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Bayesian Evaluation of DSGE Models with Financial Frictions

We evaluate two most popular approaches to implementing financial frictions into DSGE models: the Bernanke, Gertler, and Gilchrist (1999) setup, where frictions affect the price of loans, and the Kiyotaki and Moore (1997) model, where they concern the quantity of loans. We take both models to the data and check how well they fit it on several margins. Overall, comparing the models favors the Bernanke, Gertler, and Gilchrist framework. However, even this model does not make a clear improvement over the New Keynesian benchmark in terms of marginal likelihood and similarity of impulse responses to those obtained from a VAR.

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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 *inter alia* the role of financial frictions in monetary transmission (Calza, Monacelli, and Stracca 2013, Gerali et al. 2010, Christiano, Motto, and Rostagno 2010) or the impact of financial shocks on the economy (Christiano, Motto, and Rostagno 2003, Gilchrist, Ortiz, and Zakrajcek 2009, Iacoviello and Neri 2010, Brzoza-Brzezina and

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Makarski 2011). As regards the latter area, one can mention papers analyzing optimal monetary policy in the presence of financial frictions (De Fiore and Tristani 2009, Cúrdia and Woodford 2010, Carlstrom, Fuerst, and Paustian 2010, Kolasa and Lombardo Forthcoming) or the consequences of capital regulations and macroprudential policies (Angeloni and Faia 2013, Angelini et al. 2010, Meh and Moran 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 (NK) framework by Bernanke, Gertler, and Gilchrist (1999), which became the workhorse financial accelerator model in the twenty-first century. 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, Gertler, and Gilchrist (1999) setup.

What follows is a situation where important policy conclusions are derived from two different modeling frameworks. Although 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, Kolasa, and Makarski (2013) 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 Bayesian techniques, and evaluate their fit as well as power to explain the past. Several recent papers have looked at the performance of estimated DSGE models with financial frictions. Christensen and Dib (2008) estimate an EFP-type model for the United States using a maximum-likelihood procedure and find that the financial accelerator mechanism is supported by the data. This result was confirmed for both U.S. and euro area data by Queijo von Heideken (2009) using Bayesian techniques. Christiano, Motto, and Rostagno (2010) augment the standard NK model with an EFP-like financial accelerator and the banking sector similar to Chari, Christiano, and Eichenbaum (1995). They feed their model with a number of various shocks, estimate it on euro area and U.S. data 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 techniques and data for the euro area. Darracq Pariès, Kok Sørensen, and Rodriguez

Palenzuela (2010) show that predetermined, eternally binding credit constraints perform relatively poorly when confronted with the data. Unfortunately, neither study discusses whether their frameworks improve over the benchmark without financial frictions.

The existing literature does not answer the question, which of the basic financial friction models is more in line with the data. We contribute by estimating the alternative 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 setup performs even worse than the frictionless NK benchmark. As to the EFP variant, the evidence is mixed: in some exercises it performs somewhat better than the NK model, in others, worse. Definitely, a clear improvement cannot be observed. A similar picture emerges from comparing impulse responses of the three models to standard shocks. Last but not least, we document the inability of financial disturbances in both financial friction frameworks to explain a substantial portion of variability of key macroeconomic variables, even though they are essential to account for fluctuations in loans and spreads. In other words, financial shocks explain mainly financial variables.

In our view, these results suggest that the two standard financial accelerator setups do not constitute a significant improvement over the NK framework in modeling business cycle dynamics. 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 (Jeanne and Korinek 2010, Mendoza 2010, Brunnermeier and Sannikov Forthcoming), seems to be a necessary step.

The rest of the paper is organized as follows. Section 1 introduces the NK model and its two alternative extensions featuring two types of financial frictions. In Section 2 we discuss their estimation. Section 3 evaluates the models using marginal likelihoods, impulse responses, and shock decompositions. Robustness checks are presented in Section 4, and Section 5 concludes. Some results have been delegated to the supporting information.

1. THE MODEL

Our departure point is a standard medium-sized closed-economy NK model with sticky prices and a standard set of other frictions that have been found crucial for ensuring a reasonable empirical fit (see Smets and Wouters 2003, Christiano, Eichenbaum, and Evans 2005). 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, that is, 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. The full set of log-linearized equations is presented in the supporting information.

1.1 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

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

where 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:

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

where P_t denotes the price of a consumption good. As in Chari, Kehoe, and McGrattan (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:

$$n_t = \left(\int_0^1 n_t\,(h)^{\frac{1}{\phi_{w,t}}}\, dh \right)^{\phi_{w,t}}, \tag{3}$$

where $\phi_{w,t}$ is an exogenous wage markup.

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.

1.2 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.

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 investment-specific shocks Ψ_t and adjustment costs $S_t \equiv S(i_t/i_{t-1})$.[1] Thus, the technology to produce new capital is given by

$$k_t = (1 - \delta)k_{t-1} + \Psi_t(1 - S_t)i_t. \tag{4}$$

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

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:

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

where ϕ_t is an exogenous price markup.

1. We adopt the specification of Christiano, Eichenbaum, and Evans (2005) and assume that $S(1) = 0$, $S'(1) = 0$, and $S''(1) = \kappa > 0$.

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:

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

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.

1.3 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.

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, Motto, and Rostagno (2003), we assume that this distribution is log-normal, with a stochastic standard deviation of $\log a_E$ equal to $\sigma_{E,t}$.

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 nondefault 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

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

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

$$R_{E,t+1} Q_t k_t \psi_{t+1} = L_t R_t, \tag{10}$$

where $\psi_t \equiv \psi(\tilde{a}_{E,t}, \sigma_{E,t}) = \tilde{a}_{E,t}(1 - \int_0^{\tilde{a}_{E,t}} dF(a_E)) + (1-\mu) \int_0^{\tilde{a}_{E,t}} a_E dF(a_E)$ summarizes the return obtained by banks from defaulting and nondefaulting entrepreneurs.

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

$$E_t \left\{ \frac{\int_{\tilde{a}_{E,t}}^{\infty} \left(R_{E,t+1} Q_t k_t(\iota) a_E(\iota) - R_{L,t+1} L_t(\iota) \right) dF(a_E(\iota))}{R_t V_t(\iota)} \right\}, \tag{11}$$

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 $\chi_t^{EFP} \equiv \chi^{EFP}(\tilde{a}_{E,t}, \sigma_{E,t}) \geq 0$ between the rate of return on capital and the risk-free rate

$$R_{E,t+1} = (1 + \chi_{t+1}^{EFP}) R_t, \tag{12}$$

where $\chi_t^{EFP} \equiv \chi^{EFP}(\tilde{a}_{E,t}, \sigma_{E,t}) = \frac{\psi'_{t+1} + \mu \varrho'_{t+1}}{\psi'_{t+1}(1 - \psi_{t+1} - \mu \varrho_{t+1}) + (\psi'_{t+1} + \mu \varrho'_{t+1}) \psi_{t+1}} - 1 \geq 0$, $\varrho_t \equiv \varrho(\tilde{a}_{E,t}, \sigma_{E,t}) = \int_0^{\tilde{a}_{E,t}} a_E dF(a_E)$, and a prime over a function represents the derivative with respect to the first argument. It can be verified that if $\mu = 0$, that is, monitoring by banks is free, then $\chi_t^{EFP} = 0$, financial markets work without frictions and the EFP variant simplifies to the standard NK setup.

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

$$R_{L,t+1} = \frac{\tilde{a}_{E,t+1}}{\psi_{t+1}} R_t. \tag{13}$$

Proceeds from selling capital, net 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 in each period a randomly selected

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

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 transfer t_E from households, fixed in real terms. 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:

$$V_t = \nu_t \left[R_{E,t} Q_{t-1} k_{t-1} - \left(R_{t-1} + \frac{\mu_{Q_t} R_{E,t} Q_{t-1} k_{t-1}}{L_{t-1}} \right) L_{t-1} \right] + P_t t_E. \tag{14}$$

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

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

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 $R_{L,t}$

$$\begin{aligned} P_t c_{E,t}(\iota) + Q_t k_t(\iota) + R_{L,t-1} L_{t-1}(\iota) + P_t \tilde{t}_E \\ = (R_{k,t} + Q_t(1-\delta)) k_{t-1}(\iota) + L_t(\iota), \end{aligned} \tag{16}$$

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

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

where m_t is the stochastic loan-to-value ratio. We assume that β_E is sufficiently below β and so 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 $L_t(i)$ 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

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

where $\phi_{L,t}$ is a stochastic measure of substitutability between loan varieties.[3]

3. This shock introduces fluctuations in credit spreads and hence makes it possible to treat this variable as observable in estimation.

Each bank i collects deposits $D_t(i)$ 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, which gives

$$R_{L,t} = \phi_{L,t} R_t. \tag{19}$$

Solving the problem of entrepreneurs, banks and financial intermediaries yield the following analog to (12) from the EFP variant:

$$R_{E,t+1} = \left(1 + \Theta_t \chi_{t+1}^{CC}\right) \phi_{L,t} R_t, \tag{20}$$

where $\chi_t^{CC} \equiv \chi^{CC}(R_{k,t}, Q_t, Q_{t-1}, m_{t-1}) = \frac{R_{k,t}+(1-\delta)Q_t(1-m_{t-1})}{Q_{t-1}} > 0$ and Θ_t 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. Since χ_t^{CC} is strictly positive, a tighter constraint (higher Θ_t) increases the wedge, depressing the amount of capital further below the efficient level. In the special case, when the collateral constraint is not binding ($\Theta_t = 0$) and the banking industry is perfectly competitive ($\phi_{L,t} = 1$), financial frictions disappear, making the CC variant equivalent to the standard NK setup.

Comparing the alternative setups. As can be seen by comparing formulas (12) and (20), both the EFP and CC variants drive an endogenous wedge between the rate of return on capital and the risk-free rate. However, the response of these wedges to common shocks is not the same in both setups because of the differences in the underlying financial structures. Another important difference is related to the determination of the lending rate. EFP-like frictions result in an endogenous spread between the lending and deposit rates even though the banking sector is perfectly competitive (see equation (13)). In contrast, as can be seen from (19), interest rate spread is purely exogenous in the CC setup and equals zero if the banking sector is perfectly competitive. Moreover, the lending rate in the EFP framework is state contingent, that is, subject to uncertainty, while it is predetermined in the CC variant.

1.4 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 $T_t = g_t$.

As it is common in the NK literature, the 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

$$R_t = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\gamma_R} \left(\left(\frac{\pi_t}{\bar{\pi}}\right)^{\gamma_\pi} \left(\frac{y_t}{\bar{y}}\right)^{\gamma_y}\right)^{1-\gamma_R} e^{\varphi_t}, \tag{21}$$

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.

1.5 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:

$$c_t + i_t + g_t + \mu \varrho_t R_{E,t} q_{t-1} k_{t-1} = y_t. \tag{22}$$

The counterpart of (22) in the CC variant includes entrepreneurs' consumption

$$c_t + i_t + g_t + c_{E,t} = y_t. \tag{23}$$

By dropping monitoring costs from (22) or entrepreneurs' consumption from (23), we obtain the market clearing condition for the standard NK model.

1.6 Exogenous Shocks

Business cycle fluctuations in the simplest version of our model (NK) are driven by stochastic disturbances to productivity (A_t), households' preferences (Γ_t), investment technology (Ψ_t), government spending (g_t), price markups (ϕ_t), wage markups ($\phi_{w,t}$), and the Taylor rule (φ_t). This is a standard set of shocks used in medium-sized DSGE models. Each of the extensions includes two more shocks related to the financial sector. In the EFP variant, these are the standard deviation of idiosyncratic productivity ($\sigma_{E,t}$) 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 loan-to-value (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.

2. ESTIMATION

2.1 Data

We estimate the log-linearized approximations of all three model versions laid down in the previous section with Bayesian techniques. We use quarterly U.S. data spanning the 1970–2010 period. In the NK model, the observable variables are the same seven macroeconomic aggregates as in Smets and Wouters (2007): real output, real consumption, real investment, hours worked, real wages, inflation, and the nominal interest rate. In the EFP and CC variants, we additionally use two financial variables, that is, real loans to firms and spread on loans to firms, both defined as in Christiano, Motto, and Rostagno (2010). See the supporting information for exact definitions and data sources. Trending data (GDP, consumption, investment, wages, and loans) are made stationary by removing a linear trend from their logs, while the interest rate, inflation, and the spread are demeaned.

TABLE 1

CALIBRATED PARAMETERS

Parameter	Values	Description
Common parameters		
β	0.995	Discount rate
A_n	700	Weight of labor in utility
ϕ_w	1.2	Labor markup
α	0.33	Output 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_E	0.29	Steady-state st. dev. of idiosyncratic productivity
t_E	0.029	Transfers to entrepreneurs (percent of 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 (percent of steady-state output)

2.2 Calibration and Prior Assumptions

As is common in the applied DSGE literature, we keep a number of parameters fixed in the estimation. 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 U.S. data.

Parameters specific to the EFP or CC variants are calibrated in the following fashion. In each of our extensions to the NK setup, the financial sector is governed by four parameters. These 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, half of capital is financed by loans (Bernanke, Gertler, and Gilchrist 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, Motto, and Rostagno (2010). As a result, our calibration implies that the steady-state rate of return on capital, and hence

TABLE 2
PRIORS FOR ESTIMATED PARAMETERS

Parameter	Distr. type	Mean	Std.	Description
ξ	beta	0.6	0.1	Degree of external habit formation
σ_c	normal	2.0	0.5	Inverse of intertemporal elasticity of substitution
σ_n	normal	2.0	0.05	Inverse of Frisch elasticity of labor supply
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_Γ	beta	0.50	0.20	Preference shock: inertia
ρ_Ψ	beta	0.50	0.20	Investment shock: inertia
ρ_g	beta	0.50	0.20	Government spending shock: inertia
ρ_ϕ	beta	0.50	0.20	Price markup shock: inertia
ρ_{ϕ_w}	beta	0.50	0.20	Wage markup shock: inertia
ρ_ν/ρ_m	beta	0.50	0.20	Net worth/LTV shock: inertia
$\rho_{\sigma_E}/\rho_{\phi_L}$	beta	0.50	0.20	Riskiness/spread shock: inertia
σ_A	inv. gamma	0.01	Inf	Productivity shock: volatility
σ_Γ	inv. gamma	0.01	Inf	Preference shock: volatility
σ_Ψ	inv. gamma	0.01	Inf	Investment shock: volatility
σ_g	inv. gamma	0.01	Inf	Government spending shock: volatility
σ_ϕ	inv. gamma	0.01	Inf	Price markup shock: volatility
σ_{ϕ_w}	inv. gamma	0.01	Inf	Wage markup shock: volatility
σ_φ	inv. gamma	0.01	Inf	Monetary shock: volatility
σ_ν/σ_m	inv. gamma	0.01	Inf	Net worth/LTV shock: volatility
$\sigma_{\sigma_E}/\sigma_{\phi_L}$	inv. gamma	0.01	Inf	Riskiness/spread shock: volatility

the excess return on capital defined by equations (12) and (20), 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 and relatively uninformative.

2.3 Posterior Estimates

The posterior estimates are reported in Table 3.[4] They are obtained using the Metropolis–Hastings algorithm. We run 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) (see the supporting information).

Our parameter estimates for the NK model are broadly in line with the related DSGE literature based on U.S. data. In particular, the posterior means of parameters describing nominal and real rigidities, that is, Calvo probabilities and indexation in

4. The marginal prior and posterior distributions of the model parameters are plotted in the supporting information. All estimations in this paper, except the VAR model from Section 3.2, are done with Dynare (www.dynare.org).

TABLE 3
Estimation Results

Parameter	EFP Mean	EFP 5%	EFP 95%	CC Mean	CC 5%	CC 95%	NK Mean	NK 5%	NK 95%
ξ	0.491	0.389	0.590	0.714	0.642	0.788	0.488	0.363	0.613
σ_c	2.433	1.885	2.961	2.014	1.604	2.429	2.637	2.104	3.170
σ_n	2.006	1.922	2.088	2.008	1.926	2.089	2.011	1.932	2.094
θ	0.651	0.596	0.706	0.629	0.572	0.686	0.635	0.577	0.693
ζ	0.122	0.042	0.200	0.147	0.050	0.236	0.133	0.043	0.216
θ_w	0.746	0.685	0.807	0.854	0.815	0.897	0.786	0.728	0.846
ζ_w	0.626	0.460	0.786	0.631	0.489	0.777	0.604	0.447	0.759
κ	6.690	5.345	8.085	9.874	8.816	10.972	5.578	3.701	7.385
γ_R	0.774	0.744	0.805	0.778	0.750	0.807	0.785	0.753	0.819
γ_π	1.439	1.329	1.545	1.493	1.378	1.605	1.364	1.245	1.481
γ_y	−0.019	−0.044	0.006	−0.024	−0.037	−0.011	−0.028	−0.053	−0.003
ρ_A	0.983	0.970	0.997	0.993	0.988	0.997	0.984	0.973	0.996
ρ_Γ	0.832	0.731	0.939	0.425	0.237	0.627	0.784	0.647	0.916
ρ_Ψ	0.694	0.624	0.764	0.481	0.436	0.525	0.771	0.668	0.878
ρ_g	0.950	0.924	0.976	0.962	0.935	0.989	0.974	0.956	0.992
ρ_ϕ	0.748	0.669	0.829	0.751	0.680	0.824	0.767	0.681	0.853
ρ_{ϕ_w}	0.283	0.140	0.428	0.188	0.077	0.299	0.237	0.100	0.373
ρ_v/ρ_m	0.363	0.254	0.467	0.992	0.987	0.997			
$\rho_{\sigma_E}/\rho_{\phi_L}$	0.903	0.870	0.936	0.793	0.752	0.836			
σ_A	0.006	0.006	0.007	0.006	0.006	0.007	0.006	0.006	0.007
σ_Γ	0.027	0.022	0.033	0.036	0.027	0.045	0.027	0.021	0.034
σ_Ψ	0.070	0.055	0.085	0.316	0.260	0.370	0.047	0.029	0.063
σ_g	0.048	0.044	0.053	0.035	0.032	0.039	0.037	0.034	0.041
σ_ϕ	0.012	0.010	0.014	0.016	0.012	0.020	0.003	0.002	0.003
σ_{ϕ_w}	0.013	0.011	0.016	3.647	1.468	5.827	0.012	0.009	0.013
σ_φ	0.003	0.002	0.003	0.003	0.003	0.003	0.013	0.010	0.016
σ_v/σ_m	0.008	0.007	0.009	0.015	0.013	0.017			
$\sigma_{\sigma_E}/\sigma_{\phi_L}$	0.121	0.105	0.137	0.002	0.002	0.003			

prices and wages as well as investment adjustment costs, fall into the respective 90% intervals reported by Smets and Wouters (2007).

Adding financial frictions to the NK setup changes the estimates of some of the parameters significantly. First, wages appear to be more sticky (higher θ_w) according to the CC model. Second, the estimated curvature of the investment adjustment cost function κ and the degree of habit persistence ξ in the CC model are significantly larger than those in the baseline NK model or the EFP extension. This finding is consistent with Brzoza-Brzezina, Kolasa, and Makarski (2013), who point at relatively strong propagation of shocks on real variables in the EFP setup in comparison to the CC model. Thus, the latter model requires more real and nominal rigidities to match the data.

3. MODEL EVALUATION

3.1 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,

TABLE 4

MARGINAL LIKELIHOOD COMPARISON

	EFP	CC	NK
$p(Y_{nf}, Y_f)$, Y_f ~AR(1) in NK	−1470.4	−1520.5	−1491.3
$p(Y_{nf}, Y_f)$, Y_f ~AR(2) in NK	−1470.4	−1520.5	−1446.1
$p(Y_{nf} \mid Y_f)$	−1277.3	−1326.9	−1219.4

NOTE: $p(\bullet)$ is log marginal likelihood, while Y_{nf} and Y_f stand for nonfinancial (output, consumption, investment, real wage, labor, inflation, and the interest rate) and financial (loans and spreads) variables, respectively.

this poses a problem since a direct comparison of marginal likelihoods (calculation of the posterior odds ratios) is valid only if the evaluated models are estimated with the same data sets. As in our baseline setting, this is not the case (the NK model is estimated without financial variables), we take two alternative approaches that help us circumvent this problem. While some authors (e.g., Christensen and Dib 2008; Queijo von Heideken 2009) simply drop financial variables from financial models in order to compare them against their frictionless benchmark, we decided not to take this avenue. In our view, the idea of testing financial friction models without the use of financial variables could be hard to defend. In contrast, we offer two approaches that allow us to make meaningful comparisons without dropping financial variables. The results discussed later are collected in Table 4. When interpreting the differences in marginal likelihoods, we refer to Jeffreys (1961) who suggests a difference larger than 2.3 log points as strongly indicative of a superior performance of one model.

The first approach relies on enlarging the NK model with financial variables. As these variables do not show up in the model equations, this is done in a nonstructural way; that is, we assume simple time-series processes that drive the two financial variables. In particular, we introduce them as first- or second-order autoregressive processes. The priors for their parameters are parameterized as for stochastic shocks. In particular, the prior for the first and second lag is centered at 0.5 and 0, respectively. The idea of using AR(1) and AR(2) processes is to provide two most basic time-series representations for the financial variables. While not being a formal test, the failure of the financial friction models, in which the financial variables are allowed to respond to structural shocks, to beat any of these simple autoregressive processes could be interpreted as their serious deficiency.

According to our results, the EFP model performs better than the NK model if the latter is augmented with financial variables modeled as AR(1). However, adding just one extra lag in the autoregressive processes for loans and spreads flips the ranking. The CC model does even worse in this contest as it is not able to outperform the NK model with financial variables assumed to follow AR(1) processes.

The second approach follows Neri and Ropele (2012) and makes use of the notion of conditional marginal likelihood. More specifically, we calculate conditional marginal likelihoods for financial friction models as

$$p(Y_{nf}|Y_f, M_i) = \frac{p(Y_{nf}, Y_f|M_i)}{p(Y_f|M_i)} \qquad i = CC,\ EFP, \tag{24}$$

where Y_f and Y_{nf} collect financial and nonfinancial variables, respectively. These conditional likelihoods are next compared with the marginal likelihood of the NK model, estimated with nonfinancial data only. Intuitively, this procedure allows us to net out the impact of financial variables on the marginal likelihoods, while keeping these variables in the estimation process of financial models.[5] As evidenced in Table 4, this metric suggests that both financial friction models fit the data worse than the NK benchmark.

All in all, the evidence from comparisons of the marginal likelihoods casts clear doubt over the data fit of both financial friction frameworks. The CC model performs worse than the NK setup for any measure used. The EFP model is able to compete with the NK benchmark extended for financial variables only if these are introduced in a very simple way.

3.2 Comparison with VARs

As a next step, we compare the performance of all three models against an empirical benchmark. In particular, we compare the impulse responses from our models with those from a VAR. For our exercise we choose productivity and monetary policy shocks. Not only do these shocks play an important role in driving the dynamics of DSGE models, but also does the existing literature provide methods for their identification. This is unfortunately not true for the remaining shocks present in our models.

Our empirical benchmark is a VAR model estimated with the same set of observable variables as the DSGE models with financial frictions. Following the recent literature, shocks are identified using sign restrictions (Canova and Nicolo 2002, Uhlig 2005, Dedola and Neri 2007). The restrictions follow Canova and Paustian (2010), who provide evidence from a substantial selection of models and identify robust response patterns for some macroeconomic variables. In particular, in response to a contractionary monetary policy shock they document a positive response of the interest rate and negative responses of inflation and output. In response to a positive technology shock, the robust result is a positive response of output and negative responses of the interest rate and inflation. Given our data set, we augment this pool of restrictions by the reaction of investment, assumed negative in reaction to monetary policy tightening and positive after a technology improvement. The former is consistent with numerous studies on the monetary transmission mechanism (e.g., Christiano, Eichenbaum, and Evans 2005), while the latter with Dedola and Neri (2007). We believe that our restrictions are relatively uncontroversial.

As to the horizon over which the restrictions apply, there are two streams in the literature. Some authors (e.g., Canova and Paustian 2010) impose them only on

5. One should note, however, that this procedure can give an unfair advantage to models estimated on a wider data set. To see it, note that unconditional marginal likelihood for a given model can be interpreted as a measure of its out-of-sample forecasting performance. Hence, if we condition it on a subset of variables that are observed over the whole sample as in formula (24), we allow the forecasts to be influenced by future realizations of these variables. Since our results nevertheless point toward superiority of the NK model, these considerations make our conclusions even stronger.

impact. Others restrict the responses over longer horizons (e.g., Dedola and Neri 2007, impose restrictions ranging between 1 and 19 quarters). We choose an intermediate solution. While restrictions for the impact reactions only seemed too liberal, we also do not have a source of precise estimates of horizons for each variable. As a result, we decided to restrict the selected variables to react as imposed over a four-quarter horizon.[6]

The VAR is estimated with Bayesian techniques. We assume four lags for all variables and impose a Minnesota-type prior on parameters and standard deviations. In particular, our prior assumes a random walk for all variables. The precision of the priors is calibrated as proposed by Canova (2007).[7]

Figures 1 and 2 show the impulse responses from the VAR model (90% confidence intervals) together with the reactions from our three models.[8] The DSGE models manage to match the empirical benchmark in several cases. However, there are also some notable exceptions. In particular, all models seem to attach too much persistence to productivity shocks. While empirical responses usually die out in the 40-quarter horizon, the DSGE reactions often stay far from the VAR benchmark. The opposite happens after a monetary policy shock. As known from the empirical literature, inflation declines slowly and persistently in the VAR. In contrast, in the DSGE models the reaction is fast and relatively short-lived. Also, the models have a hard time matching the responses of labor market variables after a monetary policy shock.

Quite surprisingly, our empirical benchmark does not have much to say about the reaction of loans to both shocks. One explanation of this puzzle could be that, consistent with the literature, we use stock data for this category. Its reactions to macroeconomic shocks are thus muted and, as a result, hardly significant. Finally, some impulse responses document an important feature of the CC model, that is, its relatively strong reactions on impact. This is particularly visible for the reactions of output, inflation, and investment after a monetary policy shock and seems inconsistent with the hump-shaped responses known from the literature and also visible in our VAR model. This feature of the CC framework is related to the permanently binding nature of the collateral constraint and is probably one of the explanations of its relatively poor empirical performance.

A visual inspection shows that the impulse responses of the three DSGE models are relatively similar. As such it does not give any clear indication in support of the superior performance of the financial friction models over the standard NK setup. This

6. To estimate the VAR with sign restrictions we use a MATLAB code based on Fabio Canova's script SBVAR_sign_2uncert.m.

7. The standard deviation of own lag l of variable i is set to $\sigma_{ii,l} = 0.2/l$. The standard deviation for lag l of variable j's impact on variable i is set to $\sigma_{ij,l} = 0.1/l(\sigma_j/\sigma_i)^2$, where σ_i and σ_j are standard deviations of variables i and j, respectively.

8. In order to make the comparison easier, we normalized the size of VAR shocks so that the mean reaction of the VAR equals the average mean reaction of the three DSGE models. For the productivity shock the normalization standardizes the impact reaction of output and for the monetary policy shock the impact reaction of the interest rate.

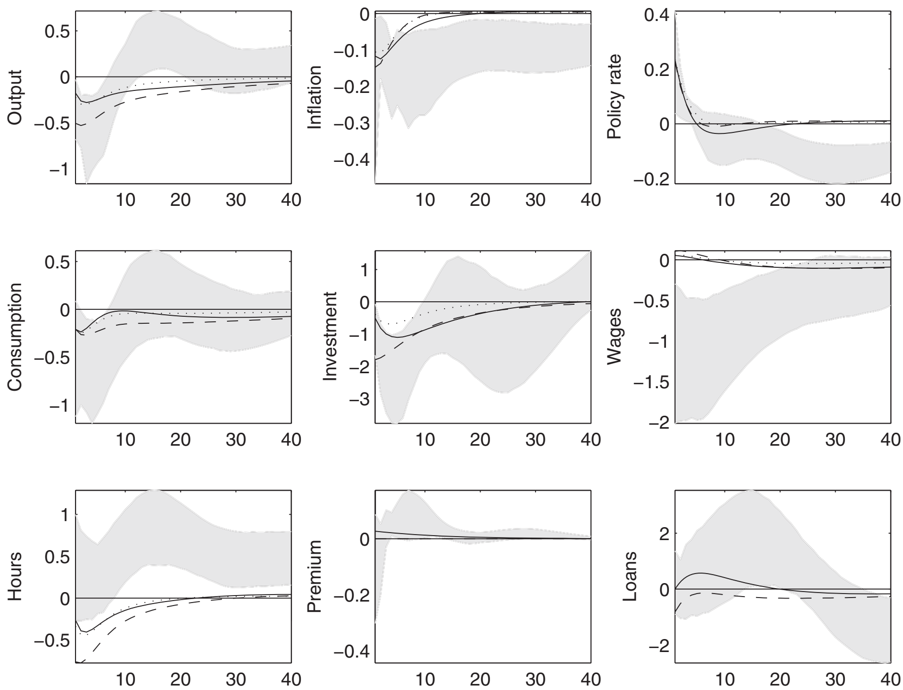

FIG. 1. Monetary Shock IRFs.

NOTE: The figure shows the posterior mean responses for the CC (dashed lines), EFP (solid lines), and NK models (dotted lines), together with 90% probability intervals for the VAR model with sign restrictions.

impression is confirmed by a formal comparison of the impulse response functions. Similar to Schorfheide (2000), we calculate for each model, shock and variable the loss based on the deviation from the mean VAR response. The loss is defined as

$$L(\varphi_i) \equiv (\varphi_i - \varphi_{VAR})' \, W \, (\varphi_i - \varphi_{VAR}) \, ,$$

where φ_i denotes the posterior mean impulse response of model $i = \{NK, \ EFP, \ CC\}$, φ_{VAR} is the posterior mean impulse response from the VAR model, and W is a positive definite weighting matrix. The loss calculated jointly for the 40-quarter horizon[9] is presented in Table 5. For most variables, the loss does not substantially differ between the models. A clear exception is the CC model, where the reactions of output, consumption, and investment to a productivity shock deviate much more from the VAR benchmark than the alternative frameworks. Looking only at the seven nonfinancial variables, the EFP model performs best in seven cases, the NK in five, and the CC in two. All in all, a comparison of the impulse responses does not yield

9. We weigh all horizons equally, that is, $W = 40^{-1} I_{[40x40]}$, where I denotes the identity matrix.

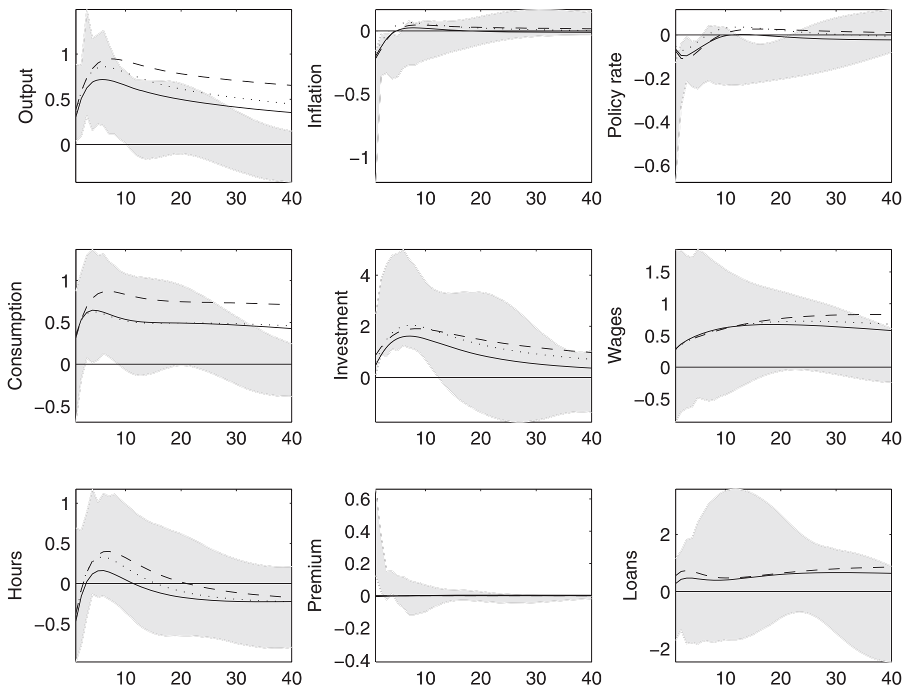

Fig. 2. Productivity Shock IRFs.

Note: The figure shows the posterior mean responses for the CC (dashed lines), EFP (solid lines), and NK models (dotted lines), together with 90% probability intervals for the VAR model with sign restrictions.

TABLE 5

Loss Function for Impulse Responses

	Productivity shock			Monetary policy shock		
Variable	NK	EFP	CC	NK	EFP	CC
Output	0.164	**0.095**	0.317	**0.079**	0.104	0.127
Inflation	0.015	0.012	**0.012**	0.014	**0.012**	0.014
Policy rate	0.013	**0.009**	0.011	0.014	**0.013**	0.014
Consumption	0.062	**0.056**	0.192	**0.042**	0.047	0.044
Investment	**0.477**	0.510	0.728	0.857	0.528	**0.442**
Wages	0.054	**0.031**	0.094	0.668	**0.621**	0.660
Hours	**0.011**	0.036	0.013	**0.510**	0.514	0.681
Premium		0.006	**0.005**		**0.002**	0.002
Loans		**0.477**	0.626		**1.462**	2.201

Note: The numbers are sums of squared deviations of DSGE models' posterior mean impulse responses from the posterior mean VAR impulse response in the 40-quarter horizon. Numbers in bold denote the smallest deviations for each variable and shock.

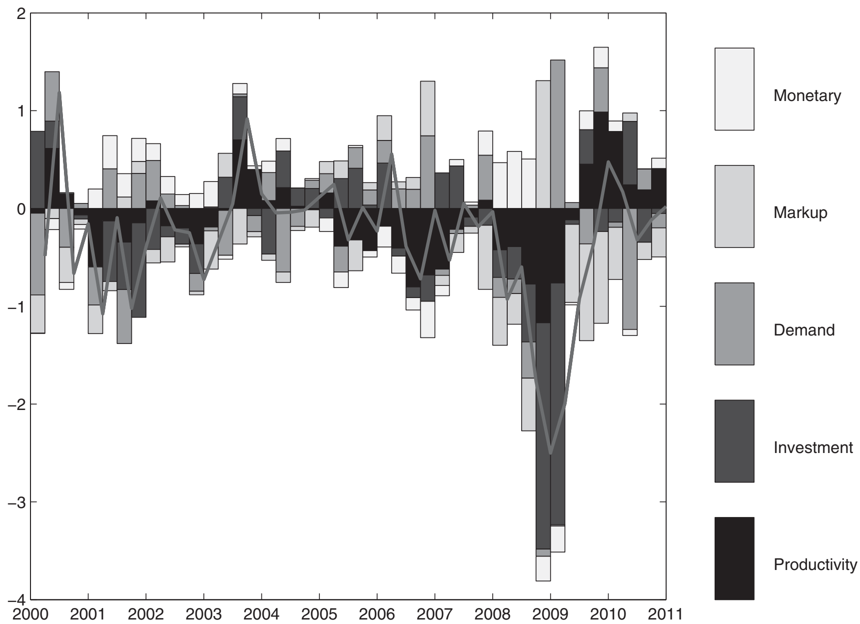

FIG. 3. Decomposition of Output Growth—NK.

NOTE: The markup category collects price and wage markup shocks, while the demand category merges consumption preference and government spending shocks.

clear support for a superior performance of any financial friction models over the nonfinancial benchmark.

3.3 The Role of Financial Shocks

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 3 to 5. For the sake of transparency, we only show data since 2000Q1 and group some of shocks into broader categories. Starting with the NK benchmark, it is clear that in this model the business cycle is driven mainly by productivity and investment-specific disturbances, which is consistent with Justiniano, Primiceri, and Tambalotti (2010). As we move to models with financial frictions, financial shocks start playing some role in determining output fluctuations. In both variants, they have a substantial, though not overwhelming, contribution to the output decline observed during the 2007–09 financial crisis. However, in normal times the role of these shocks is relatively small, especially in the EFP model.

To explore this observation in more detail, in Table 6 we present forecast error variance decompositions for output and the two financial variables used in estimation,

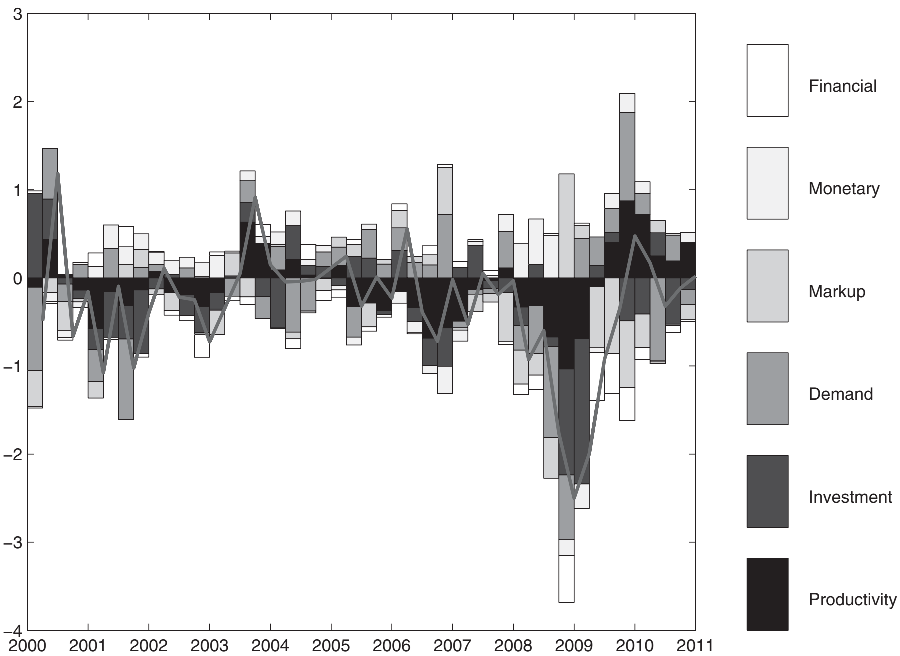

FIG. 4. Decomposition of Output Growth—EFP.

NOTE: The financial category collects net worth and riskiness shocks. The markup and demand categories are defined as in Figure 3.

as well as a related breakdown of output contraction during the Great Recession. In both EFP and CC models, financial shocks are crucial in accounting for short- and medium-term fluctuations of loans and essentially the only drivers of credit spreads.[10] However, the impact of these shocks on output is rather small. Even during the recent crisis, the contribution of financial shocks as identified by the EFP and CC setups amounted to merely 15%.

4. ROBUSTNESS CHECKS

In order to check the sensitivity of our findings we conduct a number of robustness checks. In particular, we provide additional evidence regarding the choice of sample, estimated parameters, and observable variables. The former is motivated by the

10. In the CC variant, the latter result follows from the fact that the model does not generate endogenous fluctuations in spreads and hence their movements are entirely due to exogenous spread shocks. In the EFP model, spreads are endogenous and hence can respond to all shocks. However, even in this setup credit spreads are almost entirely driven by disturbances to the volatility of idiosyncratic risk.

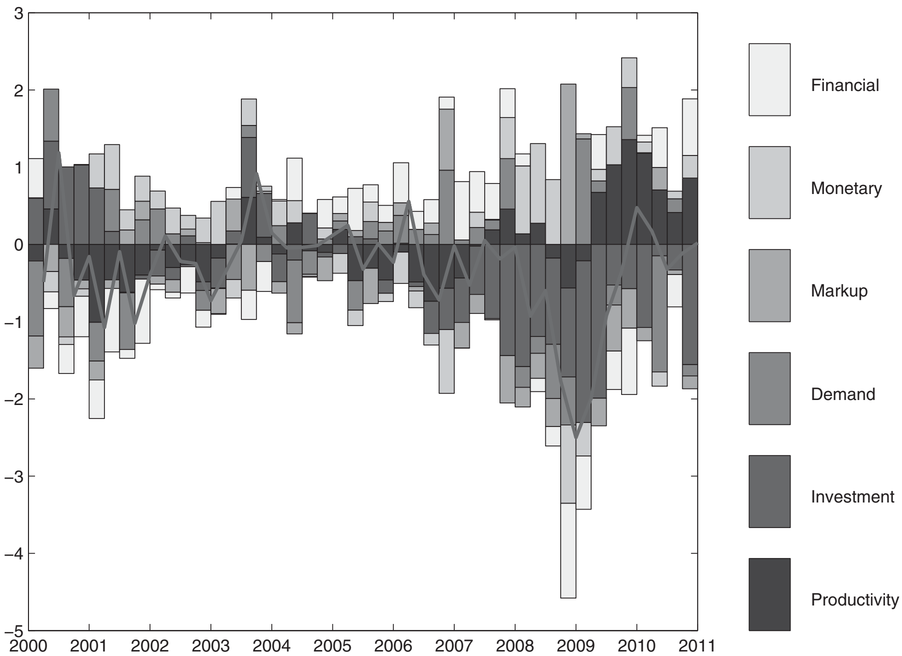

FIG. 5. Decomposition of Output Growth—CC.

NOTE: The financial category collects LTV and spread shocks. The markup and demand categories are defined as in Figure 3.

inhomogeneity of our full sample as it contains the period of relatively high inflation (1970–85), the period of low inflation and substantial macroeconomic stability (1986–2007), and the financial crisis (2008–10).[11] Table 7 provides marginal likelihood estimates for the first two subsamples and for the sample excluding the financial crisis (1970–2007). Given the number of observations, it is not possible to conduct a separate estimation for the crisis sample. As before, we compare the EFP and CC models with the NK benchmark extended for financial variables modeled as an AR(1) or AR(2) process, as well as marginal likelihoods conditioned on financial variables.

Our findings are as follows. First, the worst performance of the CC model is confirmed in all subsamples. Second, the EFP model also performs worse than the NK benchmark in all subsamples when evaluated through the lenses of conditional marginal likelihoods. The only case where the NK model augmented with AR(2) for financial variables is beaten by the EFP is the 1986–2007 subsample.

The second robustness check reflects the uncertainty with respect to the choice of the observable variable for spreads. Although in the baseline model we follow

11. Fuentes-Albero (2012) considers an EFP-like model and finds that some of its parameters, and shock volatilities in particular, differ substantially across the Great Inflation and Great Moderation periods.

TABLE 6

Role of Financial Shocks

Variable	Model	Net worth/LTV	Risk/spread	Investment	Other
Four-quarter-ahead forecast error variance decomposition					
Output	NK	–	–	37.9	62.1
	EFP	0.3	2.0	30.0	67.7
	CC	5.8	3.9	38.4	52.0
Loans	NK	–	–	–	–
	EFP	42.8	4.9	7.3	45.0
	CC	35.9	5.7	12.3	46.2
Spread	NK	–	–	–	–
	EFP	1.9	95.6	0.8	1.7
	CC	0.0	100.0	0.0	0.0
Eight-quarter-ahead forecast error variance decomposition					
Output	NK	–	–	37.9	62.1
	EFP	0.6	5.5	27.4	66.5
	CC	3.4	2.9	42.7	51.0
Loans	NK	–	–	–	–
	EFP	31.5	13.5	18.3	36.7
	CC	37.6	3.0	29.3	30.1
Spread	NK	–	–	–	–
	EFP	2.4	94.4	1.2	2.0
	CC	0.0	100.0	0.0	0.0
Cumulative contraction during Great Recession					
Output	NK	–	–	71.0	29.0
	EFP	11.0	4.4	34.8	49.8
	CC	−5.0	20.5	120.8	−36.4

Note: All numbers are expressed in percent.

TABLE 7

Marginal Likelihoods—Robustness Checks

	EFP	CC	NK
1970–2007			
$p(Y_{nf}, Y_f)$, Y_f ~AR(1) in NK	−1318.3	−1359.5	−1330.8
$p(Y_{nf}, Y_f)$, Y_f ~AR(2) in NK	−1318.3	−1359.5	−1294.0
$p(Y_{nf} \mid Y_f)$	−1133.5	−1179.2	−1077.7
1970–85			
$p(Y_{nf}, Y_f)$, Y_f ~AR(1) in NK	−709.4	−719.9	−708.9
$p(Y_{nf}, Y_f)$, Y_f ~AR(2) in NK	−709.4	−719.9	−706.1
$p(Y_{nf} \mid Y_f)$	−589.6	−591.5	−561.1
1986–2007			
$p(Y_{nf}, Y_f)$, Y_f ~AR(1) in NK	−533.0	−647.3	−576.4
$p(Y_{nf}, Y_f)$, Y_f ~AR(2) in NK	−533.0	−647.3	−550.8
$p(Y_{nf} \mid Y_f)$	−502.4	−587.8	−497.0
1973q1–2010q3, Gilchrist-Zakrajsek spread			
$p(Y_{nf}, Y_f)$, Y_f ~AR(1) in NK	−1192.2	−1334.4	−1271.1
$p(Y_{nf}, Y_f)$, Y_f ~AR(2) in NK	−1192.2	−1334.4	−1229.0
$p(Y_{nf} \mid Y_f)$	−1125.6	−1263.8	−1125.1
1970–2010, financial block estimated			
$p(Y_{nf}, Y_f)$, Y_f ~AR(1) in NK	−1438.1	−1521.4	−1491.3
$p(Y_{nf}, Y_f)$, Y_f ~AR(2) in NK	−1438.1	−1521.4	−1446.1
$p(Y_{nf} \mid Y_f)$	−1241.9	−1315.0	−1219.4

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

Christiano, Motto, and Rostagno (2010), we also decided to check the sensitivity of our findings to the use of spread estimates recently proposed by Gilchrist and Zakrajsek (2012). The results presented in Table 7 suggest that this alternative way of measuring credit spreads is favorable to the relative data fit of the EFP setup. Its conditional marginal likelihood is now very similar to that of the NK benchmark. Moreover, modeling financial variables in the NK model as simple univariate AR processes is not enough to beat the EFP extension. However, the CC model's worst performance remains unaffected by the choice of financial spreads.

Our final robustness check is related to the estimation of parameters related to the financial sector. As discussed before, they determine such key steady-state ratios as investment share in output, leverage, and spreads, the values of which cannot be easily identified with detrended data. These parameters also reflect differences in modeling concepts and hence their priors cannot be made comparable across the EFP and CC models. These are the reasons why we refrain from estimating the parameters describing the financial block in our baseline approach. However, as these parameters do affect the strength of the financial accelerator, we now allow them to be inferred from the data. More specifically, we estimate μ, ν, and σ_{a_E} in the EFP setup and β_E, ϕ_L, and m in the CC variant. In each case, the priors are centered around the values that we used to calibrate our baseline (see Table 1).[12]

The last section of Table 7 shows that allowing for estimation of the financial sector parameters does not change our main conclusions. Again, the CC model performs worst while the EFP variant fails to offer a clear improvement over the NK benchmark, even though it cannot be beaten by just adding simple AR processes for financial variables to the NK setup.

5. CONCLUSIONS

After the financial crisis 2007–09, models featuring financial frictions are promptly entering into the mainstream of macromodeling. They have been used *inter alia* 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 of 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 EFP framework of Bernanke, Gertler, and Gilchrist (1999) and the CC model of Kiyotaki and Moore (1997). We estimate their comparable versions on U.S. data together with the benchmark NK model. Our findings are as follows.

12. The types of *a priori* distributions used and their parameterization are reported in the supporting information.

First, the comparison of marginal likelihoods clearly favors the Bernanke, Gertler, and Gilchrist (1999) framework over the Kiyotaki and Moore (1997) model. However, the former improves upon the benchmark NK model without financial frictions only in some settings, and the latter always performs much worse than the benchmark.

Second, a comparison of the impulse responses from the three DSGE models to a VAR model does not render support to the superior performance of the financial friction extensions to the standard NK setup. Moreover, the CC model generates responses to monetary and productivity shocks that do not display hump-shaped patterns visible in the VAR.

Third, we examine how the models interpret the sources of U.S. business cycle fluctuations, including the output collapse during the recent financial crisis. We find that even though financial shocks account for essentially all fluctuations in spreads and a large fraction of movements in loans, their role in driving output was rather small in normal times and only moderate during the 2007–09 recession.

We conclude that none of the evaluated financial friction frameworks offers a clear improvement over the frictionless benchmark in modeling business cycle dynamics. Further research is needed to find macrofinancial models that reflect reality better. Most recent research, featuring *inter alia* a more explicit modeling of financial intermediation or introducing occasionally binding constraints seem interesting avenues.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Technical details for the results discussed.