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What Does Structural Analysis of the External Finance Premium Say About Financial Frictions?

by Jelena Zivanovic

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Acknowledgements

Abstract

I use a structural vector autoregression (SVAR) with sign restrictions to provide conditional evidence on the behavior of the US external finance premium (EFP). The results indicate that the excess bond premium, a proxy for the EFP, reacts countercyclically to supply and monetary policy shocks and procyclically to demand shocks. I confront my empirical evidence with the predictions from financial dynamic stochastic general equilibrium (DSGE) models with respect to the finance premium in order to identify an empirically relevant financial friction. The Bernanke, Gertler and Gilchrist (1999) model generates transmission mechanisms that are favored by the data.

Bank topics: Financial markets; Economic models; Recent economic and financial developments
JEL codes: E32, E44

Résumé

Je me sers d'un modèle vectoriel autorégressif structurel avec restrictions de signe dans le but de fournir des indications conditionnelles sur la dynamique de la prime de financement externe aux États-Unis. Les résultats montrent que la prime excédentaire sur les obligations, qui donne une approximation de la prime de financement externe, réagit de façon contracyclique aux chocs d'offre et de politique monétaire, et de façon procyclique aux chocs de demande. Je confronte mes résultats empiriques aux prédictions de modèles d'équilibre général dynamique et stochastique financiers à l'égard de la prime de financement afin de faire ressortir une friction financière pertinente sur le plan empirique. Le modèle construit par Bernanke, Gertler et Gilchrist (1999) génère des mécanismes de transmission soutenus par les données.

Sujets : Marchés financiers; Modèles économiques; Évolution économique et financière *récente*
Codes JEL : E32, E44

Non-technical summary

Motivation and question

The way financial frictions are introduced in dynamic stochastic general equilibrium (DSGE) models matters for assessing the effects of different aggregate shocks on the economy. In fact, the dynamics of the external finance premium (EFP) and real gross domestic product (GDP) differ across models with competing financial frictions. In this paper, I contrast the dynamics of the EFP and real GDP predicted by a structural vector autoregression (SVAR) model against those implied by three DSGE models that differ in how they model financial frictions. In this way, my analysis helps to clarify which financial friction framework is more in line with the data and consequently helps to guide modelers when choosing how to account for financial frictions in DSGE models.

Methodology

First, I use Bayesian techniques to assess three prominent DSGE models that differ in how they capture financial frictions. Second, I use US data to estimate a SVAR model with sign restrictions to document the conditional dynamics of the EFP. Finally, I conduct the SVAR analysis with the DSGE model-implied data in order to confront it with the SVAR evidence based on the US data.

Key contributions

I provide empirical evidence on the conditional dynamics of the EFP and real GDP. I also evaluate whether the predictions for these variables of the three estimated DSGE models are consistent with the SVAR evidence for the United States.

Findings

The SVAR evidence reveals that the source of the shock matters in determining the comovement between the excess bond premium, a proxy for the EFP, and economic activity. In response to demand shocks, both move in the same direction. In contrast, in response to aggregate supply and monetary policy shocks, the EFP and output move in opposite directions. Confronting the dynamics of the EFP in the DSGE models with the data, I find that the best performing model is the one with costly state verification.

Future work

By using macroeconomic data and different estimation techniques, this analysis suggests that costly state verification is the most relevant financial friction. It would be useful to explore micro-level firm data on external financing to identify which financial friction should be embedded in macro models.

1   Introduction

Since the Great Recession, modeling of financial frictions has gained in importance because these frictions affect the propagation of economic shocks. The amplification of these shocks in financial dynamic stochastic general equilibrium (DSGE) models relies on the response of the external finance premium (henceforth, EFP). This generates a wedge between the external and internal costs of financing (see Bernanke et al., 1999; DeGraeve, 2008; Cúrdia and Woodford, 2011; Kaihatsu and Kurozumi, 2014, among others) and causes financial market conditions to affect the macroeconomy.

In this paper, I examine empirically and theoretically how different economic shocks affect the response of the EFP. The objective is to investigate the conditional dynamics of the EFP in order to discriminate among models with financial frictions. This is relevant from a policy perspective because financial frictions that are consistent with the data should be incorporated into the models used for policy analysis. The work proceeds in two steps. First, I lay out three different DSGE models: Bernanke et al. (1999); Cúrdia and Woodford (2011); Gertler and Karadi (2011) (BGG, CW and GK, respectively).[1] I take these to be representative models of financial frictions. More recent contributions to literature represent elaborations of these models that are further enhanced to tackle questions of economic interest (see Christiano et al., 2014; Carlstrom et al., 2014; Gertler et al., 2012; Bailliu et al., 2015, to name a few). Since theoretical models do not provide a consensus on how the EFP should respond to macroeconomic shocks, I examine the dynamics of a DSGE model-implied premium using a structural vector autoregression (SVAR) model with sign restrictions. Second, I repeat the SVAR analysis using US data. Finally, I confront the predictions from three theoretical models on the EFP with the data in an attempt to identify an empirically relevant financial friction.

The definition of the EFP is model-specific, reflecting financial friction in a respective DSGE model. However, the empirical counterpart is the excess bond premium (henceforth, EBP), which Gilchrist and Zakrajšek (2012) estimate from US firm-level data. This proxy of the EFP can be interpreted as a compensation for corporate credit risk, which is purged of firm-specific characteristics. Since it represents additional premium above firm-specific credit risk (which can be associated with internal costs of financing), the EBP comes closer to the theoretical concept of the EFP than alternatives such as corporate spread indices. Moreover, the advantage of this measure is the focus on the broad class of non-financial firms and the controlling for effects of interest term structure, which may otherwise exacerbate movements in credit spread indices (see Gilchrist and Zakrajšek, 2012). In the DSGE models, financial frictions propagate or attenuate the reaction of the EFP. Whereas Bernanke et al. (1999) are among the first to rationalize the the EFP in the model, the works by Gertler and Karadi (2011) and Cúrdia and Woodford (2011) refer to credit spreads as a measure of external financing costs. Both terms are used interchangeably in this work.

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[1]Hereafter, I will use the authors' names when referring to their work in general and the abbreviations when referring to the models specifically.

The analysis is organized in two steps. In the first step, three prominent DSGE models are estimated using Bayesian techniques and, subsequently, simulated to generate model-based data. To make the models comparable, I assign conventional values to the parameters unrelated to the modeling of financial market, leaving the models to differ along the lines of financial frictions. The models also feature the same number of exogenous shocks, with financial shocks hitting each financial market. I use US data from 1973Q1 to 2008Q3 in the Bayesian estimation. For the assessment of the estimated models, I generate model-implied data for the SVAR analysis.

In the second step, I estimate the SVAR model with sign restrictions using US data. The identification of the SVAR is grounded in economic theory. The specification of the SVAR with sign restrictions is in the vein of Gambetti and Musso (2017). In particular, the common denominator from various DSGE frameworks that model financial frictions defines a minimal set of sign restrictions that are used to identify aggregate supply shocks, aggregate demand shocks, monetary policy shocks and financial shocks. More importantly, the SVAR specification is consistent with the implications of the three considered DSGE models. I show that the impulse response functions have different implications for the EBP. Subsequently, the simulated data from the estimated DSGE models are also assessed through the lens of the SVAR. Finally, I confront the three theoretical models with the data in an attempt to identify an empirically relevant financial friction. In the comparison, I consider to what extent these theoretical frameworks reproduce the dynamics of the EFP and are able to explain variations in the premium and output.

My results indicate that adverse aggregate supply shocks and monetary policy shocks lead to a rise in the EFP, whereas negative aggregate demand shocks generate a decrease in the EFP. This is in line with the estimated BGG model, as it replicates the dynamics of the premium and explains well the variation of the EFP and output. In a nutshell, the propagation mechanism arising in the BGG model is the following: A negative comovement between the EFP and output conditional on technology shocks arises because inflation reacts countercyclically, which leads to a countercyclical development of leverage and the EFP. A demand shock with a countercyclical effect on credit affects the leverage procyclically and, hence, generates a procyclical EFP. An unexpected monetary tightening decreases aggregate demand, which together with the decline in the price of capital and the higher value of debt, results in an increase in the EFP (making it countercyclical). The results suggest that costly state verification implies transmission mechanisms that are favored by the empirical evidence. It should be noted, nevertheless, that Cúrdia and Woodford (2011) and Gertler and Karadi (2011) manage to match certain aspects of the data and fall short of others.

This paper belongs to the growing literature on the importance of financial factors. The role of financial shocks in business cycles has been addressed using US and European data (see, e.g., Furlanetto et al., 2017; Gambetti and Musso, 2017; Gilchrist and Zakrajšek, 2012; Mumtaz et al., 2018; Meeks, 2012, among others). The main finding of these papers is that financial shocks cause a non-negligible impact on output and play an important role in business cycle fluctuations. Closest to this paper, the work by Furlanetto et al. (2017) also documents the dynamics

of the EFP in addition to quantifying the role of financial shocks for the macroeconomy in the SVAR framework with sign restrictions. They find that the premium behaves countercyclically in reaction to aggregate supply shocks and demand shocks, whereas it is procyclical in response to monetary policy shocks. My paper differs in multiple dimensions. In contrast to the Furlanetto et al. (2017) paper, I use the EBP as a proxy for the EFP, as it better captures the theoretical concept of the EFP in terms of additional compensation (above idiosyncratic firm risk) required by financial markets. Furlanetto et al. (2017) use the spread between the BAA bond index and the federal funds rate, whereby spread fluctuations can be exacerbated by changes in the term structure, thus capturing maturity risk as well. This specification can possibly cause the response of their measure to monetary policy shocks to be procyclical. In their framework, the sign restrictions on asset prices and investment are used to disentangle asset price (financial) shocks from demand shocks and investment shocks, allowing them to better explain the contribution of financial shocks to output fluctuations. However, my main focus lies with credit market dynamics, and imposing restrictions on credit enables me to differentiate financial shocks from demand shocks. For the purpose of comparing the data response of the EFP with the reaction of the one from the estimated DSGE models, the focus on the four shocks commonly incorporated in the DSGE models makes the comparison tractable. My estimates show that some of the EFP's reactions are consistent with the predictions from three DSGE models; however, the Bernanke et al. (1999) model matches the data most closely. Finally, the focus of this paper is entirely on the empirical assessment and comparison of the model-implied EFP and data.

This work also contributes to the literature on the Bayesian assessment of DSGE models with financial frictions. The performance of the new class of models with financial frictions has been assessed in many works (see Brzoza-Brzezina et al., 2013; Christensen and Dib, 2008; Christiano et al., 2014; DeGraeve, 2008; Gerali et al., 2010; Iacoviello, 2005; Queijo von Heideken, 2009, etc). In addition to comparing how theoretical models reproduce empirical impulse responses, the model comparison addresses whether the incorporation of financial frictions improves the model's fit. Villa (2016) uses US and European data to compare the Smets and Wouters (2007) model and its two model extensions, including the friction à la Bernanke et al. (1999) and Gertler and Karadi (2011). Her findings show that financial frictions improve the model's fit. More specifically, she concludes that the GK model framework outperforms the BGG one by reproducing a stronger financial amplification mechanism and a co-movement between output and the EFP. One drawback of her analysis is that she relies on the same data set used by Smets and Wouters (2007), which abstracts from financial variables. Using data on loans and credit spreads in their Bayesian estimation, Brzoza-Brzezina and Kolasa (2013) favor the BGG model over the Kiyotaki and Moore (1997) model; however, the former only outperforms in a few specifications the standard New Keynesian model, as specified in Christiano et al. (2005). My work departs from the previous work in two ways. First, the objective is to use the SVAR framework to compare whether the models recover the dynamics of the EFP in the US and to infer an empirically relevant financial friction. Second, I treat the Bayesian estimation of the three DSGE models

and the SVAR framework[2] similarly in terms of shocks of interest and the data, unlike many other applications. The identification of the small-scale SVAR with sign restrictions is in line with predictions from DSGE models with sign restrictions. The data-generating process of each DSGE model reflects the model-specific financial friction and the EFP, which is then analyzed through the lens of the SVAR model.

I also contribute to the strand of literature on the cost of external finance and business cycles (see DeGraeve, 2008; Eisfeldt and Muir, 2016; Faia and Monacelli, 2007; Gomes et al., 2003; Huh and Kim, 2018; Levin et al., 2004; Villa, 2016; Walentin, 2005, etc). The literature associates amplification of shocks through the EFP with different financial frictions. Similar to this paper, DeGraeve (2008) estimates the model-implied measure of the EFP and finds that it correlates well with the estimate of the EFP from micro-level data, based on Levin et al. (2004), and the high-yield credit spread. My work emphasizes, however, a tight relation between financial frictions and the EFP. It should be noted that the three considered DSGE models can recover the cyclicality of the premium. This is good news for macroeconomic modeling of financial frictions. In terms of the model fit, the model comparison reveals that costly state verification best recovers the conditional dynamics of the EBP.

The remainder of the paper is organized along the following lines. Section 2 addresses the Bayesian estimation of three DSGE models. Section 3 presents the main results and the robustness analysis. Section 4 concludes.

2   SVAR framework to compare theory with the data

The starting point of the analysis is the assessment of prominent DSGE models with financial frictions. Notably, leading theoretical frameworks with financial frictions, along with many other frameworks that build on the former ones, have uncovered different transmission channels of disruptions in financial markets. The diversity in the modeling of the financial sector has addressed many different questions related to the financial crisis; however, the most important one remains open: Which modeling framework is supported by the data? To answer this question, I will analyze the dynamics of the EFP, a key variable in the propagation of shocks through financial market conditions. More specifically, three prominent financial frictions models (BGG,GK,CW) will be estimated using Bayesian techniques. Subsequently, model-simulated data will be compared with the US data in the SVAR framework. The aim of my analysis is to investigate the relationship between the EFP and real output through the lens of the SVAR model with sign restrictions in order to gain insight on empirically relevant financial frictions.

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[2]The identification of structural shocks in the SVAR is in line with the predictions of the DSGE models, though general equilibrium models do not entail the same restrictions in their dynamic relations.

2.1 Bayesian assessment of prominent models

In this section, I will consider in more detail three prominent DSGE models with financial frictions. Bernanke et al. (1999) assume that financial intermediaries need to incur agency costs to observe the profitability of firms' projects and, therefore, incorporate costly state verification as a financial friction into an optimal debt contract. Cúrdia and Woodford (2011) introduce the financial friction in the process of credit intermediation between borrowers and savers as a result of the inability to identify the defaulting borrowers. In the GK model, the misbehavior of banks (which can misuse household funds) gives rise to the financial friction in the relationship between households and banks. Despite different modeling choices, these models generate similar qualitative predictions regarding the propagation of financial shocks; however, their implications for the EFP differ conditional on macroeconomic shocks. In the following, I lay out three models, together with their performance in the Bayesian estimation. In the next step, the information shared by the models will be used in the identification of shocks in the SVAR.

Bernanke et al. (1999) propose a financial accelerator mechanism that propagates through the balance sheets of firms. While this framework considers financial intermediaries as a veil, the required EFP, coming as a result of the optimal debt contract, compensates for costs associated with costly verification of firms' project outcomes. The strength of borrowers' balance sheets is inversely related to the EFP. The model economy is buffeted by technology shocks, monetary policy shocks, shocks to net worth, shocks to government spending, and shocks to the EFP (along the lines of Kaihatsu and Kurozumi, 2014). The latter two shocks are added to the original model for comparability across the respective three models.

Center stage in the CW model are the heterogeneous needs of borrowing and saving households (firms), which motivate the introduction of financial intermediation. In this framework, the financial friction arises because borrowers cannot directly obtain funds from savers. Financial intermediaries (banks) acknowledge that some borrowers cannot repay loans; however, these borrowers cannot be ex-ante identified. Therefore, banks offer the same loan contract terms to all the borrowers, taking into account that a fraction of loans will default. For the estimation exercise, I consider shocks to productivity, government spending, financial intermediation and monetary policy (included for comparability). Two financial shocks are related to the costs of financial intermediation and the quantity of defaulting loans.

Gertler and Karadi (2011) explicitly model the role of leverage banks in the amplification of the financial accelerator mechanism through the economy. In particular, they assume that banks can misappropriate the funds deposited by households. This gives rise to the leverage constraint, which limits the amount of financing extended to firms. Negative macroeconomic conditions reduce asset prices and the return of capital, which in turn contracts the banks' net worth and increases the credit spread. In the model, technology shocks, monetary policy shocks, shocks to government spending and financial shocks (shocks to net worth and capital quality) generate a countercyclical spread (or the EFP).

All three DSGE models are estimated using Bayesian techniques. The parameters shaping

the production process and market structure (the capital share, the depreciation rate, the elasticity of substitution among goods) and preferences (the intertemporal elasticity of substitution and the elasticity of labor supply) are calibrated to the standard values.[3] The models are made comparable in terms of the utility function, the monetary policy reaction function and sources of exogenous variation. I estimate the following set of parameters: policy-specific parameters in the Taylor rule; standard deviations and autoregressive parameters associated with shocks (the technology shock, the government spending shock, two financial shocks and the monetary policy shock); the Calvo probability of resetting the price; parameters specific to financial frictions; and the elasticity of investment adjustment costs.[4] I impose Minnesota-type priors for all the parameters and standard deviations. As the models are estimated with the same data set, the main dimension that differentiates them is the modeling of financial frictions. I use five macroeconomic variables in the Bayesian estimation: the real GDP per capita, the GDP deflator, the federal funds rate, the credit volume and the EBP provided by Gilchrist and Zakrajšek (2012). Except for the interest rate and the EBP, all the data are expressed in log differences. Additionally, the time series for output and credit is expressed in per-capita-terms. The period considered is from 1973Q1 to 2008Q3, excluding the period of the Great Recession and its aftermath. The data are demeaned before the estimation.

The Metropolis-Hastings algorithm is used to get posterior mean estimates and 90% probability intervals, represented in Table 1. Two chains of the algorithm produce 100,000 draws, burning one-quarter of them. I find some heterogeneity in the estimated parameters of three DSGE models based on the US data, but most of them are in line with the broader DSGE literature. As emphasized, this work focuses on the smaller number of shocks compared with other applications of Bayesian estimations (e.g., Brzoza-Brzezina and Kolasa, 2013; Gerali et al., 2010).

Regarding the parameters in the Taylor rule, the weight on inflation is low for the BGG mode and GK model, unlike the CW model. The GK model feature a higher degree of policy inertia than the remaining two models. The estimated Calvo parameter takes values similar to the standard one. The curvature of investment adjustment costs is substantially higher in the BGG model than in the other models with financial frictions. For shock processes, the estimated parameters feature little persistence in the BGG model and the GK model. Interestingly, the standard deviation of the monetary policy shock is almost the same across the models. Both estimated BGG and GK models feature one financial shock with a higher standard deviation.

With respect to the model fit, I find that the BGG model outperforms the other two models (see Table 2). The Bayes factor with the order of magnitude more than 100 (not reported) speaks

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[3]The values are taken from the GK model. The robustness exercise shows that fixing parameters to the values as in one of the other respective models gives comparable results.

[4]The process of capital accumulation affects the price of capital, which in turn contributes to the financial accelerator mechanism. For this reason, the parameter influencing costs of investment adjustment is estimated.

Table 1: Bayesian estimation

				BGG			CW			GK		
Parameter	Type	Prior	Sd	Mean	5%	95%	Mean	5%	95%	Mean	5%	95%
ρ_i, Taylor rule smoothing	Normal	0.75	0.10	0.614	0.457	0.773	0.635	0.611	0.652	0.790	0.697	0.883
ρ_π, Taylor rule coeff. on Π	Beta	1.5	0.25	1.327	1.012	1.647	1.910	1.864	1.956	1.293	1.119	1.402
η_i, investment adjustment costs	IG	4.0	1.5	8.216	6.474	9.978	-	-	-	4.010	2.288	5.487
θ, Calvo probability of resetting the price	Beta	0.75	0.05	0.748	0.668	0.827	0.693	0.671	0.710	0.718	0.662	0.763
ν, elasticity of external finance	Normal	0.05	0.05	0.221	0.182	0.262	-	-	-	-	-	-
λ, fraction of divertible capital	Beta			-	-	-	-	-	-	0.195	0.115	0.306
ρ_{as}, persistence of technology shock	Beta	0.5	0.20	0.346	0.216	0.471	0.755	0.690	0.833	0.070	0.025	0.111
ρ_{ad}, persistence of demand shock	Beta	0.5	0.20	0.344	0.084	0.593	0.652	0.614	0.685	0.663	0.426	0.996
ρ_{mp}, persistence of mon. policy shock	Beta	0.5	0.20	0.185	0.054	0.312	0.472	0.407	0.535	0.266	0.127	0.403
ρ_{fin}, persistence of financial shock	Beta	0.5	0.20	0.317	0.101	0.518	0.053	0.016	0.093	0.102	0.014	0.191
ρ_{fs}, persistence of financial shock(2)	Beta	0.5	0.20	0.155	0.035	0.268	0.389	0.305	0.459	0.116	0.084	0.147
σ_{as}, std. of technology shock	IG	0.10	2.0	0.037	0.023	0.051	0.025	0.020	0.031	0.0500	0.024	0.081
σ_{ad}, std. of demand shock	IG	0.10	2.0	0.037	0.028	0.045	0.289	0.244	0.335	0.032	0.022	0.042
σ_{mp}, std. of mon. policy shock	IG	0.10	2.0	0.007	0.006	0.008	0.007	0.006	0.008	0.007	0.006	0.008
σ_{fin}, std. of financial shock	IG	0.10	2.0	0.051	0.033	0.067	0.009	0.008	0.010	0.015	0.012	0.017
σ_{fs}, std. of financial shock(2)	IG	0.10	2.0	0.041	0.031	0.051	0.037	0.024	0.049	0.120	0.076	0.165

Notes: BGG stands for the model by Bernanke et al. (1999), GK for Gertler and Karadi (2011) and CW for Cúrdia and Woodford (2011). All the models are estimated using the same dataset.

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Table 2: Model comparison

Marginal log likelihood		
BGG	CW	GK
2061.80	1585.81	1966.97

decisively in favor of costly state verification as the empirically relevant financial friction. The comparison of the model fit reveals that the CW model is the least favored model by the data.

Based on these estimated DSGE models, I simulate 1000 data sets with the time length of 200 periods, leaving out the initial 1000 periods. These data sets are used in the SVAR analysis.

2.2 SVAR model

A VAR model is given by:

$$x_t = A + B_{(i)}x_{t-i} + u_t, \tag{1}$$

where x_t is a $N \times 1$ vector containing N endogenous variables, A is $N \times 1$ vector of constants, $B_{(i)}$ for $i = 1, \dots M$ represents $N \times N$ coefficient matrices for lag i, M is the number of lags and u_t is the $N \times 1$ one-step-ahead prediction error with a variance-covariance matrix of size $N \times N$. The SVAR methodology with sign restrictions follows the work by Uhlig (2005) and Rubio-Ramírez et al. (2010) and is summarized in the Appendix.

In my structural model specification, vector x_t contains five variables:

$$x_t = [y_t, p_t, r_t, cr_t, EFP_t], \tag{2}$$

whereby, y_t represents the real GDP in period t, p_t the GDP deflator, r_t the federal funds rate, cr_t the credit volume and EFP_t the EFP. The VAR specification includes a constant and two lags of endogenous variables in the baseline model.[5] The model is estimated for the US data from 1973Q1 to 2012Q4 and the data generated from the three DSGE models for the equivalent time horizon. The federal funds rate and the EFP are reported in levels, whereas the remaining variables are expressed in growth rates. The data overview is included in the Appendix.

The EFP is the key variable in the process of credit intermediation. It is not observable[6] and, therefore, is hard to measure. As the data on the individual bank loan rates from US firms is not available, researchers cannot construct a good measure of external financing costs. The available bank rate represents a rate posted by banks, i.e., it is not determined by the market. For these reasons, most researchers gather the market data from corporate bond yields to infer a proxy for the premium. In the main analysis, I employ the EBP, which is extracted from the credit spread index developed by Gilchrist and Zakrajšek (2012) (i.e., GZ credit spread). By matching individual corporate bond yields with their reference interest rate of the appropriate maturity, the authors provide a good measure of external financing costs for corporate firms. The GZ credit spread consists of two components: one part accounting for firm-specific default risk and the EBP, measuring the compensation for credit risk above the expected firm-specific default risk. Alternative proxies of the EFP are credit spreads: the spread between yields on BAA- and AAA-rated corporate bonds (i.e., the BAA-AAA spread), the spread between yields

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[5]The lag length is chosen based on the Akaike information criterion.
[6]The unobservability of the EFP, as argued by DeGraeve (2008), is the most problematic aspect for researchers.

on BAA-rated corporate bonds and 10-year-Treasury yields (i.e., the BAA-10Tr spread) and the high-yield spread, to name a few.

This work relies on the EBP as a measure of the EFP for the following reasons: First, the advantages of using this measure over the BAA-AAA spread is that it accounts for the maturity horizon of the micro-level data precisely.[7] It is well known that the BAA and AAA corporate bond indexes, together with other aggregate credit spread indexes, contain bond yields of different maturities and, therefore, suffer from "duration mismatch" (see Gilchrist and Zakrajšek, 2012). Second, both the EBP and the GZ credit spread encompass a wide spectrum of firms with different credit quality, which implies that these spreads are a broad indicator of financial conditions. Other measures concentrate on firms with good credit standing (e.g., BAA-AAA spread) or bad credit quality (e.g., high-yield spread); and, hence, they reflect only one narrow market segment for corporate borrowing. Third, the GZ credit spread also includes expected firm-specific default risk, whereas the EBP is purged from this risk. The EBP captures the compensation for exposure to corporate credit risk and, hence, reflects the premium that financial institutions would require in addition to firm-specific characteristics.

2.3   Identification strategy

Table 3 summarizes a minimal set of sign restrictions used to identify structural shocks.[8] The sign restrictions are based on the dynamic consequences of shocks in financial New Keynesian models. The small-scale SVAR focuses on four shocks of economic interest. A more parsimonious framework would be consistent with a wide range of financial DSGE models; however, a disadvantage of this is that unidentified shocks can arise somewhere else in the SVAR. Since the purpose of the structural analysis is to document the conditional behavior of the EFP, it is beneficial to differentiate among four sources of business cycles for two reasons. First, a sharper identification of shocks can be achieved, if the model incorporates economically interpretable shocks. Second, empirical results on four macroeconomic shocks will be used to discriminate among financial frictions models in order to identify modeling features that are supported by the data.

An adverse financial shock, i.e., the shock to the EFP, results in an increase in the EFP and a decline in credit. The identification of financial shocks as credit supply shocks follows the works of Gambetti and Musso (2017) and Mumtaz et al. (2018), who study the impact of credit supply shocks on real economy using different data sets and VAR models, respectively. The guiding principle in these identifications, including mine, is that imposed sign restrictions

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[7]For the reference rate for the spread, Gilchrist and Zakrajšek (2012) employ a synthetic Treasury security with the same cash flow characteristics as the underlying corporate bond; and, hence, both yields have the same maturities.

[8]A widespread alternative methodology is a recursive VAR, which uses the Cholesky ordering. However, the Choleski decomposition is not supported by the DSGE theory, as argued by Bjørnland and Leitemo (2009) and Furlanetto et al. (2017). Using DSGE models to achieve a theory-consistent identification, I apply the SVAR methodology with sign restrictions to analyze structural shocks.

Table 3: Sign restrictions in the model

	Supply	Demand	Monetary	Financial
Real GDP	-	-	-	-
GDP deflator	+	-	-	-
Nominal interest rate	NA	-	+	-
Credit	NA	+	NA	-
EFP	NA	NA	NA	+

Notes: "+" indicates that the impact response is positive; "-" indicates that the impact response is negative; "NA" indicates that the impact impulse response can be positive, negative or zero and, therefore, no sign is assigned. All the shocks represent adverse disturbances.

are consistent with (a large subset of) financial DSGE model predictions. In Table 4 I provide an overview of prominent modeling choices of financial frictions and financial shocks. Despite different modeling assumptions and transmission mechanisms, dynamic consequences of financial shocks from a set of DSGE models with financial frictions imply almost uniformly the same sign restrictions on financial variables on credit and the EFP in Table 4. The picture is less clear for the reactions of inflation and nominal interest rate, as some negative financial shocks give rise to inflation, calling for the restrictive monetary policy response. However, my analysis will follow the literature (e.g., Gambetti and Musso, 2017) in assuming that the financial shock has a deflationary nature. Table 4 indicates that the strength of monetary policy response differs across models with financial frictions.

Table 4: Sign restrictions on variables upon adverse financial shocks

	Shock	Financial friction	EFP	Credit	q	Y	π	R
Bernanke et al. (1999)	wealth	CSV	+	-	-	-	-	-
Carlstrom et al. (2014)	net worth	CSV	+	-	-	-	-	-
Christiano et al. (2010)	bank funding	CSV	+	-	-	-	+	+
Christiano et al. (2010)	liquidity buffer	CSV	0	-	-	-	-	-
Cúrdia and Woodford (2010)	bank technology	heterogeneity	+	-	NA	-	-	-
Cúrdia and Woodford (2010)	bad loans	heterogeneity	+	-	NA	-	-	-
Gerali et al. (2010)	bank capital	collateral constraint	+	-	-	-	+	+
Gertler and Karadi (2011)	net worth	moral hazard	+	-	-	-	-	-
Gertler and Karadi (2011)	capital quality	moral hazard	+	-	-	-	-	-
Meh and Moran (2010)	bank funding	moral hazard	+	-	-	-	+	+
Brzoza-Brzezina et al. (2013)	net worth	CSV	+	+	-	0	+	+
Brzoza-Brzezina et al. (2013)	LTV	collateral constraint	0	-	-	-	-	-
Brzoza-Brzezina et al. (2013)	spread	collateral constraint	+	-	-	-	+	-

Notes: The second column describes a type of financial shock. The third column states a financial friction arising in the model. q stands for asset prices, Y for real output, π for inflation and R for nominal interest rate. CSV denotes costly state verification and LTV is the loan-to-value ratio. "+" indicates that the impact response is positive; "-" indicates that the impact response is negative; "0" indicates a zero-response of the variable on impact; "NA" indicates that the model does not include a specific variable. The work by Brzoza-Brzezina et al. (2013) compares two main mechanisms used to model financial frictions, in particular, costly state verification in a debt contract à la Bernanke et al. (1999) and collateral constraints as in Kiyotaki and Moore (1997).

The sign restrictions used to identify aggregate supply shocks and monetary policy shocks follow common practice in Canova and Nicoló (2002). Financial New Keynesian models show a consensus regarding macroeconomic shocks: i) aggregate supply shocks move output in one direction and inflation in the opposite direction; ii) aggregate demand shocks are associated with a movement of output, inflation and the interest rate in the same direction, and credit in the opposite direction; iii) an unexpected increase in the nominal interest rate results in a decrease in output and inflation; iv) financial shocks affect the output, prices, interest rate and credit in a procyclical manner, whereas the EFP is affected in a countercyclical manner. Similar to Uhlig (2005), I impose sign restrictions for two quarters to identify monetary policy shocks.[9] In the case of the other shocks, the restrictions are imposed on impact. Examples of aggregate supply shocks include technology shocks and labor supply shocks, whereas demand shocks refer to preference shocks and government spending shocks (to the extent that my imposed sign restrictions comply with dynamic consequences of theoretical shocks).

While DSGE models show to a large extent a consensus regarding dynamic consequences of supply shocks, monetary policy shocks and financial shocks, model predictions conditional on demand shocks depend on the type of demand shocks (e.g., preference shocks, government spending shocks or investment shocks). Determining a combination of robust sign restrictions to identify demand shocks is a controversial task, since dynamic consequences of demand shocks in representative financial frictions models have diverging implications for some key variables. Furthermore, these restrictions need to be mutually exclusive. My overview of demand shocks indicates that there is a less clear consensus regarding which restriction to impose on financial variables (e.g., credit and the price of capital) to identify demand shocks (available upon request). In the case of the negative preference shock, households shift consumption towards the future. As savings increase and investment rises, firms leverage up and increase credit to maintain their capital purchases (see, e.g., DeGraeve, 2008). Similarly, contractionary fiscal shock that leads to the crowding-in of private investment and credit implies the same dynamic consequences for credit as preference shocks. Therefore, the reaction of credit enables me to disentangle financial shocks from demand shocks. The adverse demand shock in the structural model mimics a fall in the aggregate demand and prices, together with an increase in firm borrowing.[10]

The financial sector of the economy is left largely unrestricted in the presence of macroeconomic shocks, as the SVAR framework is based on a minimal set of sign restrictions. Table 5 gives an overview of the initial reactions of the key variable of interest, the EFP, in the selected financial frictions models.[11] Whereas financial DSGE models have different implications for the EFP conditional on supply shocks, demand shocks and monetary policy shocks, adverse financial

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[9]Uhlig (2005) focuses only on the monetary policy shock, which is identified by imposing sign restrictions on the GDP price deflator, the commodity price index, nonborrowed reserves and the federal funds rate for five months.

[10]An another example is the specification by Gambetti and Musso (2017), who impose the restriction on the lending rate to identify the loan demand shock as the aggregate demand shock. Their analysis differentiates between loan demand shocks and loan supply shocks by restricting the lending rate, whereas my analysis leaves the EFP unrestricted following demand shocks, letting the data speak.

[11]The summary of reactions of the remaining financial variables is available upon request.

shocks are usually associated with a rise in the premium.[12]

Table 5: Sign restrictions EFP

	Supply	Demand	Monetary	Financial
Bernanke et al. (1999)	+	NA	+	+
Carlstrom et al. (2014)	NA	NA	-	+
Christensen and Dib (2008)	-	-	+	NA
Christiano et al. (2010)	$-/+^*$	NA	+	+
Cúrdia and Woodford (2010)	-	+/-	NA	+
DeGraeve (2008)	+	-	+	NA
Gerali et al. (2010)	+	-	-	+
Gertler and Karadi (2011)	+	NA	+	+
Meh and Moran (2010)	-	NA	+	+
Brzoza-Brzezina et al. (2013)	-	NA	+	+
Brzoza-Brzezina et al. (2013)	0	NA	0	+

Notes: "+" indicates that a rise in the EFP on impact, i.e., it is countercyclical; "-" indicates a fall in the EFP on impact, i.e., it is procyclical; "0" indicates a zero-response of the EFP on impact; "NA" indicates that the model does not consider a specific shock. *Christiano et al. (2010) report that the premium increases in the model without the Fisher effect. If the EFP is not present in a particular model as such, I use the difference between the return on loan and the policy rate as a measure of external financing costs.

2.3.1 An illustration: Different transmission mechanisms and the EFP

As indicated by Table 5, there is little consensus among financial DSGE models on how the EFP behaves in response to macroeconomic shocks. The dynamic reaction of the EFP[13] to shocks depends on how capital accumulation and financial frictions are specified, as has been discussed by Furlanetto et al. (2017). In the following, I will illustrate this using some examples. In their seminal paper, Bernanke et al. (1999) are the first to introduce costly state verification to analyze the financial accelerator mechanism, i.e., the amplification of shocks due to the existence of financial frictions. The authors find a countercyclical premium conditional on the realization of technology shocks, monetary policy shocks and net worth shocks. The main intuition for the countercyclical behavior of the premium is the following: The premium develops endogenously and is related to financial positions of firms. If balance sheet conditions of firms are good and their leverage is low, e.g., following positive shocks (causing an increase in real activity), the premium is low (and, hence, countercyclical). In the model by Gertler and Karadi (2011), the financial accelerator gets transmitted through balance sheets of banks on the real economy. The model generates a negative comovement between credit spreads and output in the presence of macroeconomic shocks. When the BGG model is enriched by investment adjustment costs in the capital accumulation process, DeGraeve (2008) finds a procyclical EFP following demand shocks.

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[12]Note that tables are far from being sufficient in inclusion of all different DSGE models with financial frictions. The selection followed a criterion for including a financial DSGE model is that the model analyzed the implications of at least two of the three macroeconomic shocks: supply shocks, demand shocks, monetary policy shocks.

[13]The EFP is the modeling feature of the debt contract originally described by Bernanke et al. (1999). If the EFP is not present in a particular model as such, I use the difference between the return on loan and the policy rate as a measure of external financing costs.

His demand shock, in the form of a preference shock, has a countercyclical effect on credit and the price of capital, which leads to a procyclical development of leverage and the EFP. A further extension of the BGG framework concerns a debt-deflation channel, whereby Christensen and Dib (2008) specify the loan contract in nominal terms. The introduction of the nominal debt contract results in a procyclical EFP in the face of aggregate supply shocks. The propagation mechanism is the following: A positive comovement between the EFP and output conditional on technology shocks arises because inflation reacts countercyclically, which affects the real cost of repaying the debt procyclically and, hence, generates a procyclical EFP. As a result of the indexation of the loan contract to the aggregate return, stipulated as in Carlstrom et al. (2014), the EFP is procyclical in response to monetary policy shocks.

In the following, I will use the proposed SVAR framework to study the dynamics of the EFP using the US data and the model-implied data. The model-implied data reflect the model-specific financial friction and its respective EFP. Comparing it against the US data enables me to assess extent to which the theoretical frameworks match the data.

3 Results

### 3.1 Dynamics of the US external finance premium

Figure 1 depicts the impulse responses of the EFP to the supply shock, the demand shock, the monetary policy shock and the financial shock using the identification scheme in Table 3. The median estimated response[14] of the EFP is countercyclical following supply and monetary policy shocks,[15] i.e., the EFP rises initially and real GDP falls. The EFP is procyclical conditional on the realization of the demand shock.

Using the data responses of the EFP, it is possible to discard some modeling choices. For example, the US empirical evidence does not favor the presence of the Fisher effect, i.e., a debt deflation channel (e.g., an optimal debt contract in nominal terms as stipulated by Christensen and Dib, 2008). Neither is the modeling of a debt contract with indexed return, as in Carlstrom et al. (2014), favored by the data. These theoretical models predict a procyclical movement of the EFP conditional on the realization of the supply (technology) shock and the monetary policy shock, respectively. Overall, the estimated impulse responses cannot help to identify a dominant financial friction. Put differently, using the common information regarding the four shocks from the financial New Keynesian models, I find that a subset of financial frictions are consistent with my conditional empirical evidence – an increase in the premium on impact following adverse supply and monetary policy shocks and an initial decline in the premium in response to demand

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[14]Since the SVAR with sign restrictions generates wide credible sets in most applications, estimates are statistically insignificant (see, e.g., Canova and Paustian, 2011). Hence, impulse response functions will be interpreted with the help of median estimates. Otherwise, it would be difficult to discriminate among the models.

[15]The short-term behavior of median estimated responses of the EFP is compared with their theoretical counterparts in Table 4.

Figure 1: External finance premium
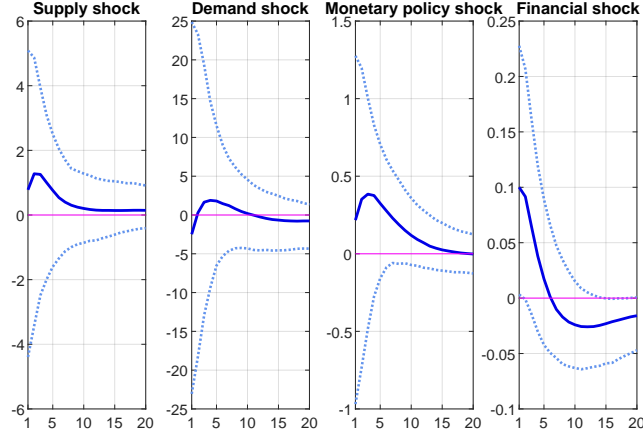
shocks. In the following, the SVAR results using data from three financial DSGE models will be compared with the ones based on the US data.

My findings on the EBP are in line with those of Furlanetto et al. (2017) with respect to the supply shock and differ with respect to the monetary policy shock and the demand shock. The key difference is the identification of the financial shock: Whereas their financial shocks refer to exogenous movement in asset prices, I consider shocks to the EBP, which have the nature of credit supply shocks. Most DSGE models (including four models discussed here) analyze adverse financial shocks to credit markets by engineering a contraction of credit and an increase in credit spreads/finance premia rather than considering negative developments in asset markets.[16] While my focus is placed with the EBP, Furlanetto et al. (2017) use the BAA-federal funds spread, which could be potentially contaminated by different maturity profile of reference rate, affecting the results. Another important difference is the identification of demand shocks. Furlanetto et al. (2017) identify structural demand and investment shocks (using restrictions on the ratio of investment and output, as well as stock prices), whereas I abstract from investment dynamics in my analysis. The estimated structural demand shocks in my framework are identified using the sign restriction on credit as implied by preference shocks or (some) fiscal shocks in theoretical models. The bottom line is that my small-scale model tries to capture the main characteristics of the role of the EFP and the credit market, abstracting from the non-trivial role of asset markets

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[16]In the extended version of their model, Furlanetto et al. (2017) consider shocks to credit and housing markets, however, they do not show the dynamics of the EFP under these identifications.

(see Galí and Gambetti, 2015).

3.2   Comparing theory with data

Figure 2 plots median responses of the EFP from the SVAR model using the DSGE model-implied data and the empirical counterparts.[17] In order to make comparison of different models easier, the shocks are normalized in the following manner: The aggregate supply shock is normalized to generate an increase in output by 0.1%. The standardization of the aggregate demand shock is associated with a decline in inflation by 0.1%. The impact response of the policy rate is normalized to increase by 0.25% following the monetary policy shock. The financial shock is normalized to increase the EFP by 0.1% on impact.

Figure 2 shows that the median estimates from the considered DSGE models match qualitatively well the true median responses. The results reveal a countercyclical development of the median estimated response[18] of the EBP, as well as the estimated premium from the three DSGE models, following supply and monetary policy shocks. On impact, the aggregate demand shock is associated with the procyclical movement of the EBP and the model-implied EFP. Overall, the DSGE models do a good job in generating the cyclicality of premium, which is present in the data. However, the model-implied EFP does not generate a hump-shaped pattern in impulse responses of the EBP, nor does it match the magnitudes seen in the data.[19] Confronting the three competing financial frictions models with the one based on the US data, I will consider the reproduced dynamics (impact and maximum responses) and the contribution to the forecast error variance of output and the EFP. Eventually, the model fit of the remaining variables will be compared with the data.

The SVAR analysis reveals that the conditional behavior of the EFP can be reproduced by the estimated models; however, there is some heterogeneity in the magnitudes of impulse responses. The BGG model comes closest to matching the initial reaction of the EBP following structural shocks. The response of the premium coming from the GK model reproduces well the conditional behavior of the EBP following the aggregate demand shock. On the other hand, the model predictions from the GK model and the CW model fall short of matching the data following aggregate supply and monetary policy shocks. Since the financial shock is normalized to generate an increase in the EFP by 10 basis points on impact, all the models match well the response of the EBP in the presence of the financial shock.

Overall, the results show that the cyclicality generated by the EBP can be captured by the data implied by the three DSGE models with financial frictions (see Figure 2). If the impact and

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[17]The median estimates of variables together with error bands are presented in Figures 3,4 and 5.

[18]Since the SVAR with sign restrictions generates wide credible sets in most applications, the estimates are statistically insignificant (see, e.g., Canova and Paustian, 2011). Hence, the impulse response functions will be interpreted with the help of median estimates.

[19]Given the focus on simplified versions of medium-scale DSGE models and a limited number of shocks, possible model dynamics from certain rigidities, such as habit formation or rigid wages, can be helpful in restoring the shape of impulse responses.

Figure 2: Comparison of responses of the EFP from DSGE-implied data and US data
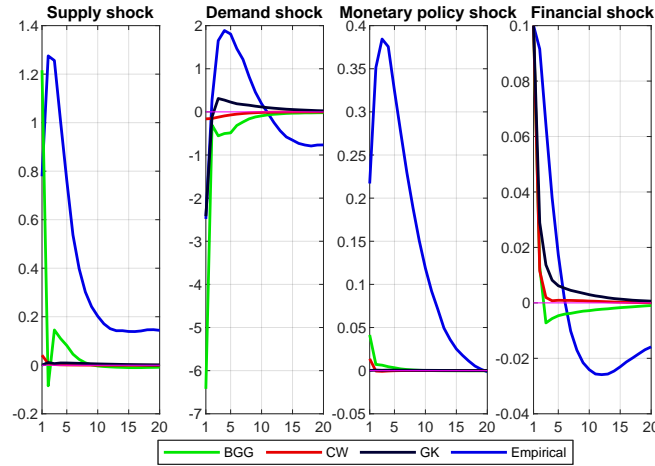
Notes: The bold lines denote the median of the impulse responses, which
are estimated from a Bayesian VAR with draws. The impulse responses
are related to an adverse one standard deviation shock. The vertical axis
is expressed in basis points. The horizontal axis is in quarters.

maximum response of the EFP are used to discriminate among the models, the SVAR responses
based on the estimated BGG model seem to provide the closest fit to the model based on the
US data. The nutshell intuition for the dynamics of the EFP in the BGG model is the following:
A negative comovement between the EFP and output conditional on technology (supply) shocks
arises because inflation reacts countercyclically, which leads to a countercyclical development of
leverage and the EFP. The unexpected monetary tightening decreases aggregate demand, which,
together with the decline in the price of capital and the higher value of debt, results in an increase
in the EFP (making it countercyclical). A demand shock with a countercyclical effect on credit
affects leverage procyclically and, hence, generates a procyclical EFP.

To further discriminate between these three models, I compare model performance in terms
of explaining the variations in the premium and output. Table 6 presents the contributions of the
four structural shocks to explaining variations in output and the EFP for one-quarter and four-
quarter horizons. The most important driver of US business cycle fluctuations is the aggregate
supply shock, which explains 39% and 38% of the variation in the US output at the one-quarter
and one-year horizons. As for financial shocks, the estimates show that the contribution of these
shocks to the forecast error variance is 11% and 25% for the output and the EBP in the US,
respectively, on the one-quarter horizon.

The estimated BGG model accounts well for the variations in output, pointing to aggregate
supply shocks as the main driver of output fluctuations. The picture is less clear when it comes to
explaining the variations in the EFP. The model assigns a non-negligible role to monetary policy
shocks and aggregate supply shocks in changes in the EFP. Higher relevance of these shocks in
comparison with the GK and CW models explains why the BGG model provides a better fit of

Table 6: Contribution of the shock to the forecast error variance

	AS	AD	MP	FS	AS	AD	MP	FS
					1 quarter			
	Y				EFP			
US data	38.83	9.04	16.68	11.05	15.56	15.59	17.80	25.89
Bernanke et al. (1999)	43.34	2.37	30.68	2.38	26.03	10.92	24.98	13.98
Cúrdia and Woodford (2011)	3.22	0.14	11.74	59.46	13.14	0.23	6.23	60.23
Gertler and Karadi (2011)	42.01	0.78	35.05	1.02	7.99	30.34	9.53	35.77
					4 quarters			
US data	37.68	9.36	17.11	11.41	17.75	14.65	21.42	22.65
Bernanke et al. (1999)	39.55	5.22	30.60	4.86	25.51	10.74	25.20	13.59
Cúrdia and Woodford (2011)	5.79	0.27	13.27	55.97	13.50	0.57	6.58	59.35
Gertler and Karadi (2011)	39.29	1.94	34.40	3.78	13.84	22.78	14.38	28.38

Notes: AS stands for the aggregate supply shock, AD for the aggregate demand shock, MP for the monetary policy shock, FS for the financial shock.

the EFP in response to these shocks.

The model estimates show that financial shocks play the most important role for the EFP in the CW model. The CW model seems to overestimate the importance of financial shocks, assigning a sizable portion of output and EFP variations to this shock. One explanation for the result is that the CW model abstracts from the capital accumulation process and focuses on the heterogeneous financing needs of households (firms), giving a prominent role to the financial intermediation process as opposed to the supply side of the economy. The model of savers and borrowers with asymmetric information in the process of financial intermediation strongly amplifies the propagation of financial shocks (see Figure 5). It also suggests that financial frictions do not need to transmit through the investment demand channel (present in the remaining two models), if the model focus is the explanation of financial disturbances. On the other hand, the CW model is not successful in reproducing the relationship between the EFP and output conditional on macroeconomic shocks.

It should be noted that the relevance of the aggregate supply shock and the financial shock for output and the EFP, respectively, in the GK model closely matches the data. The limited contract enforcement between banks and households amplifies the effects of the financial shock by causing large movements in the EFP. The key mechanism is the following: Households mistrust banks and reduce deposits, which further worsens bank leverage and net worth. The tightening of bank capital constraints restricts loan supply to firms and increases finance premia. Facing higher borrowing costs, firms demand less capital and invest less. The investment demand channel together with the financial friction amplifies further a fall in the price of capital and worsening of financial positions, thereby reproducing a comovement between output and the EFP, which is in line with the data.

To analyze which model better fits the characteristics of data, Table 7 summarizes standard deviations relative to output and cross correlations with output. The BGG model fits most of variables better than the competing financial frictions models. This does not come as a surprise, as the Bayesian assessment shows the superior performance of the BGG model and indicates that it is favored by the data. As far as the EFP is concerned, Table 7 shows that the BGG model

Table 7: Data moments

	US data	Bernanke et al. (1999)	Cúrdia and Woodford (2011)	Gertler and Karadi (2011)
		Standard deviations relative to output		
Output	1	1	1	1
Inflation rate	0.77	0.13	0.02	0.13
Interest rate	0.49	0.42	0.01	0.32
Credit	1.62	0.88	0.34	2.07
EFP	56.52	7.94	0.20	0.34
		Cross correlations with output		
Inflation rate	-0.13	0.37	0.75	0.54
Interest rate	-0.06	-0.65	0.07	-0.60
Credit	0.19	0.51	0.78	0.87
EFP	-0.34	-0.57	-0.90	-0.30

comes closest to replicating the standard deviation of the EFP relative to output. Although some statistics indicate that the results on the BGG model and the GK model are very similar, the former better matches moments of credit and the EFP, whereas the latter reproduces the cross correlation between the EFP and output. The BGG model generates the highest standard deviation of the EFP, which could be the reason why the model is able to better match the magnitudes of the premium in comparison with the remaining two models.

All three models do poorly in generating business cycle dynamics of inflation. The BGG model and the GK model underestimate the cross correlation between the interest rate and output; however, the former model closely matches its standard deviation relative to output. Furthermore, the CW model and GK model cannot generate cross correlations of credit and output, whereby the GK achieves worse performance. Though the GK model does not reproduce the standard deviation of the EFP to output, it matches well the cross correlation with output.

To provide further evidence on which financial frictions are empirically relevant, I will discuss the impulse responses of the remaining variables. The effects of each structural shock on output, inflation, interest rate, credit and the EFP from three DSGE models are evaluated against the US data. The blue solid lines refer to the median responses based on the US data, whereas the dotted lines represent their accompanying 90% error band. The responses associated with model-implied data refer to median SVAR estimates (see Figure 3, 4 and 5).

The performance of the financial frictions models varies under different shock scenarios. The CW model reproduces relatively well the overall conditional dynamics of variables following the aggregate demand shock, whereas the GK model matches well the dynamic consequences of the monetary policy shock. The BGG model appears to replicate the empirical responses of the US data in most instances. The deviations of the impulse responses from the true ones are much smaller in comparison with other models.

It is interesting to note that financial shocks propagate much more strongly in the CW model and in the GK model than in the BGG model. The former two models generate a large contraction in the output as a result of disrupted credit markets. The amplification of financial shocks through financial frictions explains why variations in the EFP are driven predominantly by financial shocks.

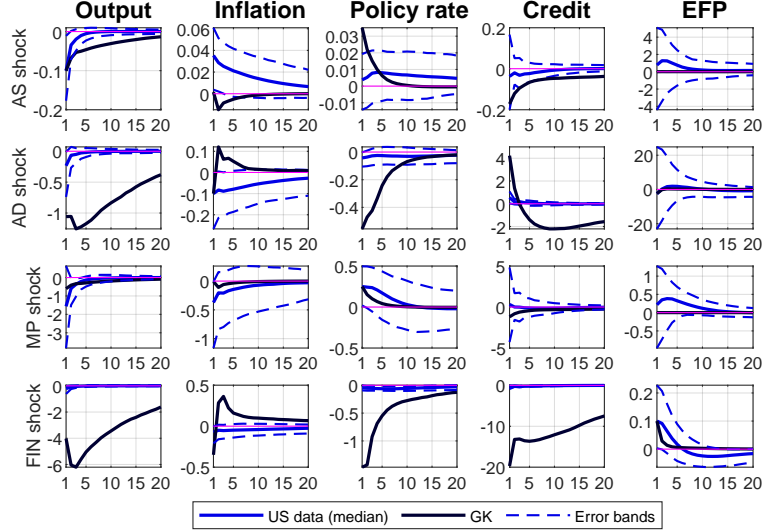Figure 3: Comparison of SVAR responses from the BGG model and US data
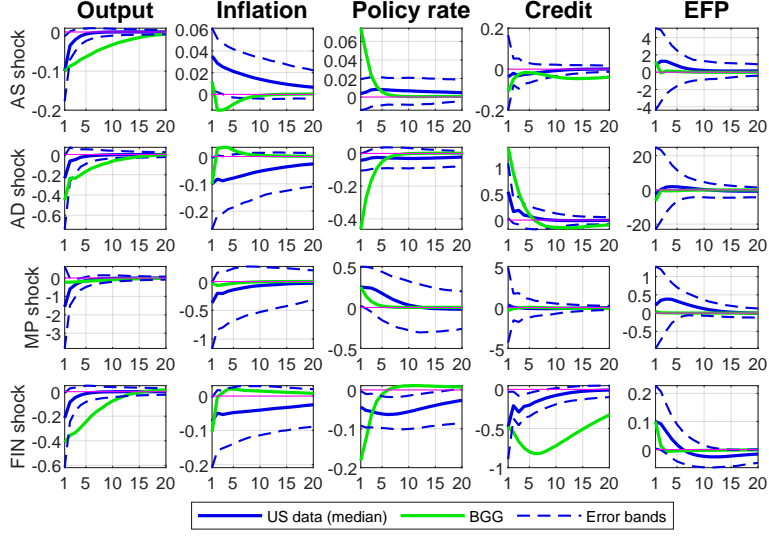
Notes: The bold lines denote the median of the impulse responses, which are estimated from a Bayesian VAR with 1000 draws. The bounds are the 5th and 95th percentiles. The horizontal axis is in quarters. BGG stands for the model by Bernanke et al. (1999). The time period is 1973Q1–2012Q4.

Even though the reactions of output and the EFP coming from the estimated BGG model come closest to the true impulse responses, there are some exceptions worth discussing. The responses of inflation lack the persistence seen in the data. A further indicator is a positive correlation between output and inflation, contrary to the data (see Table 6). The reactions of the interest rate are much more pronounced than those in the data. This is also reflected in the strong negative correlation between output and interest rate.

Based on the overall model assessment and comparison with the US data, the results indicate the BGG model displays the best performance in matching the importance of shocks for output and premium fluctuations. Hence, the estimates suggest that the empirically relevant financial friction is costly state verification. Another possible explanation for the superior performance of this model is that the EBP is the closest measure of the EFP in macroeconomic models. In particular, the BGG model generates the EFP as a compensation for additional default risks undertaken by financial institutions. Whereas my results lend support to the original modeling of the debt contract (in real terms), the same empirical approach can be applied to assess the empirical relevance of alternative frameworks such as those by Carlstrom et al. (2014) or Christensen and Dib (2008). However, some of these frameworks have been discarded as they are not in line with the empirical impulse responses.

Figure 4: Comparison of SVAR responses from the GK model and US data

Notes: The bold lines denote the median of the impulse responses, which are estimated from a Bayesian VAR with 1000 draws. The bounds are the 5th and 95th percentiles. The horizontal axis is in quarters. GK stands for the model by Gertler and Karadi (2011). The time period is 1973Q1–2012Q4.

Figure 5: Comparison of SVAR responses from the CW model and US data
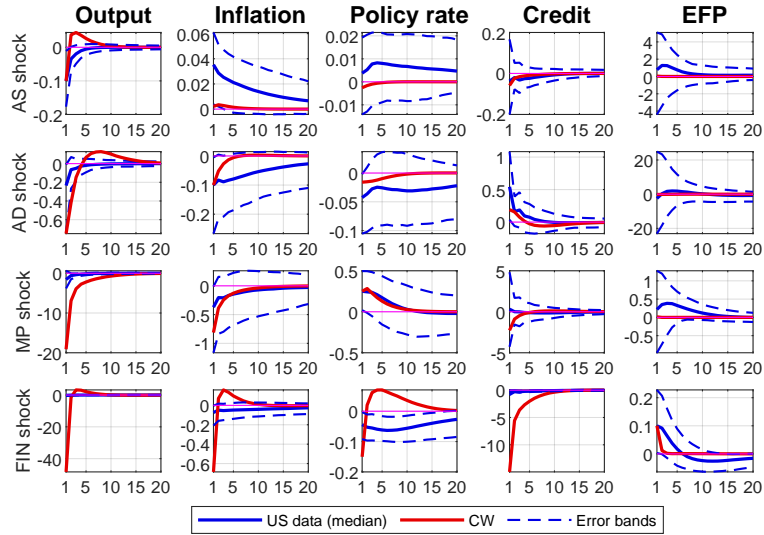
Notes: The bold lines denote the median of the impulse responses, which are estimated from a Bayesian VAR with 1000 draws. The bounds are the 5th and 95th percentiles. The horizontal axis is in quarters. CW stands for the model by Cúrdia and Woodford (2011). The time period is 1973Q1–2012Q4.

4 Conclusion

Despite extensive research on financial markets and financial frictions, there is no workhorse model with financial frictions that is fully supported by data. This paper represents one possible approach to identify relevant financial frictions.

The main focus of the paper is the analysis of the dynamics of the EFP in response to macroeconomic shocks using US data and DSGE models. To gauge which financial frictions are empirically relevant, I estimate three competing financial frictions frameworks using Bayesian techniques. Confronting the DSGE-implied dynamics of the EFP with the data within the SVAR framework, the analysis shows that the EFP is countercyclical following supply and monetary policy shocks, and procyclical following demand shocks. The estimated BGG model can recover the dynamics of the EFP well and can match the driving forces behind the variations in output and the EFP.

There are some possible avenues for future research. First, by estimating a large set of financial DSGE models, it would be possible to more precisely identify the empirically relevant financial friction framework. Second, using micro-level firm and bank data, it would be useful to isolate which financial frictions should be embedded in macro models.

References

Bailliu, J., Meh, C., and Zhang, Y. (2015). Macroprudential rules and monetary policy when financial frictions matter. *Economic Modelling*, 50:148–161.

Bernanke, B., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Monetary Economics*, 1(C):1341–1393. Edited by John B. Taylor and Michael Woodford.

Bjørnland, H. C. and Leitemo, K. (2009). Identifying the interdependence between US monetary policy and the stock market. *Journal of Monetary Economics*, 56(2):275–282.

Brzoza-Brzezina, M. and Kolasa, M. (2013). Bayesian evaluation of DSGE models with financial frictions. *Journal of Money, Credit and Banking*, 45(8):1451–1476.

Brzoza-Brzezina, M., Kolasa, M., and Makarski, K. (2013). The anatomy of standard DSGE models with financial frictions. *Journal of Economic Dynamics and Control*, 37(1):32–51.

Canova, F. and Nicoló, G. D. (2002). Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, 49(6):1131–1159.

Canova, F. and Paustian, M. (2011). Business cycle measurement with some theory. *Journal of Monetary Economics*, 58(4):345–361.

Carlstrom, C., Fuerst, T., Ortiz, A., and Paustian, M. (2014). Estimating contract indexation in a financial accelerator model. *Journal of Economic Dynamics and Control*, 46:130–149.

Christensen, I. and Dib, A. (2008). The financial accelerator in an estimated New Keynesian model. *Review of Economic Dynamics*, 11:155–178.

Christiano, L., Eichenbaum, M., and Evans, C. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1):1–45.

Christiano, L., Motto, R., and Rostagno, M. (2010). Financial factors in economic fluctuations. Working Paper Series 1192, European Central Bank.

Christiano, L., Motto, R., and Rostagno, M. (2014). Risk shocks. *American Economic Review*, 104(1):27–65.

Cúrdia, V. and Woodford, M. (2010). Credit spreads and monetary policy. *Journal of Money, Credit and Banking*, 42:3–35.

Cúrdia, V. and Woodford, M. (2011). The central-bank balance sheet as an instrument of monetary policy. *Journal of Monetary Economics*, 58(1):54–79.

DeGraeve, F. (2008). The external finance premium and the macroeconomy: US post-WWII evidence. *Journal of Economic Dynamics and Control*, 32(11):3415 – 3440.

Eisfeldt, A. L. and Muir, T. (2016). Aggregate external financing and savings waves. *Journal of Monetary Economics*, 84:116–133.

Faia, E. and Monacelli, T. (2007). Optimal interest rate rules, asset prices, and credit frictions. *Journal of Economic Dynamics and Control*, 31(10):3228–3254.

Furlanetto, F., Ravazzolo, F., and Sarferaz, S. (2017). Identification of financial factors in economic fluctuations. *The Economic Journal*, pages 1–27.

Galí, J. and Gambetti, L. (2015). The effects of monetary policy on stock market bubbles: Some evidence. *American Economic Journal: Macroeconomics*, 7(1):233–57.

Gambetti, L. and Musso, A. (2017). Loan supply shocks and the business cycle. *Journal of Applied Econometrics*, 32(4):764–782.

Gerali, A., Neri, S., Sessa, L., and Signoretti, F. (2010). Credit and banking in a DSGE model of the euro area. *Journal of Money, Credit and Banking*, 42:107–141.

Gertler, M. and Karadi, P. (2011). A model of unconventional monetary policy. *Journal of Monetary Economics*, 58(1):17–34.

Gertler, M., Kiyotaki, N., and Queralto, A. (2012). Financial crises, bank risk exposure and government financial policy. *Journal of Monetary Economics*, 59:S17–S34.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720.

Gomes, J. F., Yaron, A., and Zhang, L. (2003). Asset prices and business cycles withcostly external finance. *Review of Economic Dynamics*, 6(4):767–788.

Huh, S. and Kim, I. (2018). Limited borrowing capacity of financial intermediaries and the equity premium. Manuscript, University of California.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, 95(3):739–764.

Kaihatsu, S. and Kurozumi, T. (2014). Sources of business fluctuations: Financial or technology shocks? *Review of Economic Dynamics*, 17(2):224–242.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2):211–248.

Levin, A., Natalucci, F. M., and Zakrajšek, E. (2004). The magnitude and cyclical behavior of financial market frictions. Finance and Economics Discussion Series 70, Federal Reserve Board.

Meeks, R. (2012). Do credit market shocks drive output fluctuations? Evidence from corporate spreads and defaults. *Journal of Economic Dynamics and Control*, 36:568–584.

Meh, C. and Moran, K. (2010). The role of bank capital in the propagation of shocks. *Journal of Economic Dynamics and Control*, 34(3):555–576.

Mumtaz, H., Pinter, G., and Theodoridis, K. (2018). What do VARs tell us about the impact of a credit supply shock? *International Economic Review*, 59(2):625–646.

Queijo von Heideken, V. (2009). How important are financial frictions in the United States and the euro area? *The Scandinavian Journal of Economics*, 111(3):567–596.

Rubio-Ramírez, J., Waggoner, D., and Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696.

Smets, F. and Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review*, 67(3):586–606.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

Villa, S. (2016). Financial frictions in the euro area and the United States: A Bayesian assessment. *Macroeconomic Dynamics*, 20(5):1313–1340.

Walentin, K. (2005). Asset pricing implications of two financial accelerator models. Manuscript, New York University.

Appendix

SVAR with sign restrictions

Following Uhlig (2005) and Rubio-Ramírez et al. (2010), I consider a VAR model,

$$x_t = A + B_{(1)}x_{t-1} + B_{(2)}x_{t-2} + \ldots + B_{(M)}x_{t-M} + u_t,$$

where x_t is a $N \times 1$ vector containing N endogenous variables, A is $N \times 1$ vector of constants, $B_{(i)}$ for $i = 1,..M$ represents $N \times N$ coefficient matrices and u_t is $N \times 1$ one-step ahead prediction error with a variance-covariance matrix, Σ, of size $N \times N$.

The prediction error is related linearly to the structural shocks:

$$u_t = S\varepsilon_t,$$

whereby S is a non-singular parameter matrix and $\varepsilon_t \sim N(0, I_N)$. A Bayesian estimation is undertaken to obtain the reduced-form VAR.[20] Following Uhlig (2005), both prior and posterior for $(B_{(i)}, \Sigma)$ come from the Normal-Wishart distribution. He shows how the posterior can be analytically obtained.

The procedure can be described as follows. In the first step, the Cholesky identification is used to retrieve the matrix S. In the next step, I use the candidate identifications yielding the identity variance covariance matrix. There exists a nonsingular matrix Q, such that the new impact matrix $S^* = SQ$ and corresponding structural shocks $\varepsilon_t^* = Q^{-1}\varepsilon_t$, whereby reduced-form residuals $u_t = S^*\varepsilon_t^*$. Assuming that Q is an orthogonal matrix, i.e., $Q^{-1} = Q'$, the newly generated structural shocks have an identity variance covariance matrix:

$$E[\varepsilon_t^*\varepsilon_t^*] = E[Q^{-1}\varepsilon_t Q\varepsilon_t'] = Q^{-1}QE[\varepsilon_t\varepsilon_t'] = I_N.$$

Therefore, the candidate structural representations related to each S^* result in different impulse responses:

$$x_t = C(L)S^*\varepsilon_t^*.$$

If the matrices C_i from the reduced-form moving average in equation (4) are stacked, the response vector up to the first horizon (on impact) is given by

$$R(1) = E[S' \quad S'C_1']'Q.$$

The sign restrictions related to the specific impulse responses are imposed on the column vectors of the above matrix. The algorithm used to set the sign restrictions is described in Rubio-Ramírez et al. (2010). The functioning of the algorithm can be summarized as follows. I draw a Z matrix

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[20]The Akaike information criterion is used to determine the number of lags.

such that $Z \sim N(0, I_N)$. Afterwards I undertake a QR decomposition of Z. This decomposition enables me to get the orthogonal matrix Q. In the next step, candidate impulse responses are obtained from SQ and $B_{(i)}$ for $i = 1, ..M$. I check whether these generated impulse responses satisfy the sign restrictions. If the sign restrictions are not satisfied, a new Z is drawn and the procedure is re-iterated until the sign restrictions are satisfied. The procedure is repeated as many times as necessary to attain the 1000 draws that satisfy sign restrictions. The obtained impulse responses are used to compute the statistics as well as to generate the credible sets.

Data and sources

Data overview:

Real GDP: GDP (seasonally adjusted), divided by GDP deflator. Source: Federal Reserve Economic Database (FRED).

GDP deflator. Source: FRED.

Nominal short-term interest rate: effective federal funds (FF) rate (secondary market rate), expressed in annual units and in percentage points. Source: FRED.

Credit: sum of corporate bonds, bank loans and other loans and advances (non-financial corporate business). Source: FRED.

GZ credit spread: average credit spread on senior unsecured bonds issued by nonfinancial firms, expressed in annual units and in percentage points. Source: Gilchrist and Zakrajšek (2012).

EBP: excess bond premium (a component of GZ credit spread). Source: Gilchrist and Zakrajšek (2012).