NATIONAL BANK OF POLAND
WORKING PAPER
No. 109

Bayesian evaluation of DSGE models with financial frictions

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Warsaw 2012

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This research was financed by the MNiSW grant No. 04/BMN/22/11. The views expressed herein are those of the authors and not necessarily those of the National Bank of Poland or the Warsaw School of Economics. We would like to thank Marco Del Negro, Marek Jarociński, Frank Schorfheide, Frank Smets and Raf Wouters for helpful discussions. This paper benefited also from comments received at the NBP seminar, the EABCN Workshop and the EC2 conference.

Design:

Oliwka s.c.

Layout and print:

NBP Printshop

Published by:

National Bank of Poland
Education and Publishing Department
00-919 Warszawa, 11/21 Świętokrzyska Street
phone: +48 22 653 23 35, fax +48 22 653 13 21

ISSN 2084–624X

http://www.nbp.pl

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Abstract

We evaluate two most popular approaches to implementing financial frictions into DSGE models: the Bernanke et al. (1999) setup, where financial frictions enter through the price of loans, and the Kiyotaki and Moore (1997) model, where they concern the quantity of loans. We take both models to the US data and check how well they fit it on several margins. Overall, comparing the models favors the framework of Bernanke et al. (1999). However, even this model is not able to make a clear improvement over the benchmark New Keynesian model, and the Kiyotaki and Moore (1997) underperforms it on several margins. Furthermore, none of the extensions explains the 2007-09 recession as significantly more "financial" than several previous ones.

JEL: E30, E44

Keywords: financial frictions, DSGE models, DSGE-VAR, Bayesian analysis

1 Introduction

One of the consequences of the financial crisis 2007-09 was the emergence of widespread interest in macroeconomic models featuring financial frictions and disturbances. Economists acknowledged that financial sector imperfections are necessary for both explaining economic developments and designing appropriate stabilization policies. Studies addressing the former topic concern i.a. the role of financial frictions in monetary transmission (Calza et al., 2009; Gerali et al., 2010; Christiano et al., 2010) or the impact of financial shocks on the economy (Christiano et al., 2003; Iacoviello and Neri, 2010; Brzoza-Brzezina and Makarski, 2011). As regards the latter area, one can mention papers analyzing optimal monetary policy in the presence of financial frictions (Cúrdia and Woodford, 2008; De Fiore and Tristani, 2009; Carlstrom et al., 2010; Kolasa and Lombardo, 2011) or the consequences of capital regulations and macroprudential policies (Angelini et al., 2010; Angeloni and Faia, 2009; Meh and Moran, 2010; deWalque et al., 2010).

A dominant part of the financial frictions literature builds on two approaches developed long before the crisis. The first originates from the seminal paper of Bernanke and Gertler (1989), where financial frictions have been incorporated into a general equilibrium model. This approach was further developed by Carlstrom and Fuerst (1997) and merged with the New Keynesian framework by Bernanke et al. (1999), becoming the workhorse financial accelerator model in the 2000s. In this model, frictions arise because monitoring a loan applicant is costly, which drives an external finance premium (henceforth EFP) between the lending rate and the risk free rate.

The second direction was introduced by Kiyotaki and Moore (1997) and extended by Iacoviello (2005). This line of research introduces financial frictions via collateral constraints (henceforth CC). Agents are heterogeneous in terms of their rate of time preference, which divides them into lenders and borrowers. The financial sector intermediates between these groups and introduces frictions by requiring that borrowers provide collateral for their loans. Hence, this approach introduces frictions that affect directly the quantity of loans, rather than their price, as in the Bernanke et al. (1999) setup.

What follows is a situation where important policy conclusions are derived from two different modeling frameworks. While in economic sciences such a situation is neither rare nor necessarily unwelcome, still it seems important to understand what the alternative modeling assumptions imply and how close they come to reality. This evidence is still scarce. In a recent study Brzoza-Brzezina et al. (2011) compare the calibrated versions of the EFP and CC frameworks, finding that the business cycle properties of the former are more in line with empirical evidence.

In this paper we take the models directly to the data, estimate them using the Bayesian approach and evaluate their fit as well as power to explain the past. Several recent papers have looked at the performance and implications of estimated DSGE models with financial frictions. Christensen and Dib (2008) estimate an EFP-type model for the US using a maximum-likelihood procedure and find that the financial accelerator mechanism is supported by the data. This result was confirmed for both US and euro area data by Queijo von Heideken (2009) using Bayesian methods. Christiano et al. (2010) augment the standard New Keynesian model with an EFP-like financial accelerator and the banking sector similar to Chari et al. (1995), and estimate it on euro area and US observations. They feed their model with a number of various shocks, estimate it using Bayesian methods, and document its reasonable fit. The empirical literature using CC-like models is relatively scarce. A prominent example is Gerali et al. (2010), who estimate a model of such type, augmented by a housing sector and a bank balance sheet channel, using Bayesian inference and data for the euro area. However, they do not discuss whether their framework improves over the standard New Keynesian setup.

All these papers have studied only one of the two aforementioned ways of introducing financial frictions. As they are also heterogeneous in terms of modeling choices and data used, they leave no clue on which type of frictions better fits the data. In this paper, we contribute to the literature by estimating the alternative financial frictions frameworks, tweaked in a way that allows for both qualitative and quantitative comparisons. Another important gap in the existing literature is that it compares models with and without financial frictions relying on estimations performed without the use of financial data. We find this awkward and hence propose ways of comparing the models estimated also with financial time series (loans and spreads).

Our main findings are as follows. Evidence from marginal likelihoods shows that the EFP model is more in line with the data than the CC framework. Moreover, the CC framework performs even worse than the frictionless New Keynesian benchmark. As to the EFP model, the evidence is mixed: in some exercises it performs somewhat better than the New Keynesian model, in others worse. Definitely, a clear improvement cannot be observed. The evidence from DSGE-VARs shows that both financial friction frameworks are seriously misspecified and do not improve in this respect upon the standard New Keynesian model. Moreover, while both extensions give a substantial role to financial disturbances in explaining the business cycle, surprisingly they are not able to identify the 2007-09 crisis to be more "financial" in nature (i.e. driven to a larger extent by financial shocks) than several previous recessions. This feature is particularly acute for the CC model and stands in sharp contrast with common knowledge, supported by empirical findings, that the origins of the recent crisis can be traced to the financial sector (Brunnermeier, 2009; Gilchrist and Zakrajcek, 2011; Gorton, 2009).

In our view, these results suggests that relying on any of the two standard financial accelerator setups is not sufficient for explaining the recent financial crisis and designing tools that could help avoiding similar ones in the future. The currently observed ongoing development of alternative and more sophisticated frameworks, such as more explicit modeling of financial intermediation (Gertler and Kiyotaki, 2010; Gertler and Karadi, 2011) or allowing for occasionally rather than eternally binding collateral constraints (Brunnermeier and Sannikov, 2011; Jeanne and Korinek, 2010; Mendoza, 2010), seems to be a necessary step.

The rest of the paper is structured as follows. Section 2 introduces the New Keynesian model and its two alternative extensions featuring two types of financial frictions. In Section 3 we discuss their estimation. Section 4 evaluates the models, documents their misspecification and shows their implications for historical decompositions. Section 5 concludes.

2 The model

Our departure point is a standard medium-sized closed economy New Keynesian (henceforth NK) model with sticky prices and a standard set of other frictions that have been found crucial for ensuring a reasonable empirical fit (see Christiano et al., 2005; Smets and Wouters, 2003). Such a model economy is populated by households, producers, as well as fiscal and monetary authorities. Households consume, accumulate capital stock and work. Output is produced in several steps, including a monopolistically competitive sector with producers facing price rigidities. Fiscal authorities use lump sum taxes to finance government expenditure and monetary authorities set the short-term interest rate according to a Taylor rule.

To introduce financial frictions, this setup is modified by including two new types of agents: entrepreneurs and the banking sector. Entrepreneurs specialize in capital management. They finance their operations, i.e. renting capital services to firms, by taking loans from the banking sector, which refinances them by accepting deposits from households. It is this intermediation where financial frictions arise and their nature differs between the EFP and CC variants. The standard NK model obtains as a special case of either of the two alternative extensions.

In the EFP version, financial frictions originate from riskiness in management of capital and asymmetric information. Individual entrepreneurs are subject to idiosyncratic shocks, which are observed by them for free, while banks can learn about the shocks' realizations only after paying monitoring costs. This costly state verification problem results in a financial contract featuring an endogenous premium between the lending rate and the risk-free rate.

The key financial friction in the CC version is introduced by assuming that entrepreneurs need collateral to take a loan. Additionally, to ensure comparability with the EFP version, we assume that the interest rate on loans differs from the risk-free rate due to monopolistic competition in the banking sector.

In the rest of this section we lay down the model, highlighting the differences between the three specifications.

2.1 Households

The economy is populated by a continuum of households indexed by h. Each household chooses consumption c_t and labor supply n_t to maximize the expected lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\Gamma_t \frac{\left(c_t\left(h\right) - \xi c_{t-1}\right)^{1-\sigma_c}}{1-\sigma_c} - \frac{n_t\left(h\right)^{1+\sigma_n}}{1+\sigma_n} \right] \tag{1}$$

where ξ denotes the degree of external habit formation and Γ_t is a preference shock. Each household uses labor income $W_t n_t$, capital income $R_{k,t} k_{t-1}$ and dividends Π_t to finance its expenditure and lump sum taxes T_t, facing the following budget constraint

2

$$P_t c_t\left(h\right) + E_t\left\{\Upsilon_{t+1} B_t\left(h\right)\right\} \leq W_t n_t\left(h\right) - T_t\left(h\right) + \Pi_t\left(h\right) + B_{t-1}\left(h\right) \tag{2}$$

where P_t denotes the price of a consumption good. As in Chari et al. (2002), we assume that households have access to state contingent bonds B_t, traded at price $\Upsilon_{t,t+1}$, which allows them to insure against idiosyncratic risk. The expected gross rate of return $[E_t\{\Upsilon_{t+1}\}]^{-1}$ is equal to the risk-free interest rate R_t, fully controlled by the monetary authority.

Each household has a unique labor type h, which is sold to perfectly competitive aggregators, who pool all labor types into one undifferentiated labor service with the following function

$$n_t = \left(\int_0^1 n_t\left(h\right)^{\frac{1}{\phi_w}} dh \right)^{\phi_w} \tag{3}$$

Households set their wage rate according to the standard Calvo scheme. With probability $(1-\theta_w)$ they receive a signal to reoptimize and then set their wage to maximize the utility, subject to the demand from the aggregators. Those who do not receive the signal index their wage to the weighted average of past and steady state inflation, with the weight on the former denoted by ζ_w.

2.2 Producers

There are several stages of production in the economy. Intermediate goods firms produce differentiated goods and sell them to aggregators. Aggregators combine differentiated goods into a homogeneous final good. The final good can be used for consumption or sold to capital good producers.

2.2.1 Capital good producers

Capital good producers act in a perfectly competitive environment. In each period a representative capital good producer buys i_t of final goods and old undepreciated capital $(1-\delta)\,k_{t-1}$. Next she transforms old undepreciated capital one-to-one into new capital, while transformation of the final good is subject to an adjustment cost $S\,(i_t/i_{t-1})$.[1] Thus, the technology to produce new capital is given by

$$k_t = (1-\delta)\,k_{t-1} + \left(1 - S\left(\frac{i_t}{i_{t-1}}\right)\right) i_t \tag{4}$$

The new capital is then sold in a perfectly competitive market. The price of capital is denoted by Q_t.

2.2.2 Final good producers

Final good producers play the role of aggregators. They buy differentiated products from intermediate goods producers $y\,(j)$ and aggregate them into a single final good, which they sell in a perfectly competitive market. The final good is produced according to the following technology

$$y_t = \left(\int_0^1 y_t\,(j)^{\frac{1}{\phi}}\,dj\right)^{\phi} \tag{5}$$

2.2.3 Intermediate goods producers

There is a continuum of intermediate goods producers indexed by j. They rent capital and labor and use the following production technology

$$y_t(j) = A_t k_t(j)^{\alpha} n_t(j)^{1-\alpha} \tag{6}$$

where A_t is total factor productivity.

Intermediate goods firms act in a monopolistically competitive environment and set their prices according to the standard Calvo scheme. In each period each producer receives with probability $(1-\theta)$ a signal to reoptimize and then sets her price to maximize the expected profits, subject to demand schedules implied by final goods producers' optimization problem. Those who are not allowed to reoptimize index their prices to the weighted average of past and steady state inflation, with the weight on the former denoted by ζ.

2.3 Entrepreneurs and the banking sector

The specification of entrepreneurs and the financial sector differs between the EFP and CC versions, so we present them in two separate subsections.

[1] We adopt the specification of Christiano et al. (2005) and assume that $S\,(1) = S^{'}\,(1) = 0$ and $S^{''}\,(1) = \kappa > 0$.

2.3.1 External finance premium (EFP) version

There is a continuum of risk-neutral entrepreneurs, indexed by ι. At the end of period t, each entrepreneur purchases installed capital $k_t(\iota)$ from capital producers, partly using her own financial wealth $V_t(\iota)$ and financing the remainder with a bank loan $L_t(\iota)$

$$L_t(\iota) = Q_t k_t(\iota) - V_t(\iota) \geq 0 \tag{7}$$

After the purchase, each entrepreneur experiences an idiosyncratic productivity shock, which converts her capital to $a_E(\iota)k_t(\iota)$, where a_E is a random variable, distributed independently over time and across entrepreneurs, with a cumulative density function $F(\iota)$ and a unit mean. Following Christiano et al. (2003), we assume that this distribution is log normal, with a stochastic standard deviation of $\log a_E$ equal to $\sigma_{a_E,t}$.

Next, each entrepreneur rents out capital services, treating the rental rate $R_{k,t+1}$ as given. The average rate of return on capital earned by entrepreneurs is

$$R_{E,t+1} \equiv \frac{R_{k,t+1} + (1-\delta)Q_{t+1}}{Q_t} \tag{8}$$

and the rate of return earned by an individual entrepreneur is $a_E(\iota)R_{E,t+1}$.

Since lenders can observe the return earned by borrowers only at a cost, the optimal contract between these two parties specifies the size of the loan $L_t(\iota)$ and the gross non-default interest rate $R_{L,t+1}(\iota)$. The solvency criterion can also be defined in terms of a cutoff value of idiosyncratic productivity, denoted as $\tilde{a}_{E,t+1}$, such that the entrepreneur has just enough resources to repay the loan

$$\tilde{a}_{E,t+1} R Q_t k_t(\iota) = R_{L,t+1}(\iota) L_t(\iota) \tag{9}$$

Entrepreneurs with a_E below the threshold level go bankrupt. All their resources are taken over by the banks, after they pay a proportional monitoring cost μ.

Banks finance their loans by issuing time deposits to households at the risk-free interest rate R_t. The banking sector is assumed to be perfectly competitive and owned by risk-averse households. This, together with risk-neutrality of entrepreneurs implies that an optimal financial contract insulates the lender from any aggregate risk.[2] Hence, interest paid by entrepreneurs is state contingent and guarantees that banks break even in every period.

[2] Given the infinite number of entrepreneurs, the risk arising from idiosyncratic shocks is fully diversifiable.

The equilibrium debt contract maximizes welfare of each individual entrepreneur, defined in terms of expected end-of-contract net worth relative to the risk-free alternative

$$E_t \left\{ \frac{\int_{\tilde{a}_{E,t}}^{\infty} \left(R_{E,t+1} Q_t k_t(\iota) a_E(\iota) - R_{L,t+1} L_t(\iota) \right) dF(a_E(\iota))}{R_t V_t(\iota)} \right\} \tag{10}$$

subject to banks' zero profit condition. The solution to this problem (after dropping the expectations operator) is an endogenous and identical to all entrepreneurs wedge χ^{EFP} between the rate of return on capital and the risk free rate

$$R_{E,t+1} = (1 + \chi^{EFP}(\tilde{a}_{E,t+1}))R_t \tag{11}$$

It can be verified that if $\mu = 0$, i.e. monitoring by banks is free, then $\chi^{EFP} = 0$, financial markets work without frictions and the EFP variant simplifies to the standard NK setup.

Entrepreneurs' optimization also implies that the non-default interest rate (common to all entrepreneurs) is

$$R_{L,t+1} = \frac{\tilde{a}_{E,t+1} R_{E,t+1} Q_t k_t(\iota)}{Q_t k_t(\iota) - V_t(\iota)} \tag{12}$$

Proceeds from selling capital, net of interest paid to the banks, constitute end of period net worth. To ensure that entrepreneurs do not accumulate enough wealth to become fully self-financing, it is assumed that each period a randomly selected and stochastic fraction $(1 - \nu_t)$ of them go out of business, in which case all their financial wealth is rebated to the households. At the same time, an equal number of new entrepreneurs enters so that their total number is constant. Those who survive or enter receive a fixed transfer T_E from households. This ensures that entrants have at least a small but positive amount of wealth, without which they would not be able to buy any capital.

Aggregating across all entrepreneurs yields the following law of motion for net worth in the economy

$$V_t = \nu_t \left[R_{E,t} Q_{t-1} k_{t-1} - \left(R_{t-1} + \frac{\mu F_{2,t} R_{E,t} Q_{t-1} k_{t-1}}{L_{t-1}} \right) L_{t-1} \right] + T_E \tag{13}$$

where

$$F_{2,t} \equiv \int_0^{\tilde{a}_{E,t}} a_E dF\left(a_E\right) \tag{14}$$

2.3.2 Collateral constraint (CC) version

There is a continuum of entrepreneurs, indexed by ι. They draw utility only from their consumption c_t^E

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$$E_0 \sum_{t=0}^{\infty} \beta_E^t \frac{\left(c_t^E\left(\iota\right) - \xi c_{t-1}^E\right)^{1-\sigma_c}}{1-\sigma_c} \tag{15}$$

Entrepreneurs cover consumption and capital expenditures with revenues from renting capital services to intermediate goods producers, financing the remainder by bank loans L_t, on which the interest to pay is $R_{L,t}$

$$P_t c_t^E\left(\iota\right) + Q_t k_t(\iota) + R_{L,t-1} L_{t-1}\left(\iota\right) + \tilde{T}_E = \left(R_{k,t} + Q_t\left(1-\delta\right)\right) k_{t-1}\left(\iota\right) + L_t\left(\iota\right) \tag{16}$$

where $\tilde{T}_E$ denotes fixed transfers between households and entrepreneurs. Loans taken by the entrepreneurs are subject to the following collateral constraint

$$R_{L,t} L_t\left(\iota\right) \leq m_t E_t\left[Q_{t+1}\left(1-\delta\right) k_t\left(\iota\right)\right] \tag{17}$$

where m_t is the loan-to-value ratio. Since we assume that $\beta^E < \beta$, the constraint is binding as long as the economy does not deviate too much from its steady state.

The banking system consists of monopolistically competitive banks and financial intermediaries operating under perfect competition. This two-stage structure is necessary to introduce time-varying interest rate spreads.

Financial intermediaries take differentiated loans from banks $L_t\left(i\right)$ at the interest rate $R_{L,t}(i)$ and aggregate them into one undifferentiated loan L_t that is offered to entrepreneurs at the rate $R_{L,t}$. The technology for aggregation is

$$L_t = \left[\int_0^1 L_t\left(i\right)^{\frac{1}{\phi_{L,t}}} di\right]^{\phi_{L,t}} \tag{18}$$

where $\phi_{L,t}$ is a stochastic measure of substitutability between loan varieties.

Each bank i collects deposits $D_t\left(i\right)$ from households at the risk-free rate R_t, and uses them for lending to financial intermediaries. Banks set their interest rates to maximize profits subject to the demand for loans from the financial intermediaries.

Solving the problem of entrepreneurs, banks and financial intermediaries yields the following analog to (11) from the EFP variant

$$R_{E,t+1} = (1 + \Theta_t \chi^{CC}(m_t, Q_{t+1}, Q_t, R_{k,t+1}))\phi_{L,t} R_t \tag{19}$$

where $\chi^{CC} > 0$ and Θ is the Lagrange multiplier on constraint (17). As can be seen, the collateral constraint and monopolistic competition in the banking industry drive a wedge between the return on capital and the (risk-free) policy rate. If the collateral constraint is not binding ($\Theta_t = 0$) and the banking industry is perfectly competitive ($\phi_{L,t} = 1$), then financial frictions disappear, making the CC variant equivalent to the standard NK setup.

2.4 Fiscal and monetary authorities

The government uses lump sum taxes to finance its expenditure g_t. We assume that the budget is balanced each period so that $g_t = T_t$.

As it is common in the New Keynesian literature, we assume that monetary policy is conducted according to a Taylor rule that targets deviations of inflation and output from the deterministic steady state, allowing additionally for interest rate smoothing

$$R_t = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\gamma_R} \left(\left(\frac{\pi_t}{\bar{\pi}}\right)^{\gamma_\pi} \left(\frac{y_t}{\bar{y}}\right)^{\gamma_y}\right)^{1-\gamma_R} e^{\varphi_t} \tag{20}$$

where $\pi_t \equiv P_t/P_{t-1}$, a bar over a variable denotes its steady state value and φ_t is the monetary shock.

2.5 Market clearing

The market clearing condition for the final goods market differs between our three model variants. In the EFP variant, it must take into account that monitoring costs are real, which results in the following formula

$$c_t + i_t + g_t + \mu F_{2,t} R_{E,t} q_{t-1} k_{t-1} = y_t \tag{21}$$

The counterpart of (21) in the CC variant includes entrepreneurs' consumption

$$c_t + i_t + g_t + c_t^E = y_t \tag{22}$$

By dropping monitoring costs from (21) or entrepreneurs' consumption from (22), we obtain the market clearing condition for the standard NK model.

2.6 Exogenous shocks

Business cycle fluctuations in the simplest version of our model (NK) are driven by shocks to productivity (A_t), households' preferences (Γ_t) and Taylor rule (φ_t). They are the standard representatives of stochastic disturbances to supply, demand and monetary policy. Each of the financial extensions includes two more shocks related to the financial sector. In the EFP variant, these are the standard deviation of idiosyncratic productivity ($\sigma_{a_E,t}$) and the exit rate for entrepreneurs (ν_t). We will refer to them as riskiness and net worth shocks, respectively. In the CC version, the two additional shocks are the LTV ratio (m_t) and markup in financial intermediation ($\phi_{L,t}$), the latter referred to as a spread shock. The log of each shock follows a linear first-order autoregressive process, except for the monetary policy shock, which is assumed to be white noise.

3 Estimation

3.1 Data

We estimate the log-linearized approximations of all three model versions laid down in the previous section using Bayesian inference. We use quarterly US data spanning the 1970-2010 period. In the NK model, the observable variables are the standard three macroeconomic time series: real GDP, CPI inflation and the federal funds rate. In the EFP and CC variants, we additionally use two financial variables, i.e. real loans to firms and spread on loans to firms, both defined as in Christiano et al. (2010). More specifically, the former is credit market instruments liabilities of nonfarm nonfinancial businesses, taken from the Flow of Funds Account of the Federal Reserve Board and deflated with the GDP deflator. The latter is the difference between the industrial BBB corporate bond yield, backcasted using BAA corporate bond yields (both series taken from Bloomberg), and the federal funds rate. Trending data (GDP and loans) are made stationary by removing a linear trend from their logs, while the interest rate, inflation and the spread are demeaned.

3.2 Calibration and prior assumptions

As it is common in the applied DSGE literature, we keep a number of parameters fixed in the estimation.[3] These are the parameters that affect the steady state proportions in our models and hence most of them cannot be pinned down in the estimation procedure that uses detrended or demeaned observable variables. An additional advantage of calibrating this subset of parameters is that it can be done such that the steady state solutions of our competing models with financial frictions are identical, which facilitates comparisons. The results of our calibration are presented in Table 1.

We calibrate the structural parameters unrelated to the financial sector (and so common across the NK, EFP and CC versions) by taking their values directly from the previous literature, relying mainly on Smets and Wouters (2007), or set them to match the key steady state proportions of the US data. As regards the calibrated parameters specific to the EFP or CC extensions, we apply the same procedure as in Brzoza-Brzezina et al. (2011), the details of which are presented

[3]Both Bayesian estimation of DSGE models and fixing part of the parameters are standard in the literature (e.g. Smets and Wouters (2003); Adolfson et al. (2005)). This procedure follows the observation that for many parameters the likelihood function is almost flat. In such a case either imposing a tight prior or fixing some of the parameters is necessary to estimate the model.

below.

In each of our extensions to the NK setup, the financial sector is governed by four parameters. These parameters are μ, $\bar{\nu}$, $\bar{\sigma}_{a_E}$, T_E in the EFP model and β_E, $\bar{\phi}_L$, $\bar{m}$, $\tilde{T}_E$ in the CC variant. We use them to pin down four steady state proportions: investment share in output, interest rate spread, capital to debt ratio and the output share of monitoring costs (EFP) / entrepreneurs' consumption (CC). The first three have their natural empirical counterparts, which we match exactly. In particular, our calibration implies that in the steady state around half of capital is financed by loans (Bernanke et al., 1999) and the annualized spread is 88 basis points (the average in our data). The target value for the share of monitoring costs / entrepreneurs' consumption is set to 0.5%, which is consistent with Christiano et al. (2010). As a result, our calibration implies that the steady state rate of return on capital, and hence the excess return on capital defined by equations (11) and (19), are the same in the EFP and CC versions.

The remaining model parameters are estimated. Our prior assumptions are summarized in Table 2. Overall, they are consistent with the previous literature (e.g. Smets and Wouters, 2007) and relatively uninformative.

3.3 Posterior estimates

The posterior estimates are reported in Table 3.[4] They are obtained using the Metropolis-Hastings algorithm. We ran 1,000,000 draws from two chains, burning the first half of each chain. The stability of thus obtained sample was assessed using the convergence statistics proposed by Brooks and Gelman (1998).

Our parameter estimates for the NK model are in line with the related DSGE literature based on US data. In particular, the posterior means of parameters describing nominal and real rigidities, i.e. Calvo probabilities and indexation in prices and wages as well as investment adjustment costs, nearly coincide with those obtained by Smets and Wouters (2007). This is despite the fact that we use a narrower set of observable variables and shocks.

Adding financial frictions to the NK setup changes the estimates of some of these parameters significantly. First, prices appear to be more sticky (higher θ) according to the EFP model, while the opposite holds true for the CC variant. Together with a relatively low estimate of the Calvo probability for wages θ_w in the CC model, this result suggests that, compared to the standard NK model, one needs more (less) nominal rigidities in the EFP (CC) setup to account for

[4] All estimations in this paper are done with Dynare (www.dynare.org).

sensitivity of inflation to real activity observed in the data. Second, the estimated curvature of the investment adjustment cost function κ in the EFP model is significantly smaller than that in the baseline NK model or the CC extension. This finding is consistent with Brzoza-Brzezina et al. (2011), who point at relatively strong propagation of shocks on real variables in the EFP setup, especially in comparison to the CC model.

Differences in the degree of nominal rigidities across the three model variants translate into differences in the estimates of the monetary policy feedback rules. In particular, more (less) wage or price stickiness in the EFP (CC) variant compared to the NK baseline implies a less (more) aggressive response of the interest rate to inflation to ensure its volatility at the level close to observed in the data.

We know from the earlier literature that structural shocks in estimated DSGE models usually exhibit high persistence. This may signal misspecification, an issue we address in the next sections. According to our results, high shock inertia is particularly pronounced in the CC model. In particular, the mean posterior estimate of autocorrelation of productivity, preference and LTV shocks are around 0.95 and relatively tightly estimated.

4 Model evaluation

4.1 Marginal likelihoods

As a first step we compare the data fit of the three frameworks. In a Bayesian setting, a natural measure for model comparisons is marginal likelihood. However, comparisons of marginal likelihoods (calculation of the posterior odds ratios) are valid only if the evaluated models are estimated with the same data sets. Since in our baseline setting this is not the case (the NK model is estimated without financial variables), we take a number of alternative approaches that help us circumvent this problem. The results which we refer to are collected in Table 4.

As a first step we reestimate the models on data sets containing only non-financial variables (i.e. output, inflation and the interest rate). This is done in two variants. The first row presents marginal likelihoods for the models described in Section 2. Clearly the best performing model is EFP. Adding financial frictions of this type to the NK model helps in bringing it closer to the data. However, to our surprise, the CC model underperforms the NK model. This type of frictions seems not to be accepted. The second row provides the results of a somewhat modified exercise, where we remove financial shocks from the financial friction models. This is intended to make the "competition" more fair towards the NK model, since additional shocks can be expected to improve the fit. Moreover, the exercise becomes closest to those performed in the literature (Christensen and Dib, 2008; Queijo von Heideken, 2009), where the financial accelerator model of Bernanke et al. (1999) has been found to outperform its frictionless version. Removing financial shocks lowers the marginal likelihoods of both financial friction frameworks, but does not affect the ordering. Consistently with the literature, the EFP framework performs best (though the gain over the NK model becomes very small). Again, the CC model performs worst.

While this exercise is telling, one could (as we do) find evaluating financial friction models without using financial data somewhat unfair. For this reason, we embark on another exercise, that allows for the comparison of all models. To this end, we enlarge the NK model for the presence of financial variables. As this model does not feature financial variables, this is done in a non-structural way - we assume simple time series processes that drive the two financial variables. In particular we introduce them as either first-order (third row) or second-order (fourth row) autoregressive processes. In the former case we assume priors as for shocks, in the latter we allow the coefficients on the lags to fall outside the unit interval and hence assume normal rather than beta prior distributions, centered around 0.5 (first lag) and 0 (second lag). As evidenced in Smets and Wouters (2007), the DSGE framework can outperform time series models (Bayesian VARs in particular) in terms of marginal likelihood. Against this background our evidence is striking. While the NK model augmented by a simple AR(1) specification for financial variables performs worse than the financial friction models, allowing for just one additional lag in the atheoretical part makes the NK setup perform substantially better than both the CC and EFP frameworks. Additionally, one could note that the superior performance of the EFP model over CC remains valid after inclusion of financial variables.

All in all, the evidence from comparisons of the marginal likelihoods casts clear doubt over the performance of the CC framework. The improvement from introducing EFP type frictions is also less clear than hitherto documented in the literature, not using financial variables in estimation.

4.2 DSGE-VAR evidence

Another method used in the literature for comparison of DSGE models are DSGE-VARs, put forward by Del Negro and Schorfheide (2004). This framework has recently become a popular tool for assessing the degree of misspecification of DSGE models (Del Negro et al., 2007; An and Schorfheide, 2007; Del Negro and Schorfheide, 2009). The DSGE-VAR approach relies on a simple observation that a DSGE model can be approximated by a finite order vector autoregression (VAR). In this case, the VAR parameters are determined by the parameters of the DSGE model and cross-equation restrictions it implies. In this context, one can think of relaxing the restrictions imposed by the theoretical model, thus letting the data influence the VAR to a larger degree.

This is in a nutshell the concept of DSGE-VARs. The estimation of a VAR model is augmented with prior knowledge, stemming from the DSGE model. The extent to which the theoretical model influences the VAR coefficients can be chosen by the researcher by varying a parameter which determines the tightness of the DSGE-based prior. In what follows this parameter will be denoted as λ. If $\lambda = 0$, an unrestricted VAR is estimated. If $\lambda = \infty$, the VAR parameters approach the restrictions implied by the DSGE model. For $\lambda = 1$, the DSGE prior and the data receive equal weight in the VAR-representation posterior.

We estimate three DSGE-VAR models corresponding to the three alternative DSGE specifications described above. As in Adjemian et al. (2008), we estimate

λ directly, using a flat prior. We will refer to these values as to $\hat{\lambda}$. The results, obtained using the same parametrization of the Metropolis-Hastings algorithm as described in section 3.3, are reported in Table 5.

The posterior estimates of $\hat{\lambda}$ are very small for all three models, indicating that the data is consistent with merely a loose DSGE prior. This not only confirms the result found in the literature that standard New Keynesian models are seriously misspecified (Del Negro et al., 2007), but also shows that adding financial frictions does not help solving this problem. In fact, the posterior means of $\hat{\lambda}$ for both financial friction models are even lower than for the NK model, though it should be added that the overlap in the three relevant posterior densities is considerable.

This observation finds further support if we look at the evidence from marginal likelihoods (Table 4). For any model variant, their estimates rise substantially if we relax the DSGE-based restrictions. Interestingly, the log marginal likelihood differential between the DSGE model and its DSGE-VAR representation for the two financial frictions extensions are about four times larger than for the NK benchmark.

As explained by Del Negro and Schorfheide (2009), the superior data fit of DSGE-VARs leads to smaller forecast errors and smaller shock volatility estimates. As can be seen from Table 5, this is also the case in our results for all three model variants. Relaxing the DSGE model restrictions means that the model misspecification no longer needs to be absorbed by structural shocks, which results in processes with lower persistence and volatility.

Next, we analyze the misspecification of our three models by comparing their impulse responses with those from DSGE-VARs. In this respect we proceed along the lines drawn by Del Negro and Schorfheide (2009) and construct DSGE-VAR(∞) models, where the structural parameters (including the shock variances and autocorrelations) have been fixed at their posterior means from the corresponding DSGE-VAR($\hat{\lambda}$)'s, presented in Table 5. As explained in detail in Del Negro and Schorfheide (2009), such a procedure allows to clear the misspecification of the model from the impact of different parameter estimates. The results are depicted in Figures 1 to 5.

It should be noted that, with minor exceptions, for any given shock and variable, the DSGE-VAR impulse response functions are similar across the models. This is consistent with relatively low estimated values of $\hat{\lambda}$ and gives support to treating DSGE-VAR based responses as an empirical benchmark. Given the vast amount of information embedded in the reaction functions, we concentrate on the main findings.

First, the general impression from analyzing the responses is consistent with the finding on estimated $\hat{\lambda}$'s. All models seem misspecified to a comparable degree, as all DSGE-VAR(∞) impulse responses often leave the DSGE-VAR($\hat{\lambda}$) probability intervals. Second, in spite of the above, in most cases the direction of the impulse responses in the DSGE-VAR(∞) models and their empirical benchmarks coincide. Notable exceptions are rising inflation in the EFP model after a net worth shock and spread reactions discussed below.

Third, in response to a monetary policy shock, output and inflation do not show enough persistence. The CC model even overrides the small hump-shapes visible in the NK model, making the impulse response even less in line with the empirical benchmark. Fourth, the endogenous reaction of spreads is strongly supported by the data. This points in favor of the EFP formulation over the CC model, which lacks such a mechanism. Particular attention should be paid to the reaction of spreads to a monetary policy shock. While in the DSGE-VAR(∞) spreads rise on impact after a monetary tightening, in its DSGE-VAR($\hat{\lambda}$) counterpart they initially decline and rise only over time. The latter reaction results most probably from the stickiness of retail interest rates (as evidenced i.a. by De Bondt, 2005), which is not included in our frameworks. As shown by Gerali et al. (2010), this feature can be added to financial friction models relatively easily by allowing for staggered setting of retail interest rates.

Fifth, in some cases the behavior of loans is somewhat counterintuitive. This is especially the case in the EFP model, where loans increase after a monetary policy tightening and decline after a net worth shock. Last but not least, both financial friction models show rising inflation after a positive shock to riskiness (EFP) / spreads (CC). Although this result can be easily explained via cost-push effects of higher loan servicing, they are at odds with the empirical benchmark, where inflation declines following this kind of shock.

All in all, analyzing the impulse responses paints a picture of financial friction models whose degree of misspecification is comparable to the NK benchmark. While in general the theoretical and empirical impulse responses have much in common, in several cases the former leave the probability bounds around the latter and in some cases they even differ as to sign.

4.3 Historical decompositions

One of the aims of financial friction models is to explain the role played by financial disturbances in driving the business cycle. We follow this line and construct historical shock decompositions for all three models and present them on Figures 6 - 8. For the sake of transparency, we only show data since 2000q1. Starting with the NK benchmark, it is clear that in this model the business cycle is driven mainly by preference (demand type) disturbances. This result is consistent with an 88% share of this shock in the variance decomposition of output growth. One interesting finding is the negative contribution of monetary policy shocks to output growth since 2008q4. This reflects the zero lower bound constraint hit by the Federal Reserve. Since the interest rates could not be lowered enough, they started to exert a negative impact on GDP. It has to be noted that our models do not feature exceptional monetary policy tools like quantitative easing.

As we move to models with financial frictions, financial shocks start playing a role in determining output fluctuations. In both models financial shocks have a substantial, though not overwhelming contribution to output decline during the 2007-09 financial crisis. However, surprisingly, the visual evidence suggests that the recent recession was not necessarily more “financial” in nature than the 2001 slowdown.

To explore this observation in detail, in Table 6 we present the shock decomposition of output contraction during US recessions since 1970. Again, the dominant role of preference shocks evident in the NK model declines to the benefit of financial shocks in the EFP and CC frameworks. Financial shocks contributed to the decline of GDP during each NBER recession and, in line with intuition, their most significant impact on output was during the recent financial crisis. This conclusion, however, does not hold any more if we control for the size of recession. The relative role of financial shocks varies from 20% (EFP model, 1970 recession) to 69% (CC model, 1980 recession).[5] In this metric, the role of financial shocks during the financial crisis 2007-09 ranks second for the EFP model and only fifth for the CC model. This feature stands in sharp contrast with common knowledge, supported by empirical findings, that the origins of the recent crisis can be traced to the financial sector (Brunnermeier, 2009; Gilchrist and Zakrajcek, 2011; Gorton, 2009).

[5] The latter finding seems consistent with the result obtained by Jermann and Quadrini (2012) in a framework similar to our CC model, who report a low relative contribution of financial shocks to the development of output during the financial crisis.

5 Conclusions

After the financial crisis 2007-09, models featuring financial frictions are promptly entering into the mainstream of macromodeling. They have been used i.a. to analyze the financial crisis or to speak about optimal monetary policy in the presence of financial frictions. More importantly, however, these models are being used to analyze the consequences of capital regulations and to deliver policy advice on central banks' macroprudential policies. This calls for a thorough investigation whether they are able to reflect factual economic developments rather than creating a fictitious world of financial imperfections.

To this end, we conduct an empirical evaluation of the two most popular macrofinancial frameworks: the external finance premium framework of Bernanke et al. (1999) and the collateral constraint model of Kiyotaki and Moore (1997). We estimate their comparable versions on US data together with the benchmark New Keynesian model. For each model we also estimate its DSGE-VAR representation. Our findings are as follows.

5

First, the comparison of marginal likelihoods clearly favors the Bernanke et al. framework over the Kiyotaki and Moore model. However, the former improves upon the benchmark New Keynesian models without financial frictions only in some settings, and the latter always performs much worse than the benchmark.

Second, comparison of the DSGEs and DSGE-VARs reveals that all three models are seriously misspecified. While this result for the New Keynesian model comes as no surprise and has been described in the literature before, it is striking that introducing financial frictions does not help to solve this problem. This conclusion comes not only from the formal comparison of the optimal DSGE-VAR hyperparameters, but also from the visual inspection of misspecification revealed by the impulse response functions. Additionally, the latter point at a number of deficiencies of financial friction models (e.g. overriding the model inertia by the Kiyotaki and Moore framework, or the strong cost-push effects of riskiness / spread shocks being at odds with the data).

Third, we look how our models interpret the recent financial crisis against the background of previous recessions. Surprisingly, we find that the role of financial shocks in driving the 2007-09 recession was not more pronounced than in several past contractions. In particular, in this category, the recent recession ranks second for the Bernanke et al. model and only fifth for the Kiyotaki and Moore model.

We conclude that both financial friction frameworks show serious deficiencies and do not offer clear improvements upon the frictionless benchmark. Further research is needed to find macrofinancial models that reflect reality better. Most recent research, featuring i.a. a more explicit modeling of financial intermediation or introducing occasionally binding constraints seem interesting avenues.

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Tables and figures

Table 1: Calibrated parameters

Parameter	Values	Description
Common parameters		
β	0.995	discount rate
σ_c	2.0	inverse of intertemporal elasticity of substitution
σ_n	2.0	inverse of Frisch elasticity of labor supply
ξ	0.6	degree of external habit formation
ϕ_w	1.2	labor markup
α	0.33	product elasticity with respect to capital
ϕ	1.1	product markup
δ	0.025	depreciation rate
Financial sector parameters - EFP		
μ	0.10	monitoring costs
ν	0.977	steady state survival rate for entrepreneurs
σ_{a_E}	0.29	steady state st. dev. of idiosyncratic productivity
T_E	0.029	transfers to entrepreneurs (relative to steady state output)
Financial sector parameters - CC		
β_E	0.985	entrepreneurs discount factor
ϕ_L	1.002	steady state loan markup
m	0.52	steady state LTV
$\tilde{T}_E$	0.002	transfers to entrepreneurs (relative to steady state output)

Table 2: Priors for estimated parameters

Parameter	Distr. type	Mean	Std.	Description
θ	beta	0.66	0.10	Calvo probability for prices
ζ	beta	0.50	0.15	indexation parameter for prices
θ_w	beta	0.66	0.10	Calvo probability for wages
ζ_w	beta	0.50	0.15	indexation parameter for wages
κ	normal	4.00	1.50	investment adjustment cost
γ_R	beta	0.75	0.10	Taylor rule: interest rate smoothing
γ_π	normal	1.50	0.10	Taylor rule: response to inflation
γ_y	normal	0.50	0.10	Taylor rule: response to GDP
ρ_A	beta	0.50	0.20	productivity shock: inertia
ρ_c	beta	0.50	0.20	preference shock: inertia
ρ_ν / ρ_m	beta	0.50	0.20	net worth / LTV shock: inertia
ρ_E / ρ_{ϕ_L}	beta	0.50	0.20	riskiness / spread shock: inertia
σ_A	inv. gamma	0.01	Inf	productivity shock: volatility
σ_c	inv. gamma	0.01	Inf	preference shock: volatility
σ_R	inv. gamma	0.01	Inf	monetary shock: volatility
σ_ν / σ_m	inv. gamma	0.01	Inf	net worth / LTV shock: volatility
σ_E / σ_{ϕ_L}	inv. gamma	0.01	Inf	riskiness / spread shock: volatility

Table 3: Estimation results: DSGE

	EFP			CC			NK		
Parameter	Mean	5%	95%	Mean	5%	95%	Mean	5%	95%
θ	0.787	0.728	0.847	0.465	0.367	0.558	0.681	0.568	0.818
ζ	0.177	0.073	0.277	0.169	0.052	0.284	0.152	0.052	0.254
θ_w	0.718	0.607	0.838	0.509	0.411	0.608	0.730	0.606	0.856
ζ_w	0.517	0.274	0.752	0.305	0.113	0.489	0.409	0.166	0.650
κ	2.628	0.979	4.293	6.067	4.864	7.256	5.783	3.808	7.704
γ_R	0.912	0.888	0.937	0.813	0.786	0.841	0.878	0.845	0.910
γ_π	1.292	1.101	1.483	1.612	1.478	1.747	1.478	1.330	1.632
γ_y	0.423	0.288	0.558	0.158	0.116	0.199	0.255	0.139	0.375
ρ_A	0.846	0.789	0.906	0.944	0.914	0.973	0.862	0.773	0.948
ρ_c	0.814	0.728	0.899	0.961	0.949	0.973	0.883	0.826	0.943
ρ_ν / ρ_m	0.890	0.836	0.945	0.967	0.948	0.986			
ρ_E / ρ_{ϕ_L}	0.889	0.852	0.925	0.853	0.810	0.898			
σ_A	0.020	0.012	0.027	0.006	0.005	0.007	0.013	0.006	0.022
σ_c	0.107	0.090	0.123	0.127	0.111	0.142	0.113	0.094	0.131
σ_R	0.002	0.002	0.003	0.003	0.002	0.003	0.002	0.002	0.003
σ_ν / σ_m	0.009	0.008	0.010	0.017	0.015	0.019			
σ_E / σ_{ϕ_L}	0.130	0.118	0.142	0.002	0.002	0.003			

Table 4: Marginal likelihood comparison

	EFP	CC	NK
$p(Y_{nf})$	-358.7	-383.8	-369.9
$p(Y_{nf})$, no financial shocks in EFP and CC	-368.7	-391.1	-369.9
$p(Y_{nf}, Y_f)$, Y_f ∼AR(1) in NK	-618.8	-623.2	-631.4
$p(Y_{nf}, Y_f)$, Y_f ∼AR(2) in NK	-618.8	-623.2	-585.6
$p(Y_{nf})$, DSGE-VAR	.	.	-325.6
$p(Y_{nf}, Y_f)$, DSGE-VAR	-432.8	-448.3	.

Note: $p(\bullet)$ is log marginal likelihood, while Y_{nf} and Y_f stand for non-financial (output, inflation and the interest rate) and financial (loans and spreads) variables, respectively.

Table 5: Estimation results: DSGE-VAR

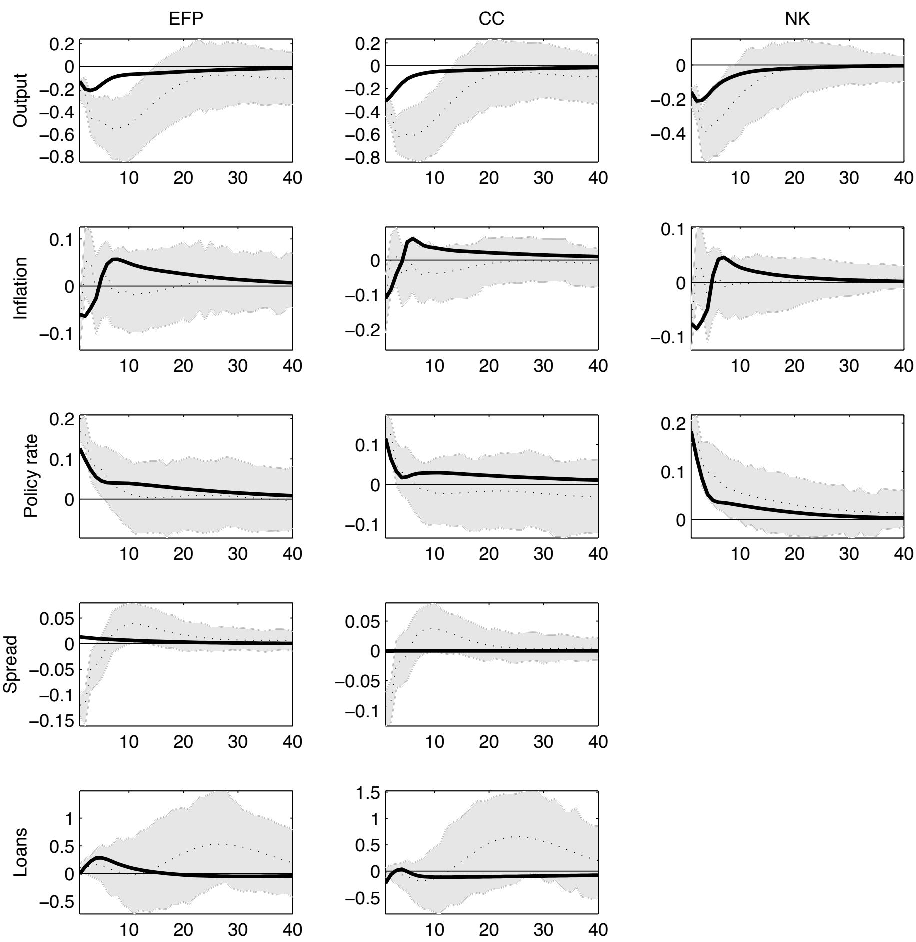
	EFP			CC			NK		
Parameter	Mean	5%	95%	Mean	5%	95%	Mean	5%	95%
θ	0.625	0.488	0.774	0.471	0.328	0.616	0.630	0.501	0.757
ζ	0.276	0.091	0.459	0.326	0.116	0.524	0.320	0.112	0.517
θ_w	0.665	0.529	0.806	0.622	0.451	0.802	0.676	0.540	0.818
ζ_w	0.465	0.216	0.704	0.428	0.189	0.663	0.493	0.238	0.738
κ	2.904	0.318	5.255	4.154	2.736	5.549	4.660	2.512	6.810
γ_R	0.912	0.881	0.947	0.856	0.809	0.904	0.866	0.824	0.910
γ_π	1.453	1.290	1.625	1.546	1.393	1.701	1.483	1.323	1.645
γ_y	0.524	0.373	0.680	0.439	0.260	0.606	0.460	0.298	0.626
ρ_A	0.661	0.350	0.970	0.406	0.133	0.678	0.439	0.112	0.779
ρ_c	0.581	0.303	0.902	0.869	0.694	0.963	0.803	0.670	0.948
ρ_ν / ρ_m	0.742	0.547	0.927	0.961	0.923	0.997			
ρ_E / ρ_{ϕ_L}	0.865	0.780	0.953	0.780	0.691	0.871			
σ_A	0.007	0.004	0.011	0.006	0.003	0.009	0.013	0.005	0.022
σ_c	0.053	0.037	0.068	0.075	0.045	0.101	0.090	0.066	0.113
σ_R	0.001	0.001	0.002	0.002	0.001	0.002	0.002	0.002	0.002
σ_ν / σ_m	0.006	0.005	0.007	0.010	0.007	0.012			
σ_E / σ_{ϕ_L}	0.053	0.041	0.064	0.001	0.001	0.002			
λ	0.292	0.237	0.347	0.331	0.260	0.399	0.371	0.218	0.523

Table 6: Decomposition of output contraction during US recessions

	I-IV'70	IV'73-I'75	I-III'80	III'81-IV'82	III'90-I'91	I-IV'01	IV'07-II'09
GDP drop	-2.7	-6.8	-4.2	-5.9	-3.6	-2.6	-8.7
NK							
Productivity	-0.1	-3.0	-1.1	1.2	-0.5	0.2	-0.6
Preference	-2.7	-6.1	-4.0	-7.2	-3.7	-4.1	-8.4
Monetary	0.5	2.2	0.9	0.0	0.6	1.3	0.3
EFP							
Productivity	0.0	-1.6	-0.9	0.5	-0.7	0.0	0.3
Preference	-2.9	-5.4	-2.3	-5.5	-2.5	-3.9	-5.9
Monetary	0.8	2.6	1.1	0.8	0.8	2.1	0.5
Net worth	-0.2	-2.1	-1.2	0.0	-0.1	-0.8	-2.1
Riskiness	-0.3	-0.3	-0.9	-1.8	-1.0	0.0	-1.6
Fin. shocks / GDP drop	20.5%	35.1%	50.1%	29.5%	32.6%	31.2%	42.7%
CC							
Productivity	0.2	-3.1	-1.6	-0.2	-0.3	-0.3	0.4
Preference	-2.3	-3.1	-1.3	-3.3	-1.7	-1.9	-4.1
Monetary	0.7	3.8	1.6	0.1	0.6	1.1	-0.6
LTV	0.1	-2.5	-1.1	-0.2	-1.8	-1.1	-3.2
Spread	-0.8	-2.1	-1.8	-2.4	-0.4	-0.4	-1.2
Fin. shocks / GDP drop	25.3%	67.6%	68.9%	44.0%	60.5%	57.9%	50.9%

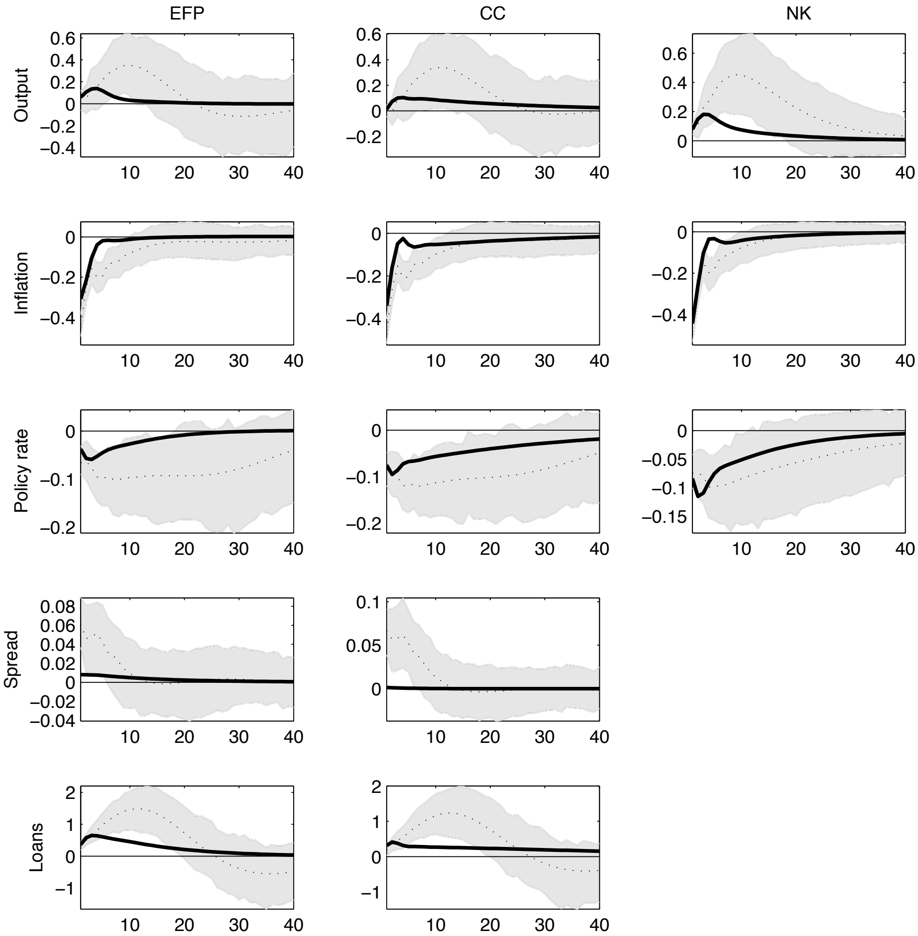
Note: The dates in columns correspond to the recessions identified by the NBER after 1970. All numbers are expressed in per cent.

Figure 1: Monetary shock IRFs



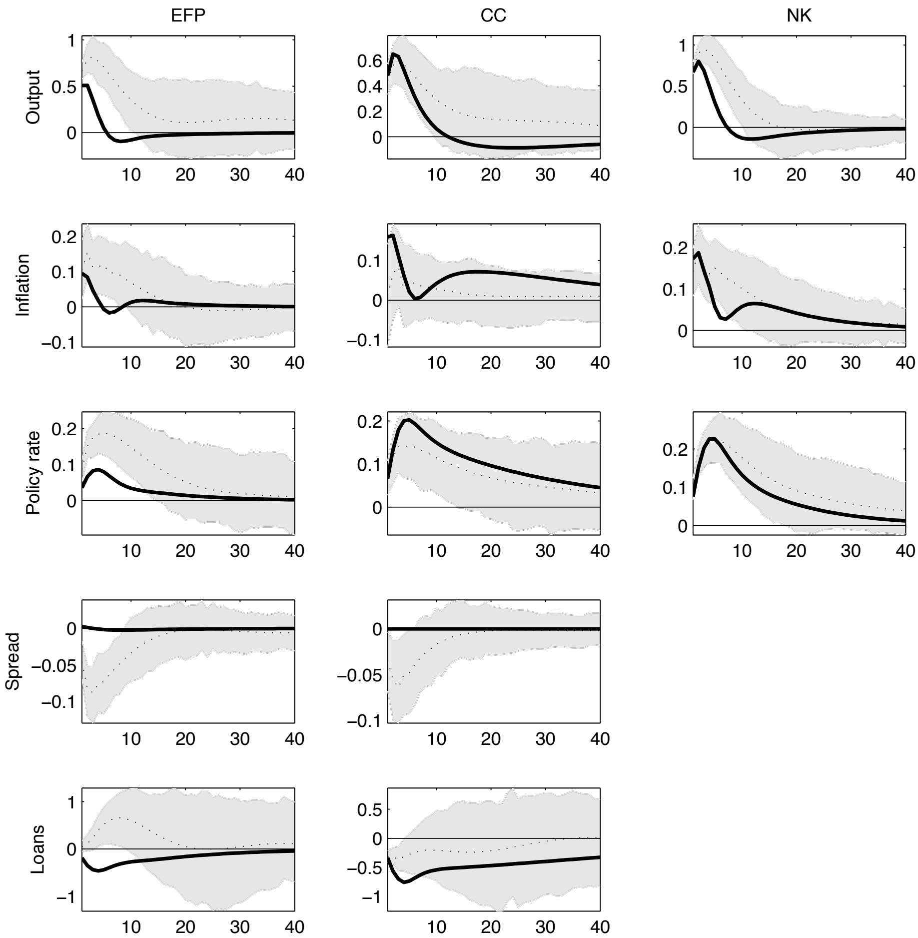
Note: The figure shows the posterior mean responses for the DSGE-VAR(∞) model based on the DSGE-VAR($\hat{\lambda}$) posterior estimates (solid lines), and for the DSGE-VAR($\hat{\lambda}$) (dotted lines) together with 90% probability intervals for the latter model (gray areas).

Figure 2: Productivity shock IRFs



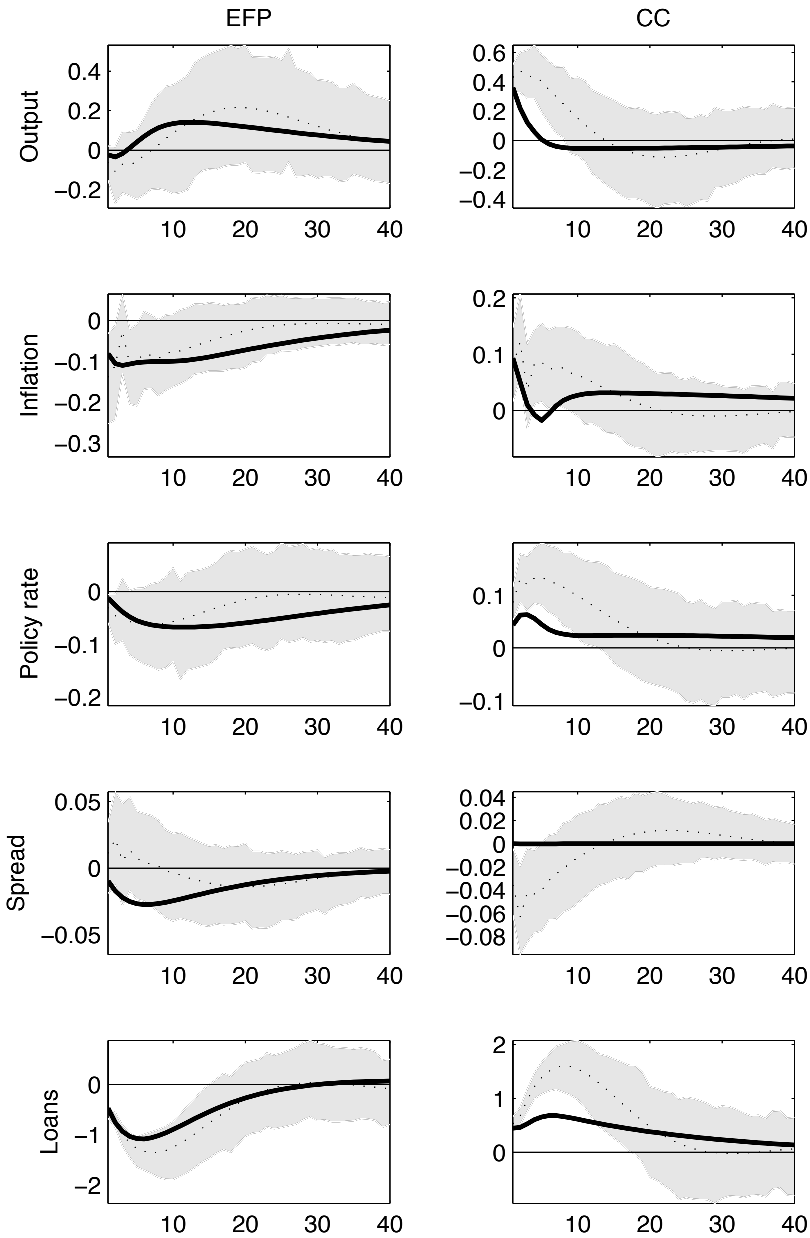
Note: The figure shows the posterior mean responses for the DSGE-VAR(∞) model based on the DSGE-VAR($\hat{\lambda}$) posterior estimates (solid lines), and for the DSGE-VAR($\hat{\lambda}$) (dotted lines) together with 90% probability intervals for the latter model (gray areas).

Figure 3: Preference shock IRFs



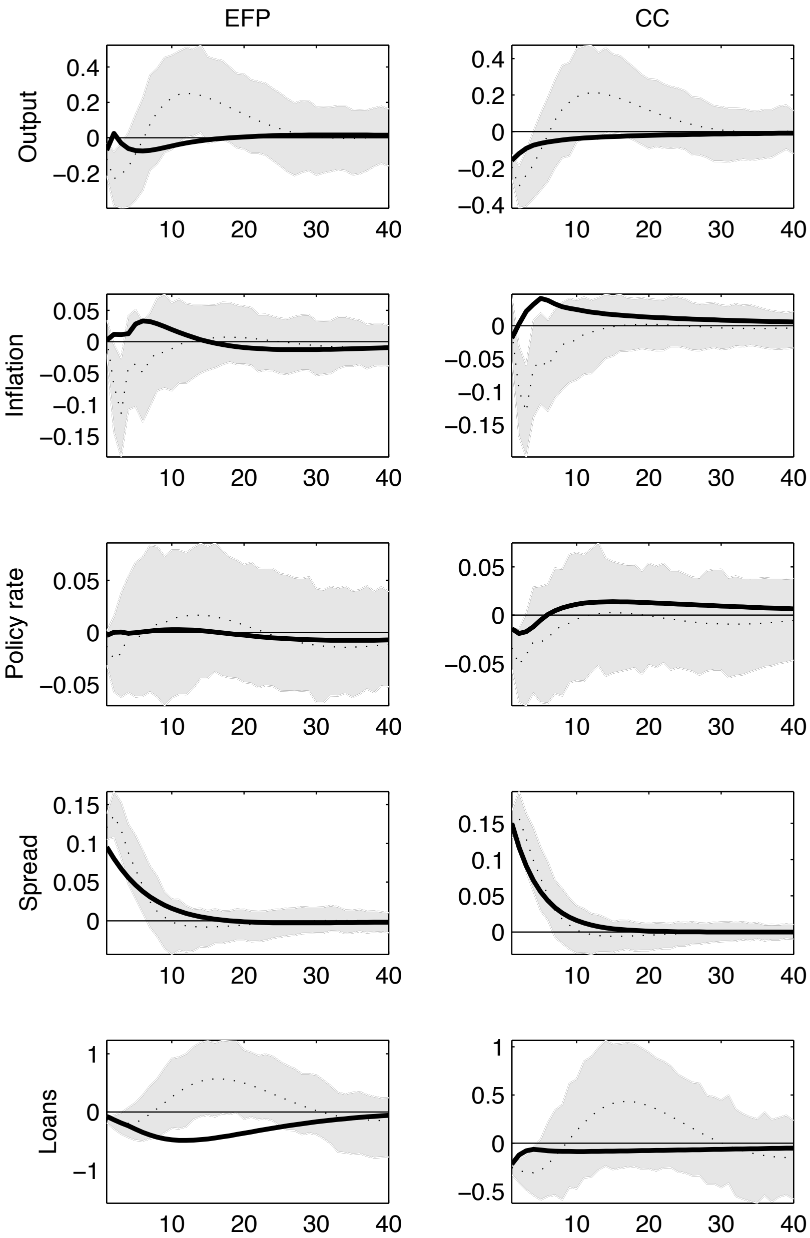
Note: The figure shows the posterior mean responses for the DSGE-VAR(∞) model based on the DSGE-VAR($\hat{\lambda}$) posterior estimates (solid lines), and for the DSGE-VAR($\hat{\lambda}$) (dotted lines) together with 90% probability intervals for the latter model (gray areas).

Figure 4: Net worth / LTV shock IRFs



Note: The figure shows the posterior mean responses for the DSGE-VAR(∞) model based on the DSGE-VAR($\hat{\lambda}$) posterior estimates (solid lines), and for the DSGE-VAR($\hat{\lambda}$) (dotted lines) together with 90% probability intervals for the latter model (gray areas).

Figure 5: Riskiness / spread shock IRFs



Note: The figure shows the posterior mean responses for the DSGE-VAR(∞) model based on the DSGE-VAR($\hat{\lambda}$) posterior estimates (solid lines), and for the DSGE-VAR($\hat{\lambda}$) (dotted lines) together with 90% probability intervals for the latter model (gray areas).

Figure 6: Decomposition of output growth: NK

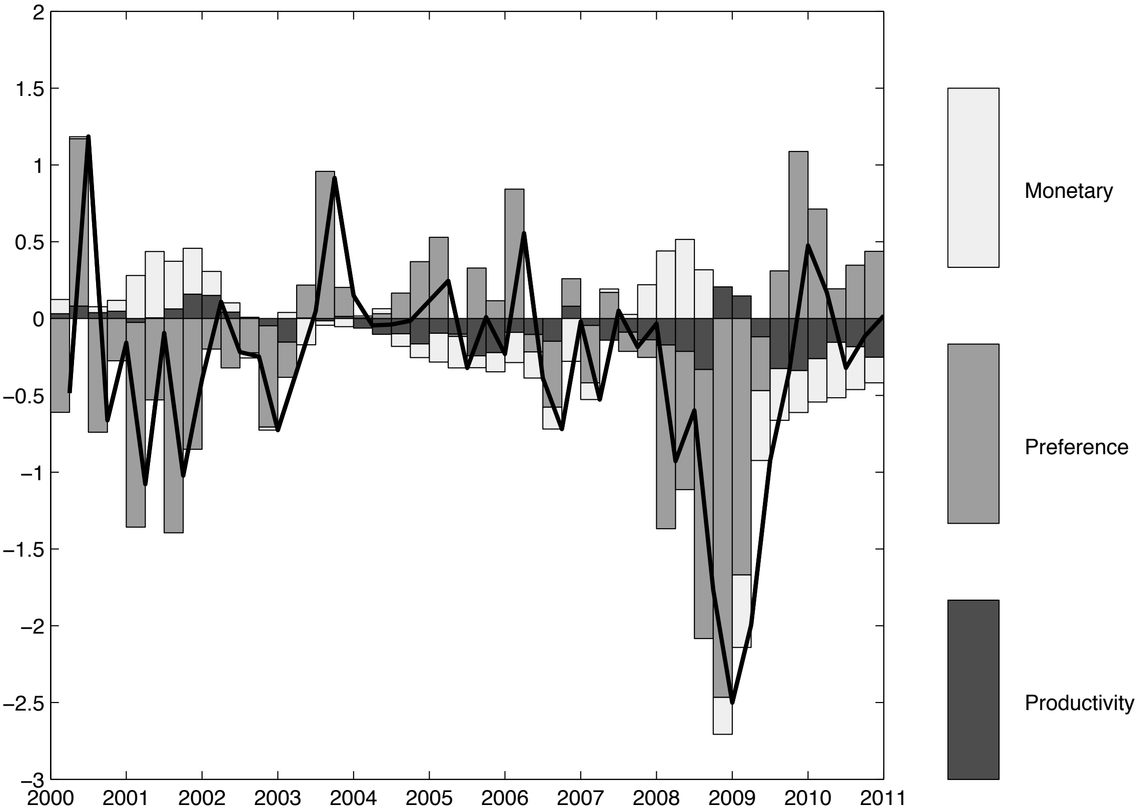


Figure 7: Decomposition of output growth: EFP

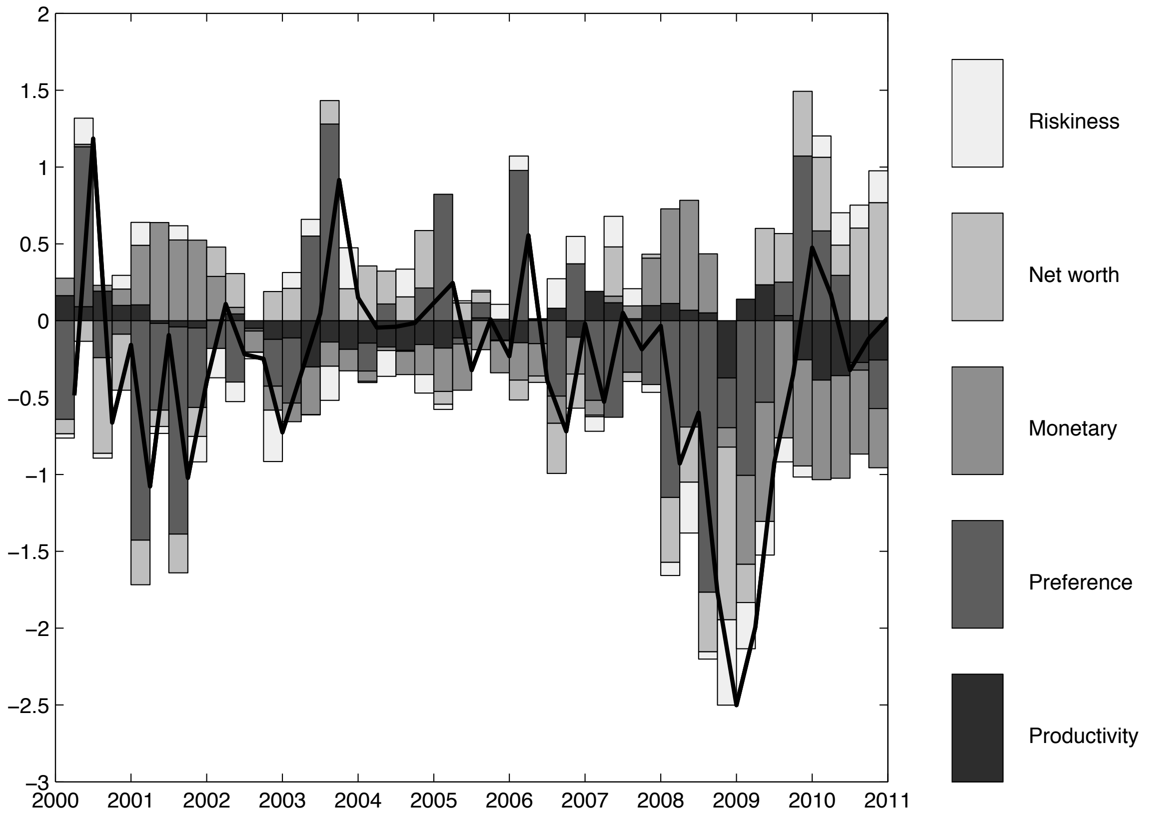


Figure 8: Decomposition of output growth: CC