.490	Steady state I-sector TFP growth (percent quarterly)
$p_i \frac{i}{c}$	0.426	Steady state investment / consumption
$\frac{G}{Y}$	0.18	Steady state government spending / output
θ_B	0.96	Fraction of bankers that survive
ϖ	0.0021	Share of assets transferred to new bankers
λ_B	0.69	Fraction of funds bankers can divert
ϱ	5.47	Steady state leverage ratio
$R^B - R$	0.5	Steady state spread (percent quarterly)

Notes. β, π_C, π_I, g_a, g_v, $p_i \frac{i}{c}$, ϱ, $R^B - R$ are based on sample averages. ϖ and λ_B are set to be consistent with the average values of the leverage ratio, ϱ, and $R^B - R$.

average growth rates of output in the two sectors. This yields $g_a = 0.097\%$ and $g_v = 0.490\%$ per quarter. There are three parameters specific to financial intermediation. The parameter θ_B, which determines the banker's average life span does not have a direct empirical counterpart and is fixed at 0.96, similar to the value used by Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). This value implies an average survival time of bankers of slightly over six years. The parameters ϖ and λ_B are fixed at values which guarantee that the steady state risk premium (the average of spreads across the two sectors) and the steady state leverage ratio matches their empirical counterparts. The average of the consumption sector and investment sector credit spreads are each equal to 50 basis points in the sample. The average leverage ratio in the data is computed from the ratio of assets (excluding loans to consumers, real estate and holdings of government bonds) to equity for all U.S. insured commercial banks and is equal to 5.47.

B Data Sources and Time Series Construction

Table 7 provides an overview of the data used to construct the observables. All the data transformations we have made in order to construct the dataset used for the estimation of the model are described in detail below. As described in the main body, a subset of variables are used for estimating the various VAR specifications and they enter in levels. The data series for aggregate utilization adjusted TFP used to estimate the VARs are taken from John Fernald's website ($www.frbsf.org/economic-research/economists/jfernald/quarterly\_tfp.xls$), and are described in Fernald (2014).

Sectoral definition. To allocate a sector to the consumption or investment category, we used the 2005 Input-Output tables. The Input-Output tables track the flows of goods and services across industries and record the final use of each industry's output into three broad categories: consumption, investment and intermediate uses (as well as net exports and government). First, we determine how much of a 2-digit industry's final output goes to consumption as opposed to investment or intermediate uses.

Then we adopt the following criterion: if the majority of an industry's final output is allocated to final consumption demand it is classified as a consumption sector; otherwise, if the majority of an industry's output is allocated to investment or intermediate demand, it is classified as an investment sector. Using this criterion, mining, utilities, transportation and warehousing, information, manufacturing, construction and wholesale trade industries are classified as the investment sector and retail trade, real estate, rental and leasing, professional and business services, educational services, health care and social assistance, arts, entertainment, recreation, accommodation and food services and other services except government are classified as the consumption sector.[32]

Real and nominal variables. Consumption (in current prices) is defined as the sum of

[32]The investment sectors' NAICS codes are: 21 22 23 31 32 33 42 48 49 51 (except 491). The consumption sector NAICS codes are: 6 7 11 44 45 53 54 55 56 81. This information is provided by the Bureau of Economic analysis (Use Tables/Before Redefinitions/Producer Value ($http://www.bea.gov/industry/io\_annual.htm$)). We have checked whether there is any migration of 2-digit industries across sectors for our sample. The only industry which changes classification (from consumption to investment) during the sample is "information" which for the majority of the sample can be classified as investment and we classify it as such.

Table 7: Time Series used to construct the observables and steady state relationships

Time Series Description	Units	Code	Source
Gross domestic product	CP, SA, billion $	GDP	BEA
Gross Private Domestic Investment	CP, SA, billion $	GPDI	BEA
Real Gross Private Domestic Investment	CVM, SA, billion $	GPDIC1	BEA
Personal Consumption Exp.: Durable Goods	CP, SA, billion $	PCDG	BEA
Real Personal Consumption Exp.: Durable Goods	CVM, SA, billion $	PCDGCC96	BEA
Personal Consumption Expenditures: Services	CP, SA, billion $	PCESV	BEA
Real Personal Consumption Expenditures: Services	CVM, SA, billion $	PCESVC96	BEA
Personal Consumption Exp.: Nondurable Goods	CP, SA, billion $	PCND	BEA
Real Personal Consumption Exp.: Nondurable Goods	CVM, SA, billion $	PCNDGC96	BEA
Civilian Noninstitutional Population	NSA, 1000s	CNP160V	BLS
Non-farm Business Sector: Compensation Per Hour	SA, Index 2005=100	COMPNFB	BLS
Non-farm Business Sector: Hours of All Persons	SA, Index 2005=100	HOANBS	BLS
Effective Federal Funds Rate	NSA, percent	FEDFUNDS	BG
Total Book Equity	NSA	EQTA	IEC
Total Assets	NSA	H.8	FRB
All Employees	SA	B-1	BLS
Average Weekly Hours	SA	B-7	BLS
S&P 500 Index			Robert Shiller
E5Y Confidence Indicator		Table 29	Michigan Survey
BAA corporate spread			St. Louis FED FRED
GZ Spread			Simon Gilchrist
Excess bond premium			Simon Gilchrist
GT Spread		authors calculations	Datastream
Market Equity			CRSP
SLOOS			Federal Reserve

CP = current prices, CVM = chained volume measures (2005 Dollars), SA = seasonally adjusted, NSA = not seasonally adjusted. BEA = U.S. Department of Commerce: Bureau of Economic Analysis, BLS = U.S. Department of Labor: Bureau of Labor Statistics and BG = Board of Governors of the Federal Reserve System, IEC = Federal Financial Institutions Examination Council, FRB = Federal Reserve Board.

personal consumption expenditures on services and personal consumption expenditures on non-durable goods. The times series for real consumption is constructed as follows. First, we compute the shares of services and non-durable goods in total (current price) consumption. Then, total real consumption growth is obtained as the chained weighted (using the nominal shares above) growth rate of real services and growth rate of real non-durable goods. Using the growth rate of real consumption we construct a series for real consumption using 2005 as the base year. The consumption deflator is calculated as the ratio of nominal over real consumption. In the DSGE model inflation of consumer prices is the growth rate of the consumption deflator. In the VAR model we use the log change in the GDP deflator as our inflation measure, however results are nearly identical when we use the consumption deflator or CPI inflation. Analogously, we construct a time series for the investment deflator using series for (current price) personal consumption expenditures on durable goods and gross private domestic investment and chain weight to arrive at the real aggregate. The relative price of investment is the ratio of the investment deflator and the consumption deflator. Real output is GDP expressed in consumption units by dividing current price GDP with the consumption deflator.

The hourly wage is defined as total compensation per hour. Dividing this series by the consumption deflator yields the real wage rate. Hours worked is given by hours of all persons in the non-farm business sector. All series described above as well as the equity capital series (described below) are expressed in per capita terms using the series of non-institutional population, ages 16 and over. The nominal interest rate is the effective federal funds rate. We use the monthly average per quarter of this series and divide it by four to account for the quarterly frequency of the model. The time series for hours is in logs. Moreover, all series used in estimation (including the financial time series described below) are expressed in deviations from their sample average.

Financial variables. The GT spread. Data for sectoral credit spreads are not directly available. However, Reuters' Datastream provides U.S. credit spreads for companies which we map into the two sectors using The North American Industry Classification Sys-

tem (NAICS) as explained above. A credit spread is defined as the difference between a company's corporate bond yield and the yield of a U.S. Treasury bond with an identical maturity which is directly provided by Datastream. In constructing credit spreads we only consider nonfinancial corporations and only bonds traded in the secondary market. In line with Gilchrist et al. (2009) we make the following adjustments to the credit spread data we construct: using ratings from Standard & Poor's and Moody's, we exclude all bonds which are below investment grade as well as the bonds for which ratings are unavailable. We further exclude all spreads with a duration below one and above 30 years and exclude all credit spreads below 10 and above 5000 basis points to ensure that the time series are not driven by a small number of extreme observations. The series for the sectoral credit spreads are constructed by taking the average over all company level spreads available in a certain quarter. These two series are transformed from basis points into percent and divided by four to guarantee that they are consistent with the quarterly frequency of our model. After these adjustments the average bond duration is 30 quarters (consumption sector) and 28 quarters (investment sector) with an average rating for both sectoral bond issues between BBB+ and A-.

The GZ spread. The GZ spread and excess bond premium series is directly obtained from Simon Gilchrist's website ($http://people.bu.edu/sgilchri/Data/data.htm$). The methodology is described in Gilchrist and Zakrajsek (2012).

The BAA spread. The BAA spread is obtained from the Federal Reserve Bank of St. Louis online database FRED ($https://fred.stlouisfed.org.$).

The S&P 500 index is obtained from Robert Shiller's website ($http://www.econ.yale.edu/ shiller/da$ and has been converted to a real per capita index by dividing with the consumption deflator and non-institutional population, ages 16 and over.

Market equity. The market value of commercial bank's equity is constructed using monthly data from CRSP. From the raw data we retain companies with the following SIC codes to cover the commercial banking sector: 6021 (National Commercial Banks), 6022 (State Commercial Banks), 6029 (Commercial Banks, not elsewhere classified), 6081 (Branches and

Agencies of Foreign Banks), 6153 (Short-Term Business Credit Institutions, except Agricultural), 6159 (Miscellaneous Business Credit Institutions) and 6111 (Federal and Federally-Sponsored Credit Agencies). Market value is calculated as the product of Price (PRC) and Shares Outstanding (SHROUT). We transform the data to quarterly frequency by considering the market value on the last trading day per quarter. For the time horizon 1990Q1-2013Q4 our dataset contains market values of 626 financial companies (18,968 observations). These observations are aggregated by quarter. Consistent with the treatment for the book value of equity series, the final series for the market value of total equity is generated by taking the log after dividing by Civilian Noninstitutional Population and the consumption deflator.

Senior officer opinion survey of bank lending practices (SLOOS). The SLOOS is obtained directly from the Federal Reserve ($http://www.federalreserve.gov/datadownload/Choose.asp$ $SLOOS$). The survey panel contains domestic banks headquartered in all 12 Federal Reserve Districts, with a minimum of 2 and a maximum of 12 domestic banks in the panel from each district. In general, up to 60 domestically chartered U.S. commercial banks participated in each survey from 1990 through mid-2012; beginning with the July 2012 survey, the size of the domestic panel was increased to include as many as 80 institutions. As described in the Federal Register Notice authorizing the SLOOS, the panel of domestic respondents as of September 30, 2011 contained 55 banks, 34 of which had assets of $20 billion or more. The combined assets of the respondent banks totaled $7.5 trillion and accounted for 69 percent of the $10.9 trillion in total assets at domestically chartered institutions. The respondent banks also held between 40 percent and 80 percent of total commercial bank loans outstanding in each major loan category regularly queried in the survey, with most categories falling in the upper end of that range. The particular survey question we consider is the net percentage of domestic respondents reporting tightening lending standards for commercial and industry loans for large and medium-sized firms.

Steady state financial parameters. The steady state leverage ratio of financial intermediaries in the model – which helps to pin down the parameters ϖ and λ_B – is calculated

by taking the sample average of the inverse of total equity over adjusted assets of all insured U.S. commercial banks available from the Federal Financial Institutions Examination Council. The same body reports a series of equity over total assets. We multiply this ratio with total assets in order to get total equity for the U.S. banking sector that we use in estimation. Total assets includes consumer loans and holdings of government bonds which we want to exclude from total assets to be consistent with the model concept. Thus, to arrive at an estimate for adjusted assets we subtract consumer, real estate loans and holdings of government and government guaranteed bonds (such as government sponsored institutions) from total assets of all insured U.S. commercial banks.

C Model Details and Derivations

We provide the model details and derivations required for solution and estimation of the model. We begin with the pricing and wage decisions of firms and households, the financial sector followed by the normalization of the model to render it stationary, the description of the steady state and the log-linearized model equations.

C.1 Intermediate and Final Goods Producers

Intermediate producers pricing decision. A constant fraction $\xi_{p,x}$ of intermediate firms in sector $x = C, I$ cannot choose their price optimally in period t but reset their price — as in Calvo (1983) — according to the indexation rule,

$$P_{C,t}(i) = P_{C,t-1}(i)\pi_{C,t-1}^{\iota_{pC}}\pi_C^{1-\iota_{pC}},$$
$$P_{I,t}(i) = P_{I,t-1}(i)\pi_{I,t-1}^{\iota_{pI}}\pi_I^{1-\iota_{pI}}\left[\left(\frac{A_t}{A_{t-1}}\right)^{-1}\left(\frac{V_t}{V_{t-1}}\right)^{\frac{1-a_c}{1-a_i}}\right]^{\iota_{pI}},$$

where $\pi_{C,t} \equiv \frac{P_{C,t}}{P_{C,t-1}}$ and $\pi_{I,t} \equiv \frac{P_{I,t}}{P_{I,t-1}}\left(\frac{A_t}{A_{t-1}}\right)^{-1}\left(\frac{V_t}{V_{t-1}}\right)^{\frac{1-a_c}{1-a_i}}$ is gross inflation in the two sectors and π_C, π_I denote steady state values. The factor that appears in the investment sector expression adjusts for investment specific progress.

The remaining fraction of firms, $(1 - \xi_{p,x})$, in sector $x = C, I$ can adjust the price in

period t. These firms choose their price optimally by maximizing the present discounted value of future profits.

The resulting aggregate price index in the consumption sector is,

$$P_{C,t} = \left[(1-\xi_{p,C})\tilde{P}_{C,t}^{\frac{1}{\lambda_{p,t}^C}} + \xi_{p,C}\left(\left(\frac{\pi_{C,t-1}}{\pi}\right)^{\iota_{pC}} \pi_C^{1-\iota_{pC}} P_{C,t-1}\right)^{\frac{1}{\lambda_{p,t}^C}}\right]^{\lambda_{p,t}^C}.$$

The aggregate price index in the investment sector is,

$$P_{I,t} = \left[(1-\xi_{p,I})\tilde{P}_{I,t}^{\frac{1}{\lambda_{p,t}^I}} + \xi_{p,I}\left(P_{I,t-1}\left(\frac{\pi_{I,t-1}}{\pi}\right)^{\iota_{pI}} \pi_I^{1-\iota_{pI}}\left[\left(\frac{A_t}{A_{t-1}}\right)^{-1}\left(\frac{V_t}{V_{t-1}}\right)^{\frac{1-a_C}{1-a_i}}\right]^{\iota_{pI}}\right)^{\frac{1}{\lambda_{p,t}^I}}\right]^{\lambda_{p,t}^I}.$$

Final goods producers. Profit maximization and the zero profit condition for final good firms imply that sectoral prices of the final goods, $P_{C,t}$ and $P_{I,t}$, are CES aggregates of the prices of intermediate goods in the respective sector, $P_{C,t}(i)$ and $P_{I,t}(i)$,

$$P_{C,t} = \left[\int_0^1 P_{C,t}(i)^{\frac{1}{\lambda_{p,t}^C}} di\right]^{\lambda_{p,t}^C}, \qquad P_{I,t} = \left[\int_0^1 P_{I,t}(i)^{\frac{1}{\lambda_{p,t}^I}} di\right]^{\lambda_{p,t}^I}.$$

The elasticity $\lambda_{p,t}^x$ is the time varying price markup over marginal cost for intermediate firms. It is assumed to follow the exogenous stochastic process,

$$\log(1+\lambda_{p,t}^x) = (1-\rho_{\lambda_p^x})\log(1+\lambda_p^x) + \rho_{\lambda_p^x}\log(1+\lambda_{p,t-1}^x) + \varepsilon_{p,t}^x,$$

where $\rho_{\lambda_p^x} \in (0,1)$ and $\varepsilon_{p,t}^x$ is $i.i.d.$ $N(0,\sigma_{\lambda_p^x}^2)$, with $x = C, I$.

C.1.1 Household's wage setting

Each household $j \in [0,1]$ supplies specialized labor, $L_t(j)$, monopolistically as in Erceg et al. (2000). A large number of competitive "employment agencies" aggregate this specialized labor into a homogenous labor input which is sold to intermediate goods producers in a competitive market. Aggregation is done according to the following function,

$$L_t = \left[\int_0^1 L_t(j)^{\frac{1}{1+\lambda_{w,t}}} dj\right]^{1+\lambda_{w,t}}.$$

The desired markup of wages over the household's marginal rate of substitution (or wage mark-up), $\lambda_{w,t}$, follows the exogenous stochastic process,

$$\log(1+\lambda_{w,t}) = (1-\rho_w)\log(1+\lambda_w) + \rho_w \log(1+\lambda_{w,t-1}) + \varepsilon_{w,t},$$

where $\rho_w \in (0,1)$ and $\varepsilon_{w,t}$ is *i.i.d.* $N(0, \sigma^2_{\lambda_w})$.

Profit maximization by the perfectly competitive employment agencies implies the labor demand function,

$$L_t(j) = \Big(\frac{W_t(j)}{W_t}\Big)^{-\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} L_t, \tag{C.1}$$

where $W_t(j)$ is the wage received from employment agencies by the supplier of labor of type j, while the wage paid by intermediate firms for the homogenous labor input is,

$$W_t = \left[\int_0^1 W_t(j)^{\frac{1}{\lambda_{w,t}}} dj\right]^{\lambda_{w,t}}.$$

Following Erceg et al. (2000), in each period, a fraction ξ_w of the households cannot freely adjust its wage but follows the indexation rule,

$$W_{t+1}(j) = W_t(j)\Big(\pi_{c,t} e^{z_t + \frac{a_c}{1-a_i} v_t}\Big)^{\iota_w} \Big(\pi_c e^{g_a + \frac{a_c}{1-a_i} g_v}\Big)^{1-\iota_w}.$$

The remaining fraction of households, $(1-\xi_w)$, chooses an optimal wage, $W_t(j)$, by maximizing,

$$E_t\left\{\sum_{s=0}^{\infty} \xi_w^s \beta^s \left[-b_{t+s}\varphi \frac{L_{t+s}(j)^{1+\nu}}{1+\nu} + \Lambda_{t+s} W_t(j) L_{t+s}(j)\right]\right\},$$

subject to the labor demand function (C.1). The aggregate wage evolves according to,

$$W_t = \left\{(1-\xi_w)(\tilde{W}_t)^{\frac{1}{\lambda_w}} + \xi_w \left[\Big(\pi_c e^{g_a + \frac{a_c}{1-a_i} g_v}\Big)^{1-\iota_w} \Big(\pi_{c,t-1} e^{z_{t-1} + \frac{a_c}{1-a_i} v_{t-1}}\Big)^{\iota_w} W_{t-1}\right]^{\frac{1}{\lambda_w}}\right\}^{\lambda_w},$$

where $\tilde{W}_t$ is the optimally chosen wage.

C.2 Physical capital producers

Capital producers in sector $x = C, I$ use a fraction of investment goods from final goods producers and undepreciated capital stock from capital services producers (as described

above) to produce new capital goods, subject to investment adjustment costs as proposed by Christiano et al. (2005). These new capital goods are then sold in perfectly competitive capital goods markets to capital services producers. The technology available for physical capital production is given as,

$$O'_{x,t} = O_{x,t} + \mu_t \left(1 - S\Big(\frac{I_{x,t}}{I_{x,t-1}}\Big)\right) I_{x,t},$$

where $O_{x,t}$ denotes the amount of used capital at the end of period t, $O'_{x,t}$ the new capital available for use at the beginning of period $t+1$. The investment adjustment cost function $S(\cdot)$ satisfies the following: $S(1) = S'(1) = 0$ and $S''(1) = \kappa > 0$, where "$'$"s denote differentiation. The optimization problem of capital producers in sector $x = C, I$ is given as,

$$\underset{I_{x,t}, O_{x,t}}{max}\ E_t \sum_{t=0}^{\infty} \beta^t \Lambda_t \left\{ Q_{x,t} \left[O_{x,t} + \mu_t \left(1 - S\Big(\frac{I_{x,t}}{I_{x,t-1}}\Big)\right) I_{x,t} \right] - Q_{x,t} O_{x,t} - \frac{P_{I,t}}{P_{C,t}} I_{x,t} \right\},$$

where $Q_{x,t}$ denotes the price of capital (i.e. the value of installed capital in consumption units). The first order condition for investment goods is,

$$\frac{P_{I,t}}{P_{C,t}} = Q_{x,t}\mu_t \left[1 - S\Big(\frac{I_{x,t}}{I_{x,t-1}}\Big) - S'\Big(\frac{I_{x,t}}{I_{x,t-1}}\Big) \frac{I_{x,t}}{I_{x,t-1}} \right] + \beta E_t Q_{x,t+1} \mu_{t+1} \frac{\Lambda_{t+1}}{\Lambda_t} \left[S'\Big(\frac{I_{x,t+1}}{I_{x,t}}\Big) \Big(\frac{I_{x,t+1}}{I_{x,t}}\Big)^2 \right].$$

From the capital producer's problem it is evident that any value of $O_{x,t}$ is profit maximizing. Let $\delta_x \in (0,1)$ denote the depreciation rate of capital and $\bar{K}_{x,t-1}$ the capital stock available at the beginning of period t in sector $x = C, I$. Then setting $O_{x,t} = (1-\delta)\xi^K_{x,t}\bar{K}_{x,t-1}$ implies the available (sector-specific) capital stock in sector x, evolves according to,

$$\bar{K}_{x,t} = (1-\delta_x)\xi^K_{x,t}\bar{K}_{x,t-1} + \mu_t \left(1 - S\Big(\frac{I_{x,t}}{I_{x,t-1}}\Big)\right) I_{x,t}, \qquad x = C, I, \tag{C.2}$$

as described in the main text.

C.3 Financial Intermediaries

This section describes in detail how the setup of Gertler and Karadi (2011) is adapted for the two sector model and describes in detail how the equations for financial intermediaries in the main text are derived.

The balance sheet for the consumption or investment sector branch can be expressed as,

$$P_{C,t}Q_{x,t}S_{x,t} = P_{C,t}N_{x,t} + B_{x,t}, \qquad x = C, I,$$

where $S_{x,t}$ denotes the quantity of financial claims held by the intermediary branch and $Q_{x,t}$ denotes the sector-specific price of a claim. The variable $N_{x,t}$ represents the bank's wealth (or equity) at the end of period t and $B_{x,t}$ are the deposits the intermediary branch obtains from households. The sector-specific assets held by the financial intermediary pay the stochastic return $R^B_{x,t+1}$ in the next period. Intermediaries pay at $t+1$ the non-contingent real gross return R_t to households for their deposits made at time t. Then, the intermediary branch equity evolves over time as,

$$\begin{aligned} N_{x,t+1}P_{C,t+1} &= R^B_{x,t+1}\pi_{C,t+1}P_{C,t}Q_{x,t}S_{x,t} - R_tB_{x,t} \\ N_{x,t+1}\frac{P_{C,t+1}}{P_{C,t}} &= R^B_{x,t+1}\pi_{C,t+1}Q_{x,t}S_{x,t} - R_t(Q_{x,t}S_{x,t} - N_{x,t}) \\ N_{x,t+1} &= \left[(R^B_{x,t+1}\pi_{C,t+1} - R_t)Q_{x,t}S_{x,t} + R_tN_{x,t}\right]\frac{1}{\pi_{C,t+1}}. \end{aligned}$$

The premium, $R^B_{x,t+1}\pi_{C,t+1} - R_t$, as well as the quantity of assets, $Q_{x,t}S_{x,t}$, determines the growth in bank's equity above the riskless return. The bank will not fund any assets with a negative discounted premium. It follows that for the bank to operate in period i the following inequality must hold,

$$E_t\beta^i\Lambda^B_{t+1+i}(R^B_{x,t+1+i}\pi_{C,t+1+i} - R_{t+i}) \geq 0, \qquad i \geq 0,$$

where $\beta^i\Lambda^B_{t+1+i}$ is the bank's stochastic discount factor, with,

$$\Lambda^B_{t+1} \equiv \frac{\Lambda_{t+1}}{\Lambda_t},$$

where Λ_t is the Lagrange multiplier on the household's budget equation. Under perfect capital markets, arbitrage guarantees that the risk premium collapses to zero and the relation always holds with equality. However, under imperfect capital markets, credit constraints rooted in the bank's inability to obtain enough funds may lead to positive risk premia. As long as the above inequality holds, banks will keep building assets by borrowing additional funds from households. Accordingly, the intermediary branch objective is to maximize ex-

pected terminal wealth,

$$\begin{aligned} V_{x,t} =& max E_t \sum_{i=0} (1-\theta_B)\theta_B^i \beta^i \Lambda^B_{t+1+i} N_{x,t+1+i} \\ =& max E_t \sum_{i=0} (1-\theta_B)\theta_B^i \beta^i \Lambda^B_{t+1+i} [(R^B_{x,t+1+i}\pi_{C,t+1+i} - R_{t+i}) \frac{Q_{x,t+i}S_{x,t+i}}{\pi_{C,t+1+i}} + \frac{R_{t+i}N_{x,t+i}}{\pi_{C,t+1+i}}], \end{aligned} \tag{C.3}$$

where $\theta_B \in (0,1)$ is the fraction of bankers at t that survive until period $t+1$.

Following the setup in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) the banks are limited from infinitely borrowing additional funds from households by a moral hazard/costly enforcement problem. On the one hand, the agent who works in the bank can choose, at the beginning of each period, to divert the fraction λ_B of available funds and transfer it back to the household. On the other hand, depositors can force the bank into bankruptcy and recover a fraction $1-\lambda_B$ of assets. Note that the fraction, λ_B, which intermediaries can divert is the same across sectors to guarantee that the household is indifferent between lending funds between different branches.

Given this tradeoff, depositors will only lend funds to the intermediary when the latter's maximized expected terminal wealth is larger or equal to the gain from diverting the fraction λ_B of available funds. This incentive constraint can be formalized as,

$$V_{x,t} \geq \lambda_B Q_{x,t} S_{x,t}, \qquad 0 < \lambda_B < 1. \tag{C.4}$$

Using equation (C.3), the expression for $V_{x,t}$ can be written as the following first-order difference equation,

$$V_{x,t} = \nu_{x,t} Q_{x,t} S_{x,t} + \eta_{x,t} N_{x,t},$$

with,

$$\begin{aligned} \nu_{x,t} &= E_t\{(1-\theta_B)\Lambda^B_{t+1}(R^B_{x,t+1}\pi_{C,t+1} - R_t) + \theta_B \beta Z^x_{1,t+1}\nu_{x,t+1}\}, \\ \eta_{x,t} &= E_t\{(1-\theta_B)\Lambda^B_{t+1}R_t + \theta_B \beta Z^x_{2,t+1}\eta_{x,t+1}\}, \end{aligned}$$

and,

$$Z^x_{1,t+1+i} \equiv \frac{Q_{x,t+1+i}S_{x,t+1+i}}{Q_{x,t+i}S_{x,t+i}}, \qquad Z^x_{2,t+1+i} \equiv \frac{N_{x,t+1+i}}{N_{x,t+i}}.$$

The variable $\nu_{x,t}$ can be interpreted as the expected discounted marginal gain of expanding assets $Q_{x,t}S_{x,t}$ by one unit while holding wealth $N_{x,t}$ constant. The interpretation of $\eta_{x,t}$ is analogous: it is the expected discounted value of having an additional unit of wealth, $N_{x,t}$, holding the quantity of financial claims, $S_{x,t}$, constant. The gross growth rate in assets is denoted by $Z^x_{1,t+i}$ and the gross growth rate of net worth is denoted by $Z^x_{2,t+i}$.

Then, using the expression for $V_{x,t}$, we can express the intermediary's incentive constraint (C.4) as,

$$\nu_{x,t}Q_{x,t}S_{x,t} + \eta_{x,t}N_{x,t} \geq \lambda_B Q_{x,t}S_{x,t}.$$

As indicated above, under perfect capital markets banks will expand borrowing until the risk premium collapses to zero which implies that in this case $\nu_{x,t}$ equals zero as well. Imperfect capital markets however, limit the possibilities for this kind of arbitrage because the intermediaries are constrained by their equity capital. If the incentive constraint binds it follows that,

$$\begin{aligned} Q_{x,t}S_{x,t} &= \frac{\eta_{x,t}}{\lambda_B - \nu_{x,t}} N_{x,t} \\ &= \varrho_{x,t}N_{x,t}. \end{aligned} \tag{C.5}$$

In this case, the quantity of assets which the intermediary can acquire depends on the equity capital, $N_{x,t}$, as well as the intermediary's leverage ratio, $\varrho_{x,t}$, limiting the bank's ability to acquire assets. This leverage ratio is the ratio of the bank's intermediated assets to equity. The bank's leverage ratio is limited to the point where its maximized expected terminal wealth equals the gains from diverting the fraction λ_B from available funds. However, the constraint (C.5) binds only if $0 < \nu_{x,t} < \lambda_B$ (given $N_{x,t} > 0$). This inequality is always satisfied with our estimates.

Using the leverage ratio (C.5) we can express the evolution of the intermediary's wealth

as,

$$N_{x,t+1} = [(R^B_{x,t+1}\pi_{C,t+1} - R_t)\varrho_{x,t} + R_t]\frac{N_{x,t}}{\pi_{C,t+1}}.$$

From this equation it also follows that,

$$Z^x_{2,t+1} = \frac{N_{x,t+1}}{N_{x,t}} = \big[(R^B_{x,t+1}\pi_{C,t+1} - R_t)\varrho_{x,t} + R_t\big]\frac{1}{\pi_{C,t+1}},$$

and,

$$Z^x_{1,t+1} = \frac{Q_{x,t+1}S_{x,t+1}}{Q_{x,t}S_{x,t}} = \frac{\varrho_{x,t+1}N_{x,t+1}}{\varrho_{x,t}N_{x,t}} = \frac{\varrho_{x,t+1}}{\varrho_{x,t}}Z^x_{2,t+1}.$$

Financial intermediaries which are forced into bankruptcy are replaced by new entrants. Therefore, total wealth of financial intermediaries is the sum of the net worth of existing, $N^e_{x,t}$, and new ones, $N^n_{x,t}$,

$$N_{x,t} = N^e_{x,t} + N^n_{x,t}.$$

The fraction θ_B of bankers at $t-1$ which survive until t is equal across branches. Then, the law of motion for existing bankers is given by,

$$N^e_{x,t} = \theta_B[(R^B_{x,t}\pi_{C,t} - R_{t-1})\varrho_{x,t-1} + R_{t-1}]\frac{N_{x,t-1}}{\pi_{C,t}}, \qquad 0 < \theta_B < 1. \tag{C.6}$$

where a main source of variation is the ex-post excess return on assets, $R^B_{x,t}\pi_{C,t} - R_{t-1}$.

New banks receive startup funds from their respective household, equal to a small fraction of the value of assets held by the existing bankers in their final operating period. Given that the exit probability is *i.i.d.*, the value of assets held by the existing bankers in their final operating period is given by $(1-\theta_B)Q_{x,t}S_{x,t}$. The transfer to new intermediaries is a fraction, ϖ, of this value, leading to the following formulation for new banker's wealth,

$$N^n_{x,t} = \varpi Q_{x,t}S_{x,t}, \qquad 0 < \varpi < 1. \tag{C.7}$$

Existing banker's net worth (C.6) and entering banker's net worth (C.7) lead to the law of motion for total net worth,

$$N_{x,t} = \big(\theta_B[(R^B_{x,t}\pi_{C,t} - R_{t-1})\varrho_{x,t-1} + R_{t-1}]\frac{N_{x,t-1}}{\pi_{C,t}} + \varpi Q_{x,t}S_{x,t}\big).$$

The excess return, $x = C, I$ can be defined as,

$$R^S_{x,t} = R^B_{x,t+1}\pi_{C,t+1} - R_t.$$

Since R_t, λ_B, ϖ and θ_B are equal across sectors, the institutional setup of the two representative banks in the two sectors is symmetric. Both branches hold deposits from households and buy assets from firms in the sector they provide specialized lending. Their performance differs because the demand for capital differs across sectors resulting in sector-specific prices of capital, $Q_{x,t}$, and nominal rental rates for capital, $R^K_{x,t}$. Note that the institutional setup of banks does not depend on firm-specific factors. Gertler and Karadi (2011) show that this implies a setup with a continuum of banks is equivalent to a formulation with a representative bank. Owing to the symmetry of the banks this also holds for our formulation of financial intermediaries in the two-sector setup.

C.4 Resource Constraints

The resource constraint in the consumption sector is,

$$C_t + (a(u_{C,t})\xi^K_{C,t}\bar{K}_{C,t-1} + a(u_{I,t})\xi^K_{I,t}\bar{K}_{I,t-1})\frac{A_t V_t^{\frac{a_c}{1-a_i}}}{V_t^{\frac{1}{1-a_i}}} = a_{lt}A_t L_{c,t}^{1-a_c}K_{c,t}^{a_c} - A_t V_t^{\frac{a_c}{1-a_i}}F_C.$$

The resource constraint in the investment sector is,

$$I_{I,t} + I_{C,t} = v_{lt}V_t L_{I,t}^{1-a_i}K_{I,t}^{a_i} - V_t^{\frac{1}{1-a_i}}F_I.$$

Hours worked are aggregated as,

$$L_t = L_{I,t} + L_{C,t}.$$

Bank equity is aggregated as,

$$N_t = N_{I,t} + N_{C,t}.$$

C.5 Stationary Economy

The model includes two non-stationary TFP shocks, A_t and V_t. This section shows how we normalize the model to render it stationary. Lower case variables denote normalized stationary variables.

The model variables can be stationarized as follows:

$$k_{x,t} = \frac{K_{x,t}}{V_t^{\frac{1}{1-a_i}}}, \qquad \bar{k}_{x,t} = \frac{\bar{K}_{x,t}}{V_t^{\frac{1}{1-a_i}}}, \qquad k_t = \frac{K_t}{V_t^{\frac{1}{1-a_i}}}, \tag{C.8}$$

$$i_{x,t} = \frac{I_{x,t}}{V_t^{\frac{1}{1-a_i}}}, \qquad i_t = \frac{I_t}{V_t^{\frac{1}{1-a_i}}}, \qquad c_t = \frac{C_t}{A_t V_t^{\frac{a_c}{1-a_i}}}, \tag{C.9}$$

$$r^K_{C,t} = \frac{R^K_{C,t}}{P_{C,t}} A_t^{-1} V_t^{\frac{1-a_c}{1-a_i}}, \qquad r^K_{I,t} = \frac{R^K_{I,t}}{P_{C,t}} A_t^{-1} V_t^{\frac{1-a_c}{1-a_i}}, \qquad w_t = \frac{W_t}{P_{C,t} A_t V_t^{\frac{a_c}{1-a_i}}}. \tag{C.10}$$

From

$$\begin{aligned}
\frac{P_{I,t}}{P_{C,t}} &= \frac{mc_{C,t}}{mc_{I,t}} \frac{1-a_c}{1-a_i} \frac{A_t}{V_t} \left(\frac{K_{I,t}}{L_{I,t}}\right)^{-a_i} \left(\frac{K_{C,t}}{L_{C,t}}\right)^{a_c} \\
&= \frac{mc_{C,t}}{mc_{I,t}} \frac{1-a_c}{1-a_i} A_t V_t^{\frac{a_c-1}{1-a_i}} \left(\frac{k_{I,t}}{L_{I,t}}\right)^{-a_i} \left(\frac{k_{C,t}}{L_{C,t}}\right)^{a_c},
\end{aligned}$$

follows that,

$$p_{i,t} = \frac{P_{I,t}}{P_{C,t}} A_t^{-1} V_t^{\frac{1-a_c}{1-a_i}}. \tag{C.11}$$

and the multipliers are normalized as,

$$\lambda_t = \Lambda_t A_t V_t^{\frac{a_c}{1-a_i}}, \qquad \phi_{x,t} = \Phi_{x,t} V_t^{\frac{1}{1-a_i}}. \tag{C.12}$$

where $\Phi_{x,t}$ denotes the multiplier on the respective capital accumulation equation. Using the growth of investment, it follows that the prices of capital can be normalized as,

$$q_{x,t} = Q_{x,t} A_t^{-1} V_t^{\frac{1-a_c}{1-a_i}}.$$

with the price of capital in sector x, defined as,

$$q_{x,t} = \phi_{x,t}/\lambda_t, \quad x = C, I.$$

Using the growth of capital, it follows,

$$s_{x,t} = \frac{S_{x,t}}{V_t^{\frac{1}{1-a_i}}}.$$

Then, it follows from entering bankers wealth equation (C.7) that,

$$n_{x,t}^n = N_{x,t}^n A_t^{-1} V_t^{\frac{-a_c}{1-a_i}}.$$

Total wealth, wealth of existing and entering bankers has to grow at the same rate,

$$n_{x,t}^e = N_{x,t}^e A_t^{-1} V_t^{\frac{-a_c}{1-a_i}}, \qquad n_{x,t} = N_{x,t} A_t^{-1} V_t^{\frac{-a_c}{1-a_i}}.$$

C.5.1 Intermediate goods producers

Firm's production function in the consumption sector:

$$c_t = a_{lt} L_{C,t}^{1-a_c} k_{C,t}^{a_c} - F_C. \tag{C.13}$$

Firm's production function in the investment sector:

$$i_t = v_{lt} L_{I,t}^{1-a_i} k_{I,t}^{a_i} - F_I. \tag{C.14}$$

Marginal costs in the consumption sector:

$$mc_{C,t} = (1-a_c)^{a_c-1} a_c^{-a_c} (r_{C,t}^K)^{a_c} w_t^{1-a_c} a_{lt}^{-1}. \tag{C.15}$$

Marginal costs in the investment sector:

$$mc_{I,t} = (1-a_i)^{a_i-1} a_i^{-a_i} w_t^{1-a_i} (r_{I,t}^K)^{a_i} v_{lt}^{-1} p_{i,t}^{-1}, \qquad \text{with} \quad p_{i,t} = \frac{P_{I,t}}{P_{C,t}}. \tag{C.16}$$

Capital labour ratios in the two sectors:

$$\frac{k_{C,t}}{L_{C,t}} = \frac{w_t}{r_{C,t}^K} \frac{a_c}{1-a_c}, \qquad \frac{k_{I,t}}{L_{I,t}} = \frac{w_t}{r_{I,t}^K} \frac{a_i}{1-a_i}. \tag{C.17}$$

C.5.2 Firms' pricing decisions

Price setting equation for firms that change their price in sector $x = C, I$:

$$0 = E_t \left\{ \sum_{s=0}^{\infty} \xi_{p,x}^s \beta^s \lambda_{t+s} \tilde{x}_{t+s} \left[\tilde{p}_{x,t} \tilde{\Pi}_{t,t+s} - (1 + \lambda_{p,t+s}^x) mc_{x,t+s} \right] \right\}, \tag{C.18}$$

with

$$\tilde{\Pi}_{t,t+s} = \prod_{k=1}^{s} \left[\left(\frac{\pi_{x,t+k-1}}{\pi_x} \right)^{\iota_{px}} \left(\frac{\pi_{x,t+k}}{\pi_x} \right)^{-1} \right] \quad \text{and} \quad \tilde{x}_{t+s} = \left(\frac{\tilde{P}_{x,t}}{P_{x,t}} \tilde{\Pi}_{t,t+s} \right)^{-\frac{1+\lambda^x_{p,t+s}}{\lambda^x_{p,t+s}}} x_{t+s}$$

and $$\frac{\tilde{P}_{x,t}}{P_{x,t}} = \tilde{p}_{x,t}.$$

Aggregate price index in the consumption sector:

$$1 = \left[(1-\xi_{x,p})(\tilde{p}_{x,t})^{\frac{1}{\lambda^x_{p,t}}} + \xi_{x,p} \left[\left(\frac{\pi_{x,t-1}}{\pi_x} \right)^{\iota_{px}} \left(\frac{\pi_{x,t}}{\pi_x} \right)^{-1} \right]^{\frac{1}{\lambda^x_{p,t}}} \right]^{\lambda^x_{p,t}}.$$

It further holds that

$$\frac{\pi_{I,t}}{\pi_{C,t}} = \frac{p_{i,t}}{p_{i,t-1}}. \tag{C.19}$$

C.5.3 Household's optimality conditions and wage setting

Marginal utility of income:

$$\lambda_t = \frac{b_t}{c_t - hc_{t-1}\left(\frac{A_{t-1}}{A_t}\right)\left(\frac{V_{t-1}}{V_t}\right)^{\frac{a_c}{1-a_i}}} - \beta h \frac{b_{t+1}}{c_{t+1}\left(\frac{A_{t+1}}{A_t}\right)\left(\frac{V_{t+1}}{V_t}\right)^{\frac{a_c}{1-a_i}} - hc_t}. \tag{C.20}$$

Euler equation:

$$\lambda_t = \beta E_t \lambda_{t+1} \left(\frac{A_t}{A_{t+1}}\right)\left(\frac{V_t}{V_{t+1}}\right)^{\frac{a_c}{1-a_i}} R_t \frac{1}{\pi_{c,t+1}}.$$

Labor supply

$$\lambda_t w_t = b_t \varphi (L_{C,t} + L_{I,t})^{\nu},$$

C.5.4 Capital services

Optimal capital utilization:

$$r^K_{C,t} = a'_C(u_{C,t}), \qquad r^K_{I,t} = a'_I(u_{I,t}).$$

Definition of capital services:

$$k_{C,t} = u_{C,t}\xi^K_{C,t}\bar{k}_{C,t-1}\left(\frac{V_{t-1}}{V_t}\right)^{\frac{1}{1-a_i}}, \qquad k_{I,t} = u_{I,t}\xi^K_{I,t}\bar{k}_{I,t-1}\left(\frac{V_{t-1}}{V_t}\right)^{\frac{1}{1-a_i}}. \tag{C.21}$$

Optimal choice of available capital in sector $x = C, I$:

$$\phi_{x,t} = \beta E_t \xi^K_{x,t+1} \left\{ \lambda_{t+1} \Big(\frac{V_t}{V_{t+1}} \Big)^{\frac{1}{1-a_i}} (r^K_{x,t+1} u_{x,t+1} - a(u_{x,t+1})) + (1-\delta) E_t \phi_{x,t+1} \Big(\frac{V_t}{V_{t+1}} \Big)^{\frac{1}{1-a_i}} \right\}, \tag{C.22}$$

C.5.5 Physical capital producers

Optimal choice of investment in sector $x = C, I$:

$$\begin{aligned} \lambda_t p_{i,t} =& \phi_{x,t} \mu_t \left[1 - S\Big(\frac{i_{x,t}}{i_{x,t-1}} \Big(\frac{V_t}{V_{t-1}} \Big)^{\frac{1}{1-a_i}} \Big) - S'\Big(\frac{i_{x,t}}{i_{x,t-1}} \Big(\frac{V_t}{V_{t-1}} \Big)^{\frac{1}{1-a_i}} \Big) \frac{i_{x,t}}{i_{x,t-1}} \Big(\frac{V_t}{V_{t-1}} \Big)^{\frac{1}{1-a_i}} \right] \\ &+ \beta E_t \phi_{x,t+1} \mu_{t+1} \Big(\frac{V_t}{V_{t+1}} \Big)^{\frac{1}{1-a_i}} \left[S'\Big(\frac{i_{x,t+1}}{i_{x,t}} \Big(\frac{V_{t+1}}{V_t} \Big)^{\frac{1}{1-a_i}} \Big) \Big(\frac{i_{x,t+1}}{i_{x,t}} \Big(\frac{V_{t+1}}{V_t} \Big)^{\frac{1}{1-a_i}} \Big)^2 \right]. \end{aligned} \tag{C.23}$$

Accumulation of capital in sector $x = C, I$:

$$\bar{k}_{x,t} = (1-\delta_x) \xi^K_{x,t} \bar{k}_{x,t-1} \Big(\frac{V_{t-1}}{V_t} \Big)^{\frac{1}{1-a_i}} + \mu_t \left(1 - S\Big(\frac{i_{x,t}}{i_{x,t-1}} \Big(\frac{V_t}{V_{t-1}} \Big)^{\frac{1}{1-a_i}} \Big) \right) i_{x,t}, \tag{C.24}$$

C.5.6 Household's wage setting

Household's wage setting:

$$E_t \sum_{s=0}^{\infty} \beta^s \xi^s_w \lambda_{t+s} \tilde{L}_{t+s} \left[\tilde{w}_t \tilde{\Pi}^w_{t,t+s} - (1+\lambda_{w,t+s}) b_{t+s} \varphi \frac{\tilde{L}^\nu_{t+s}}{\lambda_{t+s}} \right] = 0, \tag{C.25}$$

with

$$\tilde{\Pi}^w_{t,t+s} = \prod_{k=1}^{s} \left[\left(\frac{\pi_{C,t+k-1} e^{a_{t+k-1} + \frac{a_c}{1-a_i} v_{t+k-1}}}{\pi_c e^{g_a + \frac{a_c}{1-a_i} g_v}} \right)^{\iota_w} \left(\frac{\pi_{C,t+k} e^{a_{t+k} + \frac{a_c}{1-a_i} v_{t+k}}}{\pi_C e^{g_a + \frac{a_c}{1-a_i} g_v}} \right)^{-1} \right]$$

and

$$\tilde{L}_{t+s} = \Big(\frac{\tilde{w}_t \tilde{\Pi}^w_{t,t+s}}{w_{t+s}} \Big)^{-\frac{1+\lambda_{w,t+s}}{\lambda_{w,t+s}}} L_{t+s}.$$

Wages evolve according to

$$w_t = \left\{ (1-\xi_w) \tilde{w}_t^{\frac{1}{\lambda_{w,t}}} + \xi_w \left[\left(\frac{\pi_{c,t-1} e^{a_{t-1} + \frac{a_c}{1-a_i} v_{t-1}}}{\pi_c e^{g_a + \frac{a_c}{1-a_i} g_v}} \right)^{l_w} \left(\frac{\pi_{c,t} e^{a_t + \frac{a_c}{1-a_i} v_t}}{\pi_c e^{g_a + \frac{a_c}{1-a_i} g_v}} \right)^{-1} w_{t-1} \right]^{\frac{1}{\lambda_{w,t}}} \right\}^{\lambda_{w,t}}.$$

C.5.7 Financial Intermediation

The stationary stochastic discount factor can be expressed as,

$$\lambda^B_{t+1} = \frac{\lambda_{t+1}}{\lambda_t}.$$

Then, one can derive expressions for $\nu_{x,t}$ and $\eta_{x,t}$,

$$\nu_{x,t} = E_t\{(1-\theta_B)\lambda^B_{t+1}\frac{A_t}{A_{t+1}}\Big(\frac{V_t}{V_{t+1}}\Big)^{\frac{a_c}{1-a_i}}(R^B_{x,t+1}\pi_{C,t+1} - R_t) + \theta_B\beta z^x_{1,t+1}\nu_{x,t+1}\},$$
$$\eta_{x,t} = E_t\{(1-\theta_B)\lambda^B_{t+1}\frac{A_t}{A_{t+1}}\Big(\frac{V_t}{V_{t+1}}\Big)^{\frac{a_c}{1-a_i}}R_t + \theta_B\beta z^x_{2,t+1}\eta_{x,t+1}\},$$

with

$$z^x_{1,t+1+i} \equiv \frac{q_{x,t+1+i}s_{x,t+1+i}}{q_{x,t+i}s_{x,t+i}}\frac{A_{t+1}}{A_t}\Big(\frac{V_{t+1}}{V_t}\Big)^{\frac{a_c}{1-a_i}}, \qquad z^x_{2,t+1+i} \equiv \frac{n_{x,t+1+i}}{n_{x,t+i}}\frac{A_{t+1}}{A_t}\Big(\frac{V_{t+1}}{V_t}\Big)^{\frac{a_c}{1-a_i}}.$$

It follows that if the bank's incentive constraint binds it can be expressed as,

$$\nu_{x,t}q_{x,t}s_{x,t} + \eta_{x,t}n_{x,t} = \lambda_B q_{x,t}s_{x,t}$$

$$\Leftrightarrow q_{x,t}s_{x,t} = \varrho_{x,t}n_{x,t},$$

with the leverage ratio given as,

$$\varrho_{x,t} = \frac{\eta_{x,t}}{\lambda_B - \nu_{x,t}}.$$

It further follows that:

$$z^x_{2,t+1} = \frac{n_{x,t+1}}{n_{x,t}}\frac{A_{t+1}}{A_t}\Big(\frac{V_{t+1}}{V_t}\Big)^{\frac{a_c}{1-a_i}} = \big[(R^B_{x,t+1}\pi_{C,t+1} - R_t)\varrho_{x,t} + R_t\big]\frac{1}{\pi_{C,t+1}},$$

and

$$z^x_{1,t+1} = \frac{q_{x,t+1}s_{x,t+1}}{q_{x,t}s_{x,t}}\frac{A_{t+1}}{A_t}\Big(\frac{V_{t+1}}{V_t}\Big)^{\frac{a_c}{1-a_i}} = \frac{\varrho_{x,t+1}n_{x,t+1}}{\varrho_{x,t}n_{x,t}}\frac{A_{t+1}}{A_t}\Big(\frac{V_{t+1}}{V_t}\Big)^{\frac{a_c}{1-a_i}} = \frac{\varrho_{x,t+1}}{\varrho_{x,t}}z^x_{2,t+1}.$$

The normalized equation for bank's wealth accumulation is,

$$n_{x,t} = \Big(\theta_B[(R^B_{x,t}\pi_{C,t} - R_{t-1})\varrho_{x,t-1} + R_{t-1}]\frac{A_{t-1}}{A_t}\Big(\frac{V_{t-1}}{V_t}\Big)^{\frac{a_c}{1-a_i}}\frac{n_{x,t-1}}{\pi_{C,t}} + \varpi q_{x,t}s_{x,t}\Big).$$

The borrow in advance constraint:

$$\bar{k}_{x,t+1} = s_{x,t}.$$

The leverage equation:

$$q_{x,t}s_{x,t} = \varrho_{x,t}n_{x,t}.$$

Bank's stochastic return on assets can be described in normalized variables as:

$$R^B_{x,t+1} = \frac{r^K_{x,t+1}u_{x,t+1} + q_{x,t+1}(1-\delta_x) - a(u_{x,t+1})}{q_{x,t}}\xi^K_{x,t+1}\frac{A_{t+1}}{A_t}\Big(\frac{V_{t+1}}{V_t}\Big)^{-\frac{1-a_c}{1-a_i}},$$

knowing from the main model that

$$r^K_{x,t} = \frac{R^K_{x,t}}{P_{x,t}}A_t^{-1}V_t^{\frac{1-a_c}{1-a_i}}.$$

C.5.8 Monetary policy and market clearing

Monetary policy rule:

$$\frac{R_t}{R} = \Big(\frac{R_{t-1}}{R}\Big)^{\rho_R}\Big[\Big(\frac{\pi_{C,t}}{\pi_C}\Big)^{\phi_\pi}\Big(\frac{y_t}{y_{t-1}}\Big)^{\phi_{\Delta Y}}\Big]^{1-\rho_R}\eta_{mp,t},$$

Resource constraint in the consumption sector:

$$c_t + (a(u_{C,t})\xi^K_{C,t}\bar{k}_{C,t-1} + a(u_{I,t})\xi^K_{I,t}\bar{k}_{I,t-1})\Big(\frac{V_{t-1}}{V_t}\Big)^{\frac{1}{1-a_i}} = a_{lt}L^{1-a_c}_{C,t}k^{a_c}_{C,t} - F_C.$$

Resource constraint in the investment sector:

$$i_t = v_{lt}L^{1-a_i}_{I,t}k^{a_i}_{I,t} - F_I.$$

Definition of GDP:

$$y_t = c_t + p_{i,t}i_t + \Big(1 - \frac{1}{g_t}\Big)y_t. \tag{C.26}$$

Moreover

$$L_t = L_{I,t} + L_{C,t}, \qquad i_t = i_{C,t} + i_{I,t}, \qquad n_t = n_{C,t} + n_{I,t}.$$

C.6 Steady State

This section describes the model's steady state.

From the optimal choice of available capital (C.22) and the optimal choice of investment (C.23) in both sectors:

$$r_C^K = \left(\frac{e^{\frac{1}{1-a_i}g_v}}{\beta} - (1-\delta_C)\right)p_i, \tag{C.27}$$

$$r_I^K = \left(\frac{e^{\frac{1}{1-a_i}g_v}}{\beta} - (1-\delta_I)\right)p_i. \tag{C.28}$$

From firm's price setting in both sectors (C.18),

$$mc_C = \frac{1}{1+\lambda_p^C}, \qquad mc_I = \frac{1}{1+\lambda_p^I}. \tag{C.29}$$

Using equations (C.29) and imposing knowledge of the steady state expression for r_C^K and r_I^K, one can derive expressions for the steady state wage from the equations that define marginal costs in the two sectors ((C.15) and (C.16)).

Consumption sector:

$$w = \left(\frac{1}{1+\lambda_p^C}(1-a_c)^{1-a_c}a_c^{a_c}(r_C^K)^{-a_c}\right)^{\frac{1}{1-a_c}}. \tag{C.30}$$

Investment sector:

$$w = \left(\frac{1}{1+\lambda_p^I}(1-a_i)^{1-a_i}a_i^{a_i}(r_I^K)^{-a_i}p_i\right)^{\frac{1}{1-a_i}}. \tag{C.31}$$

Since labour can move across sectors the steady state wage has to be the same in the consumption and investment sector. The equality is verified by p_i. An expression for p_i can be found by setting (C.30) equal to (C.31):

$$\begin{aligned}
&\left(\frac{1}{1+\lambda_p^C}(1-a_c)^{1-a_c}a_c^{a_c}(r_C^K)^{-a_c}\right)^{\frac{1}{1-a_c}} = \left(\frac{1}{1+\lambda_p^I}(1-a_i)^{1-a_i}a_i^{a_i}(r_I^K)^{-a_i}p_i\right)^{\frac{1}{1-a_i}} \\
\Leftrightarrow &\left(\frac{1}{1+\lambda_p^C}(1-a_c)^{1-a_c}a_c^{a_c}\left(\frac{e^{\frac{1}{1-a_i}g_v}}{\beta} - (1-\delta_C)\right)^{-a_c}p_i^{-a_c}\right)^{\frac{1}{1-a_c}} \\
&= \left(\frac{1}{1+\lambda_p^I}(1-a_i)^{1-a_i}a_i^{a_i}\left(\frac{e^{\frac{1}{1-a_i}g_v}}{\beta} - (1-\delta_I)\right)^{-a_i}p_i^{-a_i}p_i\right)^{\frac{1}{1-a_i}} \\
\Leftrightarrow &p_i = \frac{\frac{1}{1+\lambda_p^C}(1-a_c)^{1-a_c}a_c^{a_c}\left(\frac{e^{\frac{1}{1-a_i}g_v}}{\beta} - (1-\delta_C)\right)^{-\alpha_c}}{\left[\frac{1}{1+\lambda_p^I}(1-a_i)^{1-a_i}a_i^{a_i}\left(\frac{e^{\frac{1}{1-a_i}g_v}}{\beta} - (1-\delta_I)\right)^{-\alpha_i}\right]^{\frac{1-a_c}{1-a_i}}}.
\end{aligned} \tag{C.32}$$

Knowing w, r_C^K and r_I^K, the expressions given in (C.17) can be used to find the steady

state capital-to-labour ratios in the two sectors:

$$\frac{k_C}{L_C} = \frac{w}{r_C^K}\frac{a_c}{1-a_c}, \tag{C.33}$$

$$\frac{k_I}{L_I} = \frac{w}{r_I^K}\frac{a_i}{1-a_c}. \tag{C.34}$$

The zero profit condition for intermediate goods producers in the consumption sector, $c - r_C^K k_C - wL_C = 0$, and (C.13) imply:

$$\begin{aligned} & L_C^{1-a_c} k_C^{a_c} - F_C - r_C^K k_C - wL_C = 0 \\ \Leftrightarrow & \frac{F_C}{L_C} = \left(\frac{k_C}{L_C}\right)^{a_c} - r_C^K \frac{k_C}{L_C} - w. \end{aligned}$$

Analogously the zero profit condition for intermediate goods producers in the investment sector, $i - r_I^K k_I - wL_I = 0$, and (C.14) imply:

$$\frac{F_I}{L_I} = \left(\frac{k_I}{L_I}\right)^{a_i} - r_I^K \frac{k_I}{L_I} - w.$$

These expressions pin down the steady state consumption-to-labour and investment-to-labour ratios which follow from the intermediate firms' production functions ((C.13) and (C.14)):

$$\frac{c}{L_C} = \left(\frac{k_C}{L_C}\right)^{a_c} - \frac{F_C}{L_C}, \qquad \frac{i}{L_I} = \left(\frac{k_I}{L_I}\right)^{a_i} - \frac{F_I}{L_I}.$$

$$1 + \lambda_p^C = \frac{c + F_C}{c} \Leftrightarrow \lambda_p^C c = F_C, \qquad \text{and} \qquad 1 + \lambda_p^I = \frac{i + F_I}{i} \Leftrightarrow \lambda_p^I i = F_I.$$

This and the steady state consumption-to-labour ratio can be used to derive an expression for steady state consumption:

$$\begin{aligned} c &= \left(\frac{k_C}{L_C}\right)^{a_c} L_C - F_C \\ \Leftrightarrow c &= \left(\frac{k_C}{L_C}\right)^{a_c} L_C - \lambda_p^C c \\ \Leftrightarrow c &= \frac{1}{1+\lambda_p^C}\left(\frac{k_C}{L_C}\right)^{a_c} L_C. \end{aligned}$$

Analogously one can derive an expression for steady state investment:

$$i = \frac{1}{1+\lambda_p^I}\Big(\frac{k_I}{L_I}\Big)^{a_i} L_I.$$

Combining these two expressions leads to,

$$\begin{aligned} p_i\frac{i}{c} &= \frac{\frac{1}{1+\lambda_p^I}\big(\frac{k_I}{L_I}\big)^{a_i} L_I}{\frac{1}{1+\lambda_p^C}\big(\frac{k_C}{L_C}\big)^{a_c} L_C} p_i \\ \Leftrightarrow \frac{L_I}{L_C} &= p_i\frac{i}{c}\frac{\frac{1}{1+\lambda_p^C}\big(\frac{k_C}{L_C}\big)^{a_c}}{\frac{1}{1+\lambda_p^I}\big(\frac{k_I}{L_I}\big)^{a_i}} p_i^{-1}. \end{aligned}$$

Total labour L is set to unity in the steady state. However, since a_i and a_c are not necessarily calibrated to be equal one needs to fix another quantity in addition to $L = 1$. We fix the steady state investment-to-consumption ratio, $p_i\frac{i}{c}$, which equals 0.399 in the data. This allows us to derive steady state expressions for labour in the two sectors. Steady state labour in the investment sector is given by

$$L_I = 1 - L_C, \tag{C.35}$$

and the two equations above imply that steady state labour in the consumption sector can be expressed as,

$$L_C = \left(1 + p_i\frac{i}{c}\frac{\frac{1}{1+\lambda_p^C}\big(\frac{k_C}{L_C}\big)^{a_c}}{\frac{1}{1+\lambda_p^I}\big(\frac{k_I}{L_I}\big)^{a_i}} p_i^{-1}\right)^{-1}. \tag{C.36}$$

The steady state values for labour in the two sectors imply:

$$k_C = \frac{k_C}{L_C}L_C, \quad k_I = \frac{k_I}{L_I}L_I, \quad c = \frac{c}{L_C}L_C, \quad i = \frac{i}{L_I}L_I, \quad F_C = \frac{F_C}{L_C}L_C, \quad F_I = \frac{F_I}{L_I}L_I.$$

It follows from (C.21) that,

$$k_C = \bar{k}_C e^{-\frac{1}{1-a_i}g_v}, \qquad \text{and} \qquad k_I = \bar{k}_I e^{-\frac{1}{1-a_i}g_v}.$$

The accumulation equation of available capital (C.24) can be used to solve for investment in the two sectors:

$$i_C = k_C\big(e^{\frac{1}{1-a_i}g_v} - (1-\delta_C)\big), \tag{C.37}$$

$$i_I = k_I\big(e^{\frac{1}{1-a_i}g_v} - (1-\delta_I)\big). \tag{C.38}$$

From the definition of GDP (C.26):

$$y = c + p_i i + \Big(1 - \frac{1}{g}\Big) y.$$

From the marginal utility of income (C.20):

$$\lambda = \frac{1}{c - hce^{-g_a - \frac{a_c}{1-a_i} g_v}} - \frac{\beta h}{ce^{g_a + \frac{a_c}{1-a_i} g_v} - hc}.$$

From the household's wage setting (C.25)

$$\sum_{s=0}^{\infty} \beta^s \xi_w^s \lambda L \big[w - (1 + \lambda_w) \varphi \frac{L^\nu}{\lambda} \big] = 0,$$

follows the expression for L:

$$w - (1 - \lambda_w) \varphi \frac{L^\nu}{\lambda} = 0 \quad \Rightarrow \quad L = \Big[\frac{w\lambda}{(1 + \lambda_w)\varphi} \Big]^{\frac{1}{\nu}}.$$

This expression can be solved for φ to be consistent with $L = 1$:

$$1 = \Big[\frac{w\lambda}{(1 + \lambda_w)\varphi} \Big]^{\frac{1}{\nu}}$$
$$\Leftrightarrow \varphi = \frac{\lambda w}{1 + \lambda_w}.$$

It further holds from equation (C.19) that,

$$\frac{\pi_I}{\pi_C} = e^{g_a - \frac{1-a_c}{1-a_i} g_v}$$

A system of 10 equations (C.27, C.28, C.30, C.32, C.33, C.34, C.35, C.36, C.37, C.38) can be solved for the 10 steady state variables k_C, k_I, w, i_C, i_I, r_C^K, r_I^K, L_C, L_I and p_i. The steady state values for the remaining variables follow from the expressions above.

Given these steady state variables, the remaining steady state values which are mainly related to financial intermediaries can be derived as follows.

The nominal interest rate is given from the Euler equation as,

$$R = \frac{1}{\beta} e^{g_a + \frac{a_c}{1-a_i} g_v} \pi_C.$$

The bank's stationary stochastic discount factor can be expressed in the steady state as

$$\lambda^B = 1.$$

The steady state borrow in advance constraint implies that

$$\bar{k}_x = s_x.$$

The steady state price of capital is given by

$$q_{x,t} = p_{i,t}.$$

The steady state leverage equation is set equal to it's average value in the data over the sample period.

$$\frac{q_x s_x}{n_x} = \varrho_x = 5.47.$$

The parameters ϖ and λ_B help to align the value of the leverage ratio and the corporate bond spread with their empirical counterparts. Using the calibrated value for θ_B, the average value for the leverage ratio (5.47) and the weighted quarterly average of the corporate spreads ($R_x^B - R = 0.5\%$) allows calibrating ϖ using the bank's wealth accumulation equation,

$$\varpi = \left[1 - \theta_B[(R_x^B \pi_C - R)\varrho_x + R]e^{-g_a - \frac{a_c}{1-a_i} g_v} \frac{1}{\pi_C}\right] \left(\frac{q_x s_x}{n_x}\right)^{-1}.$$

Given the non-linearity in the leverage ratio, we solve numerically for the steady state expressions for η and ν using,

$$\nu_x = (1-\theta_B)\lambda^B e^{-g_a - \frac{a_c}{1-a_i} g_v}(R_x^B \pi_C - R) + \theta_B \beta z_1^x \nu_x,$$
$$\eta_x = (1-\theta_B)\lambda^B e^{-g_a - \frac{a_c}{1-a_i} g_v} R + \theta_B \beta z_2^x \eta_x,$$

with

$$z_2^x = \left[(R_x^B \pi_C - R)\varrho_x + R\right]\frac{1}{\pi_C}, \qquad \text{and} \qquad z_1^x = z_2^x,$$

and the steady state leverage ratio,

$$\varrho_x = \frac{\eta_x}{\lambda_B - \nu_x}.$$

C.7 Log-linearized Economy

This section collects the log-linearized model equations. The log-linear deviations of all variables are defined as

$$\hat{\varsigma}_t \equiv \log \varsigma_t - \log \varsigma,$$

except for

$$\begin{aligned}
\hat{z}_t &\equiv z_t - g_a, \\
\hat{v}_t &\equiv v_t - g_v, \\
\hat{\lambda}^C_{p,t} &\equiv \log(1+\lambda^C_{p,t}) - \log(1+\lambda^C_p), \\
\hat{\lambda}^I_{p,t} &\equiv \log(1+\lambda^I_{p,t}) - \log(1+\lambda^I_p), \\
\hat{\lambda}_{w,t} &\equiv \log(1+\lambda_{w,t}) - \log(1+\lambda_w).
\end{aligned}$$

C.7.1 Firm's production function and cost minimization

Production function for the intermediate good producing firm (i) in the consumption sector:

$$\hat{c}_t = \frac{c+F_I}{c}[\hat{a}_{lt} + a_c \hat{k}_{C,t} + (1-a_c)\hat{L}_{C,t}].$$

Production function for the intermediate good producing firm (i) in the investment sector:

$$\hat{i}_t = \frac{i+F_I}{i}[\hat{v}_{lt} + a_i \hat{k}_{I,t} + (1-a_i)\hat{L}_{I,t}].$$

Capital-to-labour ratios for the two sectors:

$$\hat{r}^K_{C,t} - \hat{w}_t = \hat{L}_{C,t} - \hat{k}_{C,t}, \qquad \hat{r}^K_{I,t} - \hat{w}_t = \hat{L}_{I,t} - \hat{k}_{I,t}. \tag{C.39}$$

Marginal cost in both sectors:

$$\hat{mc}_{C,t} = a_c \hat{r}^K_{C,t} + (1-a_c)\hat{w}_t - \hat{a}_{lt}, \qquad \hat{mc}_{I,t} = a_i \hat{r}^K_{I,t} + (1-a_i)\hat{w}_t - \hat{v}_{lt} - \hat{p}_{i,t}. \tag{C.40}$$

C.7.2 Firm's prices

Price setting equation for firms that change their price in sector $x = C, I$:

$$0 = E_t\left\{ \sum_{s=0}^{\infty} \xi_{p,x}^s \beta^s \left[\hat{\tilde{p}}_{x,t} \hat{\tilde{\Pi}}_{t,t+s} - \hat{\lambda}_{p,t+s}^x - \hat{mc}_{x,t+s} \right] \right\},$$

with

$$\hat{\tilde{\Pi}}_{t,t+s} = \sum_{k=1}^{s} [\iota_{p_x} \hat{\pi}_{t+k-1} - \hat{\pi}_{t+k}].$$

Solving for the summation

$$\begin{aligned}
\frac{1}{1-\xi_{p,x}\beta} \hat{\tilde{p}}_{x,t} =& E_t\left\{ \sum_{s=0}^{\infty} \xi_{p,x}^s \beta^s \big[-\hat{\Pi}_{t,t+s} + \hat{\lambda}_{p,t+s}^x + \hat{mc}_{x,t+s} \big] \right\} \\
=& -\hat{\Pi}_{t,t} + \hat{\lambda}_{p,t}^x + \hat{mc}_{x,t} - \frac{\xi_{p,x}\beta}{1-\xi_{p,x}\beta} \hat{\Pi}_{t,t+1} \\
&+ \xi_{p,x}\beta E_t\left\{ \sum_{s=1}^{\infty} \xi_{p,x}^{s-1} \beta^{s-1} \big[-\hat{\Pi}_{t+1,t+s} + \hat{\lambda}_{p,t+s}^x + \hat{mc}_{x,t+s} \big] \right\} \\
=& \hat{\lambda}_{p,t}^x + \hat{mc}_{x,t} + \frac{\xi_{p,x}\beta}{1-\xi_{p,x}\beta} E_t\big[\hat{\tilde{p}}_{x,t+1} - \hat{\Pi}_{t,t+1} \big],
\end{aligned}$$

where we used $\hat{\Pi}_{t,t} = 0$.

Prices evolve as

$$0 = (1-\xi_{p,x}) \hat{\tilde{p}}_{x,t} + \xi_{p,x}(\iota_{p_x} \hat{\pi}_{t-1} - \hat{\pi}),$$

from which we obtain the Phillips curve in sector $x = C, I$:

$$\begin{aligned}
&\hat{\pi}_{x,t} = \frac{\beta}{1+\iota_{p_x}\beta} E_t \hat{\pi}_{x,t+1} + \frac{\iota_{p_x}}{1+\iota_{p_x}\beta} \hat{\pi}_{x,t-1} + \kappa_x \hat{mc}_{x,t} + \kappa_x \hat{\lambda}_{p,t}^x, \qquad \text{(C.41)} \\
&\text{with} \quad \kappa_x = \frac{(1-\xi_{p,x}\beta)(1-\xi_{p,x})}{\xi_{p,x}(1+\iota_{p_x}\beta)}.
\end{aligned}$$

From equation (C.19) it follows that

$$\hat{\pi}_{I,t} - \hat{\pi}_{C,t} = \hat{p}_{I,t} - \hat{p}_{I,t-1}.$$

C.7.3 Households

Marginal utility:

$$\begin{aligned}\hat{\lambda}_t =&\frac{e^G}{e^G-h\beta}\left[\hat{b}_t+\left(\hat{z}_t+\frac{a_c}{1-a_i}\hat{v}_t\right)-\left(\frac{e^G}{e^G-h}\left(\hat{c}_t+\hat{z}_t+\frac{a_c}{1-a_i}\hat{v}_t\right)-\frac{h}{e^G-h}\hat{c}_{t-1}\right)\right]\\&-\frac{h\beta}{e^G-h\beta}E_t\left[\hat{b}_{t+1}-\left(\frac{e^G}{e^G-h}\left(\hat{c}_{t+1}+\hat{z}_{t+1}+\frac{a_c}{1-a_i}\hat{v}_{t+1}\right)-\frac{h}{e^G-h}\hat{c}_t\right)\right]\\\Leftrightarrow\ \hat{\lambda}_t =&\alpha_1E_t\hat{c}_{t+1}-\alpha_2\hat{c}_t+\alpha_3\hat{c}_{t-1}+\alpha_4\hat{z}_t+\alpha_5\hat{b}_t+\alpha_6\hat{v}_t,\end{aligned}\tag{C.42}$$

with

$$\begin{aligned}&\alpha_1=\frac{h\beta e^G}{(e^G-h\beta)(e^G-h)},\quad \alpha_2=\frac{e^{2G}+h^2\beta}{(e^G-h\beta)(e^G-h)},\quad \alpha_3=\frac{he^G}{(e^G-h\beta)(e^G-h)},\\&\alpha_4=\frac{h\beta e^G\rho_z-he^G}{(e^G-h\beta)(e^G-h)},\quad \alpha_5=\frac{e^G-h\beta\rho_b}{e^G-h\beta},\quad \alpha_6=\frac{(h\beta e^G\rho_v-he^G)\frac{a_c}{1-a_i}}{(e^G-h\beta)(e^G-h)},\\&e^G=e^{g_a+\frac{a_c}{1-a_i}g_v}.\end{aligned}$$

This assumes the shock processes for $\hat{z}_t$ and $\hat{b}_t$.

Euler equation:

$$\hat{\lambda}_t=\hat{R}_t+E_t\left(\hat{\lambda}_{t+1}-\hat{z}_{t+1}-\hat{v}_{t+1}\frac{a_c}{1-a_i}-\hat{\pi}_{C,t+1}\right).\tag{C.43}$$

C.7.4 Investment and Capital

Capital utilization in both sectors:

$$\hat{r}^K_{C,t}=\chi_C\hat{u}_{C,t},\qquad \hat{r}^K_{I,t}=\chi_I\hat{u}_{I,t},\qquad \text{where}\quad \chi_x=\frac{a_x''(1)}{a_x'(1)}.\tag{C.44}$$

Choice of investment for the consumption sector:

$$\begin{aligned}\hat{q}_{C,t} =&e^{2(\frac{1}{1-a_i}g_v)}\kappa\left(\hat{i}_{C,t}-\hat{i}_{C,t-1}+\frac{1}{1-a_i}\hat{v}_t\right)-\beta e^{2(\frac{1}{1-a_i}g_v)}\kappa E_t\left(\hat{i}_{C,t+1}-\hat{i}_{C,t}+\frac{1}{1-a_i}\hat{v}_{t+1}\right)\\&+\hat{p}_{i,t}-\hat{\mu}_t,\end{aligned}\tag{C.45}$$

with $\hat{q}_{C,t} = \hat{\phi}_{C,t} - \hat{\lambda}_t$.

Choice of investment for the investment sector:

$$\begin{aligned}\hat{q}_{I,t} =& e^{2(\frac{1}{1-a_i}g_v)}\kappa\Big(\hat{i}_{I,t} - \hat{i}_{I,t-1} + \frac{1}{1-a_i}\hat{v}_t\Big) - \beta e^{2(\frac{1}{1-a_i}g_v)}\kappa E_t\Big(\hat{i}_{I,t+1} - \hat{i}_{I,t} + \frac{1}{1-a_i}\hat{v}_{t+1}\Big) \\ &+ \hat{p}_{i,t} - \hat{\mu}_t, \end{aligned} \tag{C.46}$$

with $\hat{q}_{I,t} = \hat{\phi}_{I,t} - \hat{\lambda}_t$.

Capital services input in both sectors:

$$\hat{k}_{C,t} = \hat{u}_{C,t} + \xi^K_{C,t} + \hat{\bar{k}}_{C,t-1} - \frac{1}{1-a_i}\hat{v}_t, \qquad \hat{k}_{I,t} = \hat{u}_{I,t} + \xi^K_{I,t} + \hat{\bar{k}}_{I,t-1} - \frac{1}{1-a_i}\hat{v}_t. \tag{C.47}$$

Capital accumulation in the consumption and investment sector:

$$\hat{\bar{k}}_{C,t} = (1-\delta_C)e^{-\frac{1}{1-a_i}g_v}\Big(\hat{\bar{k}}_{C,t-1} + \xi^K_{C,t} - \frac{1}{1-a_i}\hat{v}_t\Big) + \Big(1 - (1-\delta_C)e^{-\frac{1}{1-a_i}g_v}\Big)\hat{i}_{C,t}, \tag{C.48}$$

$$\hat{\bar{k}}_{I,t} = (1-\delta_I)e^{-\frac{1}{1-a_i}g_v}\Big(\hat{\bar{k}}_{I,t-1} + \xi^K_{I,t} - \frac{1}{1-a_i}\hat{v}_t\Big) + \Big(1 - (1-\delta_I)e^{-\frac{1}{1-a_i}g_v}\Big)\hat{i}_{I,t}. \tag{C.49}$$

C.7.5 Wages

The wage setting equation for workers renegotiating their salary:

$$0 = E_t\Big\{\sum_{s=0}^{\infty}\xi^s_w\beta^s\Big[\hat{\tilde{w}}_t + \hat{\tilde{\Pi}}^w_{t,t+s} - \hat{\lambda}_{w,t+s} - \hat{b}_{t+s} - \nu\hat{\tilde{L}}_{t+s} + \hat{\lambda}_{t+s}\Big]\Big\},$$

with

$$\hat{\tilde{\Pi}}^w_{t,t+s} = \sum_{k=1}^{s}\Big[\iota_w\Big(\hat{\pi}_{c,t+k-1} + \hat{z}_{t+k-1} + \frac{a_c}{1-a_i}\hat{v}_{t+k-1}\Big) - \Big(\hat{\pi}_{c,t+k} + \hat{z}_{t+k} + \frac{a_c}{1-a_i}\hat{v}_{t+k}\Big)\Big],$$

and

$$\hat{\tilde{L}}_{t+s} = \hat{L}_{t+s} - \Big(1 + \frac{1}{\lambda_w}\Big)\big(\hat{\tilde{w}}_t + \hat{\tilde{\Pi}}^w_{t,t+s} - \hat{w}_{t+s}\big).$$

Then using the labor demand function,

$$\begin{aligned}
0 =& E_t\Big\{\sum_{s=0}^{\infty}\xi_w^s\beta^s\Big[\hat{\tilde{w}}_t + \hat{\tilde{\Pi}}^w_{t,t+s} - \hat{\lambda}_{w,t+s} - \hat{b}_{t+s} \\
& - \nu\Big(\hat{L}_{t+s} - \Big(1+\frac{1}{\lambda_w}\Big)\big(\hat{\tilde{w}}_t + \hat{\tilde{\Pi}}^w_{t,t+s} - \hat{w}_{t+s}\big)\Big) + \hat{\lambda}_{t+s}\Big]\Big\} \\
\Leftrightarrow 0 =& E_t\Big\{\sum_{s=0}^{\infty}\xi_w^s\beta^s\Big[\hat{\tilde{w}}_t\Big(1+\nu\Big(1+\frac{1}{\lambda_w}\Big)\Big) + \hat{\tilde{\Pi}}^w_{t,t+s} - \hat{\lambda}_{w,t+s} - \hat{b}_{t+s} \\
& - \nu\Big(\hat{L}_{t+s} - \Big(1+\frac{1}{\lambda_w}\Big)\big(\hat{\tilde{\Pi}}^w_{t,t+s} - \hat{w}_{t+s}\big)\Big) + \hat{\lambda}_{t+s}\Big]\Big\}.
\end{aligned}$$

Solving for the summation,

$$\begin{aligned}
\frac{\nu_w}{1-\xi_w\beta}\hat{\tilde{w}}_t =& E_t\Big\{\sum_{s=0}^{\infty}\xi_w^s\beta^s\Big[-\Big(1+\nu\big(1+\frac{1}{\lambda_w}\big)\Big)\hat{\tilde{\Pi}}^w_{t,t+s} + \hat{\psi}_{t+s}\Big]\Big\} \\
=& -\nu_w\hat{\tilde{\Pi}}^w_{t,t} + \hat{\psi}_t + E_t\Big\{\sum_{s=0}^{\infty}\xi_w^s\beta^s\Big[-\nu_w\hat{\tilde{\Pi}}^w_{t,t+s} + \hat{\psi}_{t+s}\Big]\Big\} \\
=& \hat{\psi}_t - \frac{\xi_w\beta}{1-\xi_w\beta}\nu_w\hat{\Pi}^w_{t,t+1} + \xi_w\beta E_t\Big\{\sum_{s=0}^{\infty}\xi_w^s\beta^s[-\nu_w\hat{\Pi}^w_{t+1,t+1+s} + \hat{\psi}_{t+1+s}]\Big\} \\
=& \hat{\psi}_t + \frac{\xi_w\beta}{1-\xi_w\beta}\nu_w E_t\big[\hat{\tilde{w}}_{t+1} - \hat{\tilde{\Pi}}^w_{t,t+1}\big]. \qquad \text{(C.50)}
\end{aligned}$$

where

$$\begin{aligned}
\hat{\psi}_t &\equiv \hat{\lambda}_{w,t} + \hat{b}_t + \nu\hat{L}_t + \nu\Big(1+\frac{1}{\lambda_w}\Big)\hat{w}_t - \hat{\lambda}_t, \qquad \text{(C.51)} \\
\nu_w &\equiv 1 + \nu\Big(1+\frac{1}{\lambda_w}\Big),
\end{aligned}$$

and recall that $\hat{\tilde{\Pi}}^w_{t,t} = 0$.

Wages evolve as,

$$\begin{aligned}
\hat{w}_t &= (1-\xi_w)\hat{\tilde{w}}_t + \xi_w\Big(\hat{w}_{t-1} + \iota_w\hat{\pi}_{c,t-1} + \iota_w\Big(\hat{z}_{t-1} + \frac{a_c}{1-a_i}\hat{v}_{t-1}\Big) - \hat{\pi}_{c,t} - \hat{z}_t - \frac{a_c}{1-a_i}\hat{v}_t\Big) \\
\Leftrightarrow \hat{w}_t &= (1-\xi_w)\hat{\tilde{w}}_t + \xi_w(\hat{w}_{t-1} + \hat{\tilde{\Pi}}^w_{t,t-1}). \qquad \text{(C.52)}
\end{aligned}$$

Equation (C.52) can be solved for $\hat{\tilde{w}}_t$. This expression, as well as the formulation for $\hat{\psi}_t$ given in (C.51) can be plugged into equation (C.50). After rearranging this yields the wage Phillips curve,

$$\begin{aligned}\hat{w}_t =&\frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\beta}{1+\beta}E_t\hat{w}_{t+1} - \kappa_w\hat{g}_{w,t} + \frac{\iota_w}{1+\beta}\hat{\pi}_{c,t-1} - \frac{1+\beta\iota_w}{1+\beta}\hat{\pi}_{c,t}\\ &+ \frac{\beta}{1+\beta}E_t\hat{\pi}_{c,t+1} + \kappa_w\hat{\lambda}_{w,t} + \frac{\iota_w}{1+\beta}\big(\hat{z}_{t-1} + \frac{a_c}{1-a_i}\hat{v}_{t-1}\big)\\ &- \frac{1+\beta\iota_w-\rho_z\beta}{1+\beta}\hat{z}_t - \frac{1+\beta\iota_w-\rho_v\beta}{1+\beta}\frac{a_c}{1-a_i}\hat{v}_t. \end{aligned} \tag{C.53}$$

where

$$\kappa_w \equiv \frac{(1-\xi_w\beta)(1-\xi_w)}{\xi_w(1+\beta)\big(1+\nu\big(1+\frac{1}{\lambda_w}\big)\big)},$$

$$\hat{g}_{w,t} \equiv \hat{w}_t - (\nu\hat{L}_t + \hat{b}_t - \hat{\lambda}_t).$$

C.7.6 Financial sector

The part of the economy concerned with the banking sector is described by the following equations:

The stochastic discount factor:

$$\hat{\lambda}^B_t = \hat{\lambda}_t - \hat{\lambda}_{t-1}. \tag{C.54}$$

Definition of ν for $x = C, I$:

$$\begin{aligned}\hat{\nu}_{x,t} =&(1-\theta_B\beta z_1^x)[\hat{\lambda}^B_{t+1} - \hat{z}_{t+1} - \frac{a_c}{1-a_i}\hat{v}_{t+1}]\\ &+ \frac{1-\theta_B\beta z_1^x}{R^B_x\pi_C - R}[R^B_x\pi_C\hat{R}^B_{x,t+1} + R^B_x\pi_C\hat{\pi}_{C,t+1} - R\hat{R}_t] + \theta_B\beta z_1^x[\hat{z}^x_{1,t+1} + \hat{\nu}_{x,t+1}]. \end{aligned} \tag{C.55}$$

Definition of η:

$$\begin{aligned}\hat{\eta}_{x,t} =&(1-\theta_B\beta z_2^x)[\hat{\lambda}^B_{t+1} - \hat{z}_{t+1} - \frac{a_c}{1-a_i}\hat{v}_{t+1} + \hat{R}_t]\\ &+ \theta_B\beta z_2^x[\hat{z}^x_{2,t+1} + \hat{\eta}_{t+1}], \qquad x = C, I. \end{aligned} \tag{C.56}$$

Definition of z_1:

$$\hat{z}^x_{1,t} = \hat{\varrho}_{x,t} - \hat{\varrho}_{x,t-1} + \hat{z}^x_{2,t}, \qquad x = C, I. \tag{C.57}$$

Definition of z_2 for $x = C, I$:

$$\hat{z}^x_{2,t} = \frac{\pi_C}{(R^B_x - R)\varrho_x + R}[R^B_x \varrho_x[\hat{R}^B_{x,t} + \hat{\pi}_{C,t}] + \frac{R}{\pi_C}(1-\varrho_x)\hat{R}_{t-1} + (R^B_x \pi_C - R)\frac{\varrho_x}{\pi_C}\hat{\varrho}_{x,t-1}] - \hat{\pi}_{C,t}. \tag{C.58}$$

The leverage ratio:

$$\hat{\varrho}_{x,t} = \hat{\eta}_{x,t} + \frac{\nu}{\lambda_B - \nu}\hat{\nu}_{x,t}, \qquad x = C, I. \tag{C.59}$$

The leverage equation:

$$\hat{q}_{x,t} + \hat{s}_{x,t} = \hat{\varrho}_{x,t} + \hat{n}_{x,t}. \tag{C.60}$$

The bank's wealth accumulation equation

$$\begin{aligned}\hat{n}_{x,t} =& \theta_B \frac{\varrho_x}{\pi_C} e^{-g_a - \frac{a_c}{1-a_i}g_v}\Big[R^B_x \pi_C[\hat{R}^B_{x,t} + \hat{\pi}_{C,t}] + \Big(\frac{1}{\varrho_x} - 1\Big)R\hat{R}_{t-1} + (R^B_x \pi_C - R)\hat{\varrho}_{x,t-1}\Big] \\ &+ \frac{\theta_B}{\pi_C} e^{-g_a - \frac{a_c}{1-a_i}g_v}[(R^B_x \pi_C - R)\varrho_x + R]\Big[-\hat{z}_t - \frac{a_c}{1-a_i}\hat{v}_t + \hat{n}_{x,t-1} - \hat{\pi}_{C,t}\Big] \\ &+ (1 - \frac{\theta_B}{\pi_C} e^{-g_a - \frac{a_c}{1-a_i}g_v}[(R^B_x \pi_C - R)\varrho_x + R])[\hat{q}_{x,t} + \hat{s}_{x,t}], \qquad x = C, I.\end{aligned} \tag{C.61}$$

The borrow in advance constraint:

$$\hat{\bar{k}}_{x,t+1} = \hat{s}_{x,t}, \qquad x = C, I. \tag{C.62}$$

The bank's stochastic return on assets in sector $x = C, I$:

$$\hat{R}^B_{x,t} = \frac{1}{r^K_x + q_x(1-\delta_x)}[r^K_x(\hat{r}^K_{x,t} + \hat{u}_{x,t}) + q_x(1-\delta_x)\hat{q}_{x,t}] - \hat{q}_{x,t-1} + \xi^K_{x,t} + \hat{z}_t - \frac{1-a_c}{1-a_i}\hat{v}_t. \tag{C.63}$$

Excess (nominal) return:

$$\hat{R}^S_{x,t} = \frac{R^B_x \pi_C}{R^B_x \pi_C - R}(\hat{R}^B_{x,t+1} + \hat{\pi}_{C,t+1}) - \frac{R}{R^B_x \pi_C - R}\hat{R}_t, \qquad x = C, I. \tag{C.64}$$

C.7.7 Monetary policy and market clearing

Monetary policy rule:

$$\hat{R}_t = \rho_R \hat{R}_{t-1} + (1-\rho_R)\Big[\phi_\pi \hat{\pi}_{c,t} + \phi_{\Delta Y}(\hat{y}_t - \hat{y}_{t-1})\Big] + \hat{\eta}_{mp,t} \tag{C.65}$$

Resource constraint in the consumption sector:

$$\hat{c}_t + \left(r_C^K \frac{\bar{k}_C}{c}\hat{u}_{C,t} + r_I^K \frac{\bar{k}_I}{c}\hat{u}_{I,t}\right)e^{-\frac{1}{1-a_i}g_v} = \frac{c+F_c}{c}[\hat{a}_{lt} + a_c\hat{k}_{C,t} + (1-a_c)\hat{L}_{C,t}] \tag{C.66}$$

Resource constraint in the investment sector:

$$\hat{i}_t = \frac{i+F_I}{i}[\hat{v}_{lt} + a_i\hat{k}_{I,t} + (1-a_i)\hat{L}_{I,t}] \tag{C.67}$$

Definition of GDP:

$$\hat{y}_t = \frac{c}{c+p_i i}\hat{c}_t + \frac{p_i i}{c+p_i i}(\hat{i}_t + \hat{p}_{i,t}) + \hat{g}_t. \tag{C.68}$$

Market clearing:

$$\frac{L_C}{L}\hat{L}_{C,t} + \frac{L_I}{L}\hat{L}_{I,t} = \hat{L}_t, \quad \frac{i_C}{i}\hat{i}_{C,t} + \frac{i_I}{i}\hat{i}_{I,t} = \hat{i}_t, \quad \frac{n_C}{n}\hat{n}_{C,t} + \frac{n_I}{n}\hat{n}_{I,t} = \hat{n}_t. \tag{C.69}$$

C.7.8 Exogenous processes

The 11 exogenous processes of the model can be written in log-linearized form as follows:

Price markup in sector $x = C, I$:

$$\hat{\lambda}_{p,t}^x = \rho_{\lambda_p^x}\hat{\lambda}_{p,t-1}^x + \varepsilon_{p,t}^x. \tag{C.70}$$

The TFP growth (consumption sector):

$$\hat{z}_t = \rho_z\hat{z}_{t-1} + \varepsilon_t^z. \tag{C.71}$$

The TFP growth (investment sector):

$$\hat{v}_t = \rho_v\hat{v}_{t-1} + \varepsilon_t^v. \tag{C.72}$$

Wage markup:

$$\hat{\lambda}_{w,t} = \rho_w\hat{\lambda}_{w,t-1} + \varepsilon_{w,t}. \tag{C.73}$$

Preference:

$$\hat{b}_t = \rho_b\hat{b}_{t-1} + \varepsilon_t^b. \tag{C.74}$$

Monetary policy:

$$\hat{\eta}_{mp,t} = \varepsilon_t^{mp}. \tag{C.75}$$

Government spending:

$$\hat{g}_t = \rho_g \hat{g}_{t-1} + \varepsilon_t^g. \tag{C.76}$$

The Marginal Efficiency of Investment (MEI):

$$\hat{\mu}_t = \rho_\mu \hat{\mu}_{t-1} + \varepsilon_t^\mu \tag{C.77}$$

The TFP stationary (consumption sector):

$$\hat{a}_{lt} = \rho_{a_l} \hat{a}_{l,t-1} + \varepsilon_t^{a_l}. \tag{C.78}$$

The TFP stationary (investment sector):

$$\hat{v}_{lt} = \rho_{v_l} \hat{v}_{l,t-1} + \varepsilon_t^{v_l}. \tag{C.79}$$

The entire log-linear model is summarized by equations (C.39) - (C.49) and (C.53) - (C.69) as well as the shock processes (C.70) - (C.79).

C.8 Measurement equations

For estimation, model variables are linked with observables using measurement equations. Letting a superscript "d" denote observable series, then the model's measurement equations are as follows:

Real consumption growth,

$$\Delta C_t^d \equiv \log\left(\frac{C_t}{C_{t-1}}\right) = \log\left(\frac{c_t}{c_{t-1}}\right) + \hat{z}_t + \frac{a_c}{1-a_i}\hat{v}_t,$$

Real investment growth,

$$\Delta I_t^d \equiv \log\Big(\frac{I_t}{I_{t-1}}\Big) = \log\Big(\frac{i_t}{i_{t-1}}\Big) + \frac{1}{1-a_i}\hat{v}_t,$$

Real wage growth,

$$\Delta W_t^d \equiv \log\Big(\frac{W_t}{W_{t-1}}\Big) = \log\Big(\frac{w_t}{w_{t-1}}\Big) + \hat{z}_t + \frac{a_c}{1-a_i}\hat{v}_t,$$

Real output growth,

$$\Delta Y_t^d \equiv \log\Big(\frac{Y_t}{Y_{t-1}}\Big) = \log\Big(\frac{y_t}{y_{t-1}}\Big) + \hat{z}_t + \frac{a_c}{1-a_i}\hat{v}_t,$$

Consumption sector inflation,

$$\pi_{C,t}^d \equiv \pi_{C,t} = \hat{\pi}_{C,t} \quad \text{and} \quad \hat{\pi}_{C,t} = \log(\pi_{C,t}) - \log(\pi_C),$$

Relative price of investment

$$\Delta\Big(\frac{P_t^I}{P_t^C}\Big)^d \equiv \log\Big(\frac{p_t^i}{p_{t-1}^i}\Big) + \hat{z}_t + \frac{a_c - 1}{1-a_i}\hat{v}_t,$$

Total hours worked,

$$L_t^d \equiv \log L_t = \hat{L}_t,$$

Nominal interest rate (federal funds rate),

$$R_t^d \equiv \log R_t = \log \hat{R}_t,$$

Consumption sector corporate spread,

$$R_{C,t}^{S,d} \equiv \log R_{C,t}^S = \frac{R_x^B \pi_C}{R_x^B \pi_C - R}(\log \hat{R}_{C,t+1}^B + \log \hat{\pi}_{C,t+1}) - \frac{R}{R_x^B \pi_C - R}\log \hat{R}_t,$$

Investment sector corporate spread,

$$R_{I,t}^{S,d} \equiv \log R_{I,t}^S = \frac{R_x^B \pi_C}{R_x^B \pi_C - R}(\log \hat{R}_{I,t+1}^B + \log \hat{\pi}_{C,t+1}) - \frac{R}{R_x^B \pi_C - R}\log \hat{R}_t,$$

Real total equity capital growth,

$$\begin{aligned}\Delta N_t^d \equiv& \log\Big(\frac{N_t}{N_{t-1}}\Big)\\ =& e^{g_a + \frac{a_c}{1-a_i} g_v}\Big(\frac{n_C}{n_C + n_I}(\hat{n}_{C,t} - \hat{n}_{C,t-1}) + \frac{n_I}{n_C + n_I}(\hat{n}_{I,t} - \hat{n}_{I,t-1}) + \hat{z}_t + \frac{a_c}{1-a_i}\hat{v}_t\Big).\end{aligned}$$

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