Financial Shocks and the Debt Structure*

David Gauthier†

November 2019

This paper identifies financial shocks based on firm funding choices. I develop a general equilibrium model where firms fund production with bonds and loans. I show that only financial shocks generate opposite movements in the two types of debt as firms adjust their debt composition to the new credit conditions. In contrast, other shocks imply co-movements in the two types of debt. I use this result to identify financial shocks in a sign-restriction VAR model estimated with US data. The general equilibrium model allows me to recover a measure of financial stress and test the identification strategy.

JEL Classification: C11, E32, E44, G21.

I. Introduction

Understanding how financial and economic activity interact is key to determine what causes recessions. Over the past 20 years, various methods have been proposed to identify financial disturbances often relying on models including spreads and asset prices to proxy credit conditions. While such strategies have led to a better understanding of how credit disruptions shape the business cycle, identification of financial shocks still is a hazardous task. Several reasons explain the difficulty to establish causal links between the financial sector and the rest of the economy. First, financial variables are procyclical and forward-looking, making it arduous to separate financial shocks from the economic cycle with standard recursive identification schemes.[1] Second, because financial stress can turn out in credit rationing rather than in price changes, using statistical indicators of financial stress to proxy credit conditions faced by firms can be misleading. Third, structural models such as DSGE models used to identify sources of economic fluctuations do not always qualitatively distinguish shocks to credit conditions from other macroeconomic shocks, rendering the identification very sensitive to the model structure.

In this paper, I try to address these issues by developing a method to identify financial shocks based on qualitative criteria and relying on quantities rather than prices or other financial stress indicators. To do so, I identify financial shocks using firm funding decisions: because some firms can fund production with intermediated and direct debt, their debt arbitrage can be interpreted as

*I thank Antoine d'Autume, Yvan Bécard, Ambrogio Cesa-Bianchi, Fiorella De Fiore, Matteo Iacoviello, Michel Juillard, Riccardo Masolo, Julien Matheron, Francesca Monti, Gabor Pinter, Ricardo Reis, Stephanie Schmitt-Grohe and Harald Uhlig for their invaluable comments and suggestions.

†Paris School of Economics (e-mail: david.gauthier@psemail.eu). Click here for the last version of the paper. Additional materials can be found in the appendix.

[1]See for instance Mumtaz, Pinter, and Theodoridis (2018) for a critical review of financial shock identification using SVAR models.

a direct measure of the credit condition they face.[2] More precisely, firms able to fund from markets and banks can adjust both the level *and* composition of their debt what can be used to identify the type of shock driving economic fluctuations. As an illustration, consider a shock increasing firm debt demand but leaving credit conditions unchanged. From a partial equilibrium perspective, this shock implies an increase in both loan and bond volumes. On the other hand, an exogenous shock to credit conditions leaving debt demand unchanged implies a new debt arbitrage and *opposite* movements in the two forms of debt.

To investigate how the level and compositional effects articulate in response to macroeconomic shocks, I augment the workhorse NK model with the mechanism of debt choice from De Fiore and Uhlig (2011). The model implies that only financial shocks generate opposite movements in loan and bond volumes on impact. On the other hand, supply, monetary, and other demand shocks generate co-movement in the two types of debt. The reason is that in response to a financial shock, firms adjust their funding choice to the new credit conditions and substitute the most efficient type of debt for the other. In contrast, adverse non-financial shocks imply that both types of debt become less desirable for firms what triggers a simultaneous fall in bonds and loans. The signs of the impulse responses obtained from the model are robust for a wide set of calibrations.

In the second part of the paper, I implement the qualitative distinctions implied by the modified NK framework to inform a sign-restriction VAR model. The latter is estimated with US corporate firm balance-sheet data and standard macroeconomic series. The model is used to identify financial shocks and assess their business cycle implications. Because this identification scheme relies on firm funding decisions in place of the more usual spreads and asset prices extensively used to instrument financial perturbations, the method allows to circumvent the problem of co-movements between macroeconomic and potentially fast-moving financial variables, as pointed out in Kashyap, Stein, and Wilcox (1993), Meeks (2012), and Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) and Romer and Romer (2017). A byproduct of this method is that financial shocks need *not* to be identified as demand shocks. This restriction is commonly imposed to identify financial shocks in sign-restriction VAR and DSGE models but at odds with recent evidence brought up by Gilchrist, Schoenle, Sim, and Zakrajšek (2017) who show that financial disturbances can induce constrained firms to raise prices following adverse financial shocks and Angeletos, Collard, and Dellas (2018) who find that shocks most likely driving output fluctuations are orthogonal to the ones responsible for price dynamics.

In the final part of the paper, I estimate the modified NK model so as to minimize the distance between its impulse responses and those from the VAR model. I find that the modified NK model can reproduce the qualitative and quantitative features implied by the data for all types of shock. The estimated model is then used to recover a structural measure of the financial shocks observed over the past 30 years. The financial shocks obtained match other indices of financial stress and are highly predictive of the bond spread.

Over the past 20 years, various papers have studied financial shocks using bond spreads and asset prices to proxy credit conditions. Justiniano, Primiceri, and Tambalotti (2011), Christiano, Motto, and Rostagno (2014) and Ajello (2016) use general equilibrium models embedding credit frictions to show that financial shocks are the best candidates to jointly explain fluctuations in financial and non-financial variables. Gilchrist and Zakrajšek (2012a,b) construct a measure of bond spread purged of components other than the excess bond premium to identify exogenous changes in credit supply. In the meantime, many economists have pointed to the identification

[2] In the rest of the paper, I use interchangeably intermediated debt or bank loan and direct debt or bond.

challenge arising from jointly studying economic activity and financial markets. This fact is exemplified by Stock and Watson (2012) who underline the difficulty to distinguish financial and uncertainty disturbances as reflected by the high correlation of shocks identified respectively with the Gilchrist and Zakrajšek (2012b) spread and with the policy uncertainty index from Baker, Bloom, and Davis (2016). Meeks (2012) highlights similar issues when using spreads to capture financial shocks. He shows that much of the fluctuations observed in US bond spreads are better qualified as endogenous responses to shifts in default risk rather than as the result of exogenous changes in credit conditions.

In reaction, sign-restriction methods as developed by Faust (1998), Uhlig (2005) and Rubio-Ramirez, Waggoner, and Zha (2010), have become increasingly popular to identify financial shocks. Using a sign-restriction Bayesian VAR, Fornari and Stracca (2012) identify financial shocks as demand shocks increasing the share price of financial firms relative to the share price of non-financial firms. Furlanetto, Ravazzolo, and Sarferaz (2017) identify financial shocks as demand shocks simultaneously increasing the ratio of investment over output and the share price of firms. Cesa-Bianchi and Sokol (2017) combine an external instrument approach with sign-restriction methods to identify adverse financial shocks as the only type of demand shock leading to a rise in lending rates. Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) use a penalty-function approach to construct uncorrelated series of uncertainty and financial shocks.

The identification strategy I propose is also tightly related to a literature initiated by Kashyap, Stein, and Wilcox (1993) who use the evolution of commercial papers relative to corporate loans to evaluate the strength of the monetary policy credit channel. Since the 2007 financial crisis and the renewed interest for financial disruptions, their approach has been extended to capture exogenous contractions in credit supply. Becker and Ivashina (2014) use the share of firms substituting bonds for loans as a proxy for credit conditions to capture adverse credit supply shocks. They show that the ratio of intermediated debt to direct debt is negatively affected by depressed aggregate lending, poor bank performances, and tight monetary policy. Altavilla, Darracq Pariès, and Nicoletti (2015) use bank lending surveys to instrument credit conditions. They find that adverse credit supply shocks imply strong contractions in corporate borrowing along with the increase of bond issuance as firms substitute direct debt for bank loans. Adrian, Colla, and Song Shin (2013) provide evidence that corporate firms have massively substituted bonds for loans during the 2007 financial crisis and show that changes in US corporate debt composition account for most of the simultaneous increase in bond spread.

To model non-trivial firm arbitrage between direct and indirect debt in a general equilibrium model, I include risky firms that fund working capital using external debt in the NK framework. I follow De Fiore and Uhlig (2011, 2015) in assuming the existence of banks that are more efficient than markets at resolving asymmetric information problems but also more costly. As in Berlin and Mester (1992) and Holmstrom and Tirole (1997), the model assumes that bank-funded firms can transmit private information to their lender and renegotiate their debt contract conditional on their own characteristics. The mechanism of debt choice is also closely related to the debt arbitrage mechanism from Repullo and Suarez (2000). In their model, banks with high monitoring intensity are the only possible source of funds for firms with low net worth. Closely related, Crouzet (2018) constructs a mechanism of firm debt arbitrage where banks provide flexible contracts to producing firms. As in De Fiore and Uhlig (2015), he finds that firms' access to direct funding dampens the impact of financial shocks. Including the debt choice mechanism from De Fiore and Uhlig (2011) into the NK framework preserves the tractable structure of the original model and allows to study the main shocks from the business cycle literature within a general equilibrium framework.

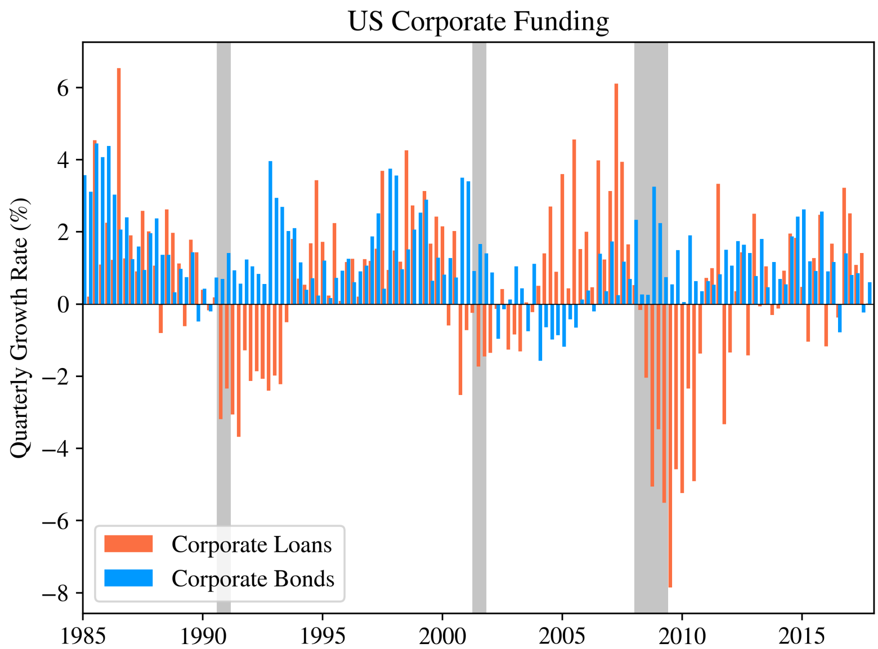

Figure 1: Bond and Loan Growth Rates.

Note: Bond and loan quarterly growth rates for US non-financial corporate firms. Orange bars correspond to bank loans and blue bars correspond to bonds. Grey bands correspond to NBER recession dates. Source: Flow of Funds.

Figure 1 illustrates the key characteristics of the evolution of intermediated and direct debt in the US since the mid-'80s. A few facts are worth noticing. First, bank loans are strongly procyclical, rising during episodes of expansion and falling during recessions. Second, all three recessions in the sample are characterized by opposite movements in bond and loan growth rates. Third, the joint evolution of loans and bonds is different prior to each recession: i) the early '90s recession is preceded by a strong decline in the growth rates of the two types of debt, ii) the 2001 recession follows a sudden contraction in loans coinciding with a surge in bonds, iii) the Great Recession follows a protracted increase in loans with a stable bonds until the end of 2008.

The rest of the paper is organized as follows. Section II introduces the modified NK model, section III presents the calibration of the model and discusses its properties. Section IV estimates a sign-restriction VAR model. Section V estimates the modified NK model and provides out-of-sample exercises. Section VI concludes.

II. A New Keynesian Model with Debt Arbitrage

In this section, I present a general equilibrium model used to investigate the dynamics of firm debt choice. The model is based on De Fiore and Uhlig (2011) where producing entrepreneurs with idiosyncratic productivity can hedge some of their processing risk by engaging in costly contracts with banks, thereby giving rise to arbitrage between intermediated and direct debt. This section provides an overview of the model, a complete derivation and the full set of equations can be found in section A.II of the appendix.

The model is populated by three types of agents: households who consume, work and save, firms that use capital and labor to produce final goods and financial intermediaries that channel funds from households to the productive sector.

A. Households

The model assumes a large number of identical and competitive households. Each household contains every type of labor, h_{it} with $i \in [0,1]$. A representative household maximizes its utility function defined as:

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_{c,t} \left\{ \log(c_t - bc_{t-1}) - \psi_L \int_0^1 \frac{h_{it}^{1+\sigma_L}}{1+\sigma_L} di \right\},$$

where c_t is household consumption, $\zeta_{c,t} > 0$ is a preference shock, $\sigma^L > 1$ is the inverse of the Frisch elasticity of labor supply, b is the degree of habits and ψ_L is a weighting parameter for labor desutility. Each household is subject to the following budget constraint:

$$P_t c_t + P_t d_t + Q_t^k k_t \leq \int_0^1 W_{it} h_{it} di + R_t P_{t-1} d_{t-1} + \left[Q_t^k (1-\delta) + u_t r_t^k - a(u_t) \right] k_{t-1} + \Omega_t. \quad (1)$$

Households spend on both consumption of the final goods priced at P_t, and on capital purchases k_t, bought from capital installers at price Q_t^k and sold back to them at the end of the period. Households get their revenues from selling differentiated labors h_{it} supplied by individuals at a real wage rate W_{it} set by monopoly unions. Previous period real deposits d_{t-1} are remunerated at a nominal rate R_t. Each period, households decide the utilization rate of capital u_t and supply effective capital $u_t k_t$ to entrepreneurs at a competitive rental rate r_t^k. The function $a(.)$ designates capital utilization costs. Finally, Ω_t corresponds to transfers from entrepreneurs.

Labor Market.—A representative competitive labor contractor aggregates the differentiated labor h_{it} into homogeneous labor services l_t, using the following technology:

$$l_t = \left[\int_0^1 h_{it}^{\frac{1}{\lambda_w}} di \right]^{\lambda_w}, \quad 1 \leq \lambda_w. \quad (2)$$

The labor contractor sells labor services to entrepreneurs at a real wage rate w_t. A monopoly union represents workers of each type i and set the corresponding wage subject to Calvo frictions: each period a fraction $1-\xi_w$ of unions can set wages to their optimal level while the rest of the wages evolve according to an indexation rule defined as: $W_{it} = (\pi)^{\iota_w} (\pi_{t-1})^{1-\iota_w} W_{it-1}$, where π_t is the inflation rate, π is the steady-state level of inflation and ι_w is a parameter.

Capital Installers.—Capital installers buy investment goods I_t^k from the final good producer and turn it into installed capital which is sold to households in a competitive market at a price Q_t^k. Capital installers maximize their discounted sum of profits using household stochastic discount rate $\beta^t \zeta_{c,t} \Lambda_{z,t}$:

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_{c,t} \Lambda_{z,t} \left\{ Q_t^k k_t - P_t I_t^k \right\},$$

using the following technology:

$$k_t = (1-\delta) k_{t-1} + \left[1 - S\left(\zeta_{I,t} \frac{I_t^k}{I_{t-1}^k} \right) \right] I_t^k,$$

where $0 < \delta < 1$ is the depreciation rate of capital, $S(.)$ is an increasing adjustment cost function defined below, and $\zeta_{I,t}$ is a shock to the marginal efficiency of investment in producing capital.

B. Firms

Firms produce final goods using capital and labor inputs. I follow Gali (2010) in assuming a three-sector structure for firms. Entrepreneurs produce homogeneous goods transformed by monopolistically competitive retailers into intermediate goods. The final good producers then combine intermediate goods bought from retailers to produce homogeneous final goods sold to households in competitive markets.

B.1. Entrepreneurs

Entrepreneurs are heterogeneous agents modeled as in De Fiore and Uhlig (2011). They contract with financial intermediaries to fund working capital used to produce homogeneous goods sold to intermediate producers. Because there exist different types of financial intermediaries, entrepreneurs can select the form of debt they prefer according to their own characteristics.

Production.—There is a continuum $e \in [0, 1]$ of risk neutral entrepreneurs operating in competitive markets. An entrepreneur e produces goods Y_{et}^E using capital and labor according to the following Cobb-Douglas technology:

$$Y_{et}^E = \varepsilon_{et}^E A_t (u_t k_{et-1})^\alpha l_{et}^{1-\alpha}, \tag{3}$$

where l_{et} and k_{et} denote respectively labor and capital inputs used for production. Variable A_t corresponds to the Solow residual and ε_{et}^E is a sequence of independent idiosyncratic shock realizations. To produce, entrepreneurs must fund labor and capital inputs with available funds x_{et}, according to the following debt constraint:

$$x_{et} \geq r_t^k k_{et} + w_t l_{et}, \tag{4}$$

where x_{et} corresponds to the sum of their net worth n_{et} and external debt d_{et}:

$$x_{et} = n_{et} + d_{et}. \tag{5}$$

Entrepreneur e starts the period t with net worth n_{et}, which corresponds to past period profits minus dividends transferred to the households. To obtain external funds d_{et} from a financial intermediary, an entrepreneur must pledge her net worth according to the following leverage constraint:

$$x_{et} = \xi n_{et}, \tag{6}$$

where ξ is a parameter defining entrepreneurs' leverage.[3] After production, Y_{et}^E is sold to retailers at a competitive price P_t^E. The problem of an entrepreneur given available funds x_{et} is to choose

[3]Similar to De Fiore and Uhlig (2011) and in contrast with the standard debt contracts from the canonical model of Bernanke, Gertler, and Gilchrist (1999), one need to assume fixed leverage for entrepreneurs to obtain an interior solution to the borrowing decision problem. The reason is that entrepreneurs have different credit worthinesses. In the practical case where the distribution of ε_{et}^E is bounded, optimal leverage implies a corner solution with all available funds going to the best entrepreneur.

the combination of capital and labor inputs maximizing her real profits defined as:

$$\frac{P_t^E Y_{et}^E}{P_t} - r_t^k k_{et} - w_t l_{et}, \tag{7}$$

subject to the debt constraint defined in equation (4). The solution to the optimization problem of an entrepreneur implies the following first order conditions:

$$\alpha x_{et} = r_t^k k_{et}, \tag{8}$$

$$(1-\alpha) x_{et} = w_t l_{et}. \tag{9}$$

Defining s_t as the aggregate component of the marginal cost of production expressed in terms of the final goods yields:

$$s_t = \frac{1}{A_t u_t^\alpha} \left(\frac{P_t}{P_t^E}\right) \left(\frac{r_t^k}{\alpha}\right)^\alpha \left(\frac{w_t}{1-\alpha}\right)^{1-\alpha}. \tag{10}$$

For further use, it is also convenient to define $q_t = \frac{1}{s_t}$, where q_t can be interpreted as the aggregate entrepreneurial markup over input costs.[4]

Idiosyncrasy.—Before production takes place, each entrepreneur is hit by a series of successive idiosyncratic productivity shocks which determine whether an entrepreneur produces or not and her preferred type of financial intermediary. Three successive idiosyncratic shocks are considered here. First, a shock $\varepsilon_{1,et}$ is publicly observed and creates heterogeneity in the productivity of entrepreneurs. This shock realizes along with aggregate shocks and before entrepreneurs have contracted with financial intermediaries. Second, a shock $\varepsilon_{2,et}$ occurs after financial contracts are set and is observed only by bank-funded entrepreneurs and their banks. This shock creates a rationale for choosing intermediated finance over direct finance. The third shock $\varepsilon_{3,et}$ is privately observed by entrepreneurs and realizes just before production takes place. This final shock justifies the existence of risky debt contracts between entrepreneurs and financial intermediaries. Both privately observed shocks $\varepsilon_{2,et}$ and $\varepsilon_{3,et}$ can be monitored at a cost by financial intermediaries.

Entrepreneurs have the option to contract with banks to decrease their residual processing risk. To do so they must pay a share τ^b of their net worth that is used to resolve part of their productivity uncertainty. A bank-funded entrepreneur e pays a cost $\tau^b n_{et}$ to observe the realization of $\varepsilon_{2,et}$ and to share it with her bank. Before production takes place and based on the realization of $\varepsilon_{2,et}$, bank-funded entrepreneurs have the possibility to renegotiate their contract, in which case they simply recover their pledged net worth and abstain from production. Denoting ω_{et}^f the realization of the uncertain productivity factor for entrepreneur e conditional on contracting with a financial intermediary of type f which can be b for bank or c for market,

$$\omega_{et}^f = \begin{cases} \varepsilon_{2,et}\varepsilon_{3,et} & \text{, \textit{if bond financing}} \\ \varepsilon_{3,et} & \text{, \textit{if loan financing.}} \end{cases}$$

After the first idiosyncratic shock $\varepsilon_{1,et}$ is observed, each entrepreneur decides whether she wants to produce and if so selects her optimal source of funds. An entrepreneur can choose either

[4] Here s_t must not be confounded with the marginal cost of the intermediate good producer, $pc_t = \frac{P_t^E}{P_t}$, which is taken as given by entrepreneurs.

to contract with banks in which case production is conditioned on the realization of $\varepsilon_{2,et}$, or to fund from markets in which case she produces regardless of her residual uncertainty factor ω^f_{et}. Entrepreneurs abstaining from production keep their net worth until the end of the period. Producing entrepreneurs rent capital k_{et} and hire labor h_{et} from households. Factors repayment is done at the end of the period and backed by the value of pledged collateral and funds obtained from financial intermediaries. The net worth of an entrepreneur after having contracted with a financial intermediary is:

$$n^f_{et} = \begin{cases} n_{et} & \text{, if bond financing} \\ (1-\tau^b)n_{et} & \text{, if loan financing.} \end{cases}$$

In the final stage of period t, the shock $\varepsilon_{3,et}$ realizes and is privately observed. Entrepreneurs announce the outcome of their production, sell it to retailers, repay production factors to households and reimburse their financial intermediary. The realization of ω^f_{et} is kept private unless the financial intermediary decides to monitor defaulting entrepreneurs in which case a fraction μ^f of seized assets is lost in the monitoring process.

In application, I assume that all three types of idiosyncratic shocks are normally and independently distributed across entrepreneurs such that $\varepsilon_{1,et} \sim \mathcal{N}(0,\sigma_1^2)$, $\varepsilon_{2,et} \sim \mathcal{N}(0,\sigma_2^2+\nu_t)$ and $\varepsilon_{3,et} \sim \mathcal{N}(0,\sigma_3^2-\nu_t)$, where ν_t is a shock shifting the relative share of idiosyncratic productivity that bank-funded entrepreneurs can observe and transmit to their bank. Variable σ^f_t is the standard deviation of the residual uncertainty productivity factor $\omega^f_{e,t}$ conditional on the entrepreneur funding decision:

$$\sigma^f_t = \begin{cases} \sqrt{\sigma_2^2+\sigma_3^2} & \text{, if bond financing} \\ \sqrt{\sigma_3^2-\nu_t} & \text{, if loan financing.} \end{cases}$$

Notice that this specification implies that the standard deviation of entrepreneur productivity prior to their funding decision - what also corresponds to the standard deviation of productivity conditional on funding with bonds, is left unchanged after a shock ν_t.

Financial Contracts.—The model assumes the existence of a continuum of risk-neutral financial intermediaries of each type, bank b or market c, able to fully diversify risk among entrepreneurs. After the realization of the first two idiosyncratic shocks, an entrepreneur e and a financial intermediary agree on a standard debt contract conditional on the expected productivity of the contracting entrepreneur ε^f_{et}, where:

$$\varepsilon^f_{et} = \begin{cases} \varepsilon_{1,et} & \text{, if bond financing} \\ \varepsilon_{1,et}\varepsilon_{2,et} & \text{, if loan financing.} \end{cases}$$

Denoting $\varphi(\omega^f_{et};\sigma^f_t)$ and $\Phi(\omega^f_{et};\sigma^f_t)$ the distribution and cumulative density functions of ω^f_{et} implied by the distributional assumptions for the idiosyncratic shock distributions and given an optimal threshold $\bar{\omega}$, the expected share of final output accruing to a contracting entrepreneur is:

$$v(\bar{\omega};\sigma) = \int_{\bar{\omega}}^{\infty} (\omega-\bar{\omega})\varphi(\omega;\sigma)d\omega,$$

and the expected share of final output accruing to the lender is:

$$g(\bar{\omega}; \sigma) = \int_0^{\bar{\omega}} (1 - \mu)\omega\varphi(\omega; \sigma)d\omega + \bar{\omega}[1 - \Phi(\bar{\omega}; \sigma)].$$

The optimal contract chosen by an entrepreneur sets a threshold $\bar{\omega}_{et}^f$ under which monitoring occurs and maximizing the expected fixed repayment $\varepsilon_{et}^f \bar{\omega}_{et}^f q_t x_{et}$ paid to the financial intermediary subject to the constraint defined by equation 4 and,

$$\varepsilon_{et}^f q_t g(\bar{\omega}_{et}^f, \sigma_t^f) x_{et} \geq (x_{et} - n_{et}^f) R_t, \tag{11}$$

$$v(\bar{\omega}_{et}^f, \sigma_t^f) + g(\bar{\omega}_{et}^f, \sigma_t^f) \leq 1 - G_\omega^f(\bar{\omega}_{et}^f, \sigma_t^f), \tag{12}$$

$$\varepsilon_{et}^f q_t v(\bar{\omega}_{et}^f, \sigma_t^f) x_{et} \geq n_{et}^f, \tag{13}$$

where $G_\omega^f(\bar{\omega}_t^f, \sigma_t^f) = \mu^f \int_0^{\bar{\omega}_t^f} \omega\varphi(\omega, \sigma_t^f) d\omega$ is the share of output lost to monitoring. Equation 11 implies that financial intermediary expected returns must exceed repayment for households, equation 12 ensures the feasibility of the debt contract, and equation 13 guarantees the entrepreneur's willingness to borrow from a financial intermediary. Notice that because the problem of the entrepreneur is linear in net worth, the optimal solution implies that each entrepreneur invests all or none of her net worth.

Under optimal contracts and assuming free entry for financial intermediaries such that equation 11 is always binding, the optimal threshold $\bar{\omega}_{et}^f$ is given as the minimal solution to:

$$g(\bar{\omega}_{et}^f, \sigma_t^f) = \left(\frac{\xi - 1}{\xi}\right) \frac{R_t}{\varepsilon_{et}^f q_t}. \tag{14}$$

This equation can be used to implicitly define thresholds $\bar{\omega}_{et}^f$ as functions of aggregate variables q_t, R_t, ν_t and idiosyncratic expected productivity $\varepsilon_{et}^f q_t$ such that:

$$\bar{\omega}_{et}^f = \begin{cases} \bar{\omega}^c(\varepsilon_{1,et}, q_t, R_t) & \text{, if bond financing} \\ \bar{\omega}^b(\varepsilon_{1,et}\varepsilon_{2,et}, q_t, R_t, \nu_t) & \text{, if loan financing,} \end{cases}$$

where it can be seen from equation 14 that $\bar{\omega}_{et}^f$ is increasing in R_t and decreasing in q_t, ν_t and ε_{et}.

Funding Choices.—Following De Fiore and Uhlig (2011) it is possible to prove the existence and uniqueness of thresholds in the realization of idiosyncratic productivity shocks characterizing entrepreneur funding decisions.

Consider an entrepreneur e having contracted with a bank in period t. After having observed the realization of the second idiosyncratic shock $\varepsilon_{2,et}$, this entrepreneur decides to proceed with its loan only if her expected share of profit is higher than the opportunity cost of producing, what corresponds to her net worth. Defining $V^d(\varepsilon_{1,et}, \varepsilon_{2,et}, q_t, R_t, \nu_t) n_{et}^b$ the expected output share accruing to entrepreneur e, this yields:

$$V^d(\varepsilon_1, \varepsilon_2, q, R, \nu) = \varepsilon_1 \varepsilon_2 q v(\bar{\omega}^b(\varepsilon_1 \varepsilon_2, q, R, \nu)). \tag{15}$$

Conditional on the realization of $\varepsilon_{1,et}$ and aggregate factors, entrepreneur e proceeds with bank finance only if the realization of $\varepsilon_{2,et}$ is higher than a threshold $\bar{\varepsilon}_d(\varepsilon_{1,et}, q_t, R_t, \nu_t)$ satisfying:

$$1 = V^d(\varepsilon_{1,et}, \bar{\varepsilon}_{2,et}, q_t, R_t, \nu_t). \tag{16}$$

The funding decision of an entrepreneur having observed $\varepsilon_{1,et}$ can be deduced similarly by comparing her expected payoffs conditional on her funding choice. The expected payoff for an entrepreneur proceeding with bank finance conditional on the realization of $\varepsilon_{1,et}$ is $V^b(\varepsilon_{1,et}, q_t, R_t, \nu_t)n^b_{et}$, where:

$$V^b(\varepsilon_1, q, R, \nu) = (1-\tau^b)\left(\int_{\bar{\varepsilon}_d} V^d(\varepsilon_1, \varepsilon_2, q, R, \nu)\Phi(d\varepsilon_2) + \Phi(\bar{\varepsilon}_d(\varepsilon_1, q, R, \nu)\right). \tag{17}$$

Similarly, the expected payoff for an entrepreneur proceeding with bond finance conditional on $\varepsilon_{1,et}$ is $V^c(\varepsilon_{1,et}, q_t, R_t)n^c_{et}$, where:

$$V^c(\varepsilon_1, q, R) = \varepsilon_1 q v(\bar{\omega}^c(\varepsilon_1, q, R))\xi. \tag{18}$$

Finally, the expected payoff for an entrepreneur abstaining from production is n_{et}. Conditional on $\varepsilon_{1,et}$ each entrepreneur selects the funding option delivering the maximum expected payoff $V(\varepsilon_{1,et}, q_t, R_t)n_{et}$ defined as:

$$V(\varepsilon_1, q, R, \nu) = max\{1, V^b(\varepsilon_1, q, R, \nu), V^c(\varepsilon_1, q, R)\}. \tag{19}$$

Under the conditions that $\frac{\partial V^b(.)}{\partial \varepsilon_1} \geq 0$ and $\frac{\partial V^c(.)}{\partial \varepsilon_1} > \frac{\partial V^b(.)}{\partial \varepsilon_1}$, it can be shown that there exists a unique threshold $\bar{\varepsilon}^b$ for ε_1 implicitly defined by the condition $V^b(\bar{\varepsilon}_{b,t}, q_t, R_t, \nu_t) = 1$ and under which entrepreneurs do not rise external finance. Because this cutoff point depends only on aggregate variables such that $\bar{\varepsilon}_{b,t} = \bar{\varepsilon}_b(q_t, R_t, \nu_t)$, it is identical across all entrepreneurs. Similarly, there exists a unique threshold $\bar{\varepsilon}_c$ for ε_1 above which entrepreneurs prefer to fund from markets and implicitly defined by the condition $V^b(\bar{\varepsilon}_{c,t}, q_t, R_t, \nu_t) = V^c(\bar{\varepsilon}_{c,t}, q_t, R_t)$ such that: $\bar{\varepsilon}_{c,t} = \bar{\varepsilon}_c(q_t, R_t, \nu_t)$. Conditional on q_t, R_t, and ν_t entrepreneurs split into three distinct sets mapping the realization of the first idiosyncratic productivity shock $\varepsilon_{1,et}$ to their optimal funding choice.

Defining s^a_t, s^b_t, s^c_t and s^{bp}_t respectively the shares of entrepreneurs that abstain from production, contract with banks, proceed with bonds and proceed with bank loans, I obtain:

$$s^a_t = \Phi\left(\bar{\varepsilon}^b(q_t, R_t, \nu_t)\right), \tag{20}$$

$$s^b_t = \Phi\left(\bar{\varepsilon}^c(q_t, R_t, \nu_t)\right) - \Phi\left(\bar{\varepsilon}^b(q_t, R_t, \nu_t)\right), \tag{21}$$

$$s^c_t = 1 - \Phi\left(\bar{\varepsilon}^c(q_t, R_t, \nu_t)\right), \tag{22}$$

$$s^{bp}_t = \int_{\bar{\varepsilon}^b(q_t,R_t,\nu_t)}^{\bar{\varepsilon}^c(q_t,R_t,\nu_t)} \int_{\bar{\varepsilon}^d(\varepsilon_1,q_t,R_t,\nu_t)} \Phi\left(d\varepsilon_2\right)\Phi\left(d\varepsilon_1\right). \tag{23}$$

Financial Variables.—Using the productivity thresholds $\bar{\varepsilon}^b_t$ and $\bar{\varepsilon}^c_t$, it is possible to express entrepreneur average risk premia and default rates conditional on entrepreneur funding decisions. Denoting respectively ψ^{mb}_t and ψ^{mc}_t the default rates for bank-funded and market-funded firms yields:

$$\psi^{mb}_t = \int_{\bar{\varepsilon}_b(q,R,\nu)}^{\bar{\varepsilon}_c(q,R,\nu)} \int_{\bar{\varepsilon}_d(\varepsilon_1,q,R,\nu)} \Phi(\bar{\omega}^b(\varepsilon_1\varepsilon_2, q, R, \nu))\Phi(d\varepsilon_2)\Phi(d\varepsilon_1), \tag{24}$$

$$\psi_t^{mc} = \int_{\bar{\varepsilon}_c(q,R,\nu)} \Phi(\bar{\omega}^c(\varepsilon_1, q, R, \nu))\Phi(d\varepsilon_1). \tag{25}$$

With expected fixed repayment for the financial intermediary being $\varepsilon_{et}^f \bar{\omega}_{et}^f q_t$ per unit of fund x_t, the credit spread for an entrepreneur e writes:

$$\Lambda_{e,t}^f = \frac{\xi}{\xi - 1} \frac{q_t \varepsilon_{e,t}^f \bar{\omega}_{e,t}^f}{R_t} - 1. \tag{26}$$

Denoting ψ_t^{rb} and ψ_t^{rc} the aggregate realizations of entrepreneur credit spreads for bank-funded and market-funded firms:

$$\psi_t^{rb} = \int_{\bar{\varepsilon}_b(q,R,\nu)}^{\bar{\varepsilon}_c(q,R,\nu)} \int_{\bar{\varepsilon}_d(\varepsilon_1,q,R,\nu)} \left\{ \frac{\xi}{\xi - 1} \frac{\varepsilon_1 \varepsilon_2 \bar{\omega}_{e,t}^b q_t}{R_t} - 1 \right\} \Phi(d\varepsilon_2)\Phi(d\varepsilon_1), \tag{27}$$

$$\psi_t^{rc} = \int_{\bar{\varepsilon}_c(q,R,\nu)} \left\{ \frac{\xi}{\xi - 1} \frac{\varepsilon_1 \bar{\omega}_{e,t}^c q_t}{R_t} - 1 \right\} \Phi(d\varepsilon_1). \tag{28}$$

Finally, it is possible to express Λ_t^b the average spread for bank-financed firms and Λ_t^c the average spread for bond-financed firms express as:

$$\Lambda_t^b = \frac{\psi_t^{rb}(q, R, \nu)}{s_t^{bp}}, \tag{29}$$

$$\Lambda_t^c = \frac{\psi_t^{rc}(q, R, \nu)}{s_t^c}. \tag{30}$$

Aggregation.—Integrating across entrepreneurs for the first order conditions 8 and 9 yields aggregate capital and labor demands:

$$h_t = (1 - \alpha)\frac{x_t}{w_t}, \tag{31}$$

$$k_t = \alpha \frac{x_t}{r_t^k}. \tag{32}$$

Using equations 3 and 10 yields entrepreneur final aggregate production:

$$\begin{aligned} Y_t^E &= \int_0^1 Y_{et}^E de, \\ &= \frac{\psi_t^y \xi n_t}{s_t}, \end{aligned}$$

where n_t corresponds to the aggregate entrepreneur net worth and variable ψ_t^y aggregates the realizations of the different idiosyncratic productivity shocks of period t into a single productivity factor similarly. The aggregate profits of entrepreneurs Π_t^E are defined as:

$$\Pi_t^E = \psi_t^V n_t, \tag{33}$$

where ψ_t^V is defined in section A.II of the appendix and aggregates the overall profits across all entrepreneurs. Each period, a share $1 - \gamma$ of entrepreneur past period profits is transferred to households as dividends o_t. The rest of the profits are accumulated as net worth with the following law of motion:

$$n_t = \gamma \psi_{t-1}^V n_{t-1}, \tag{34}$$

accordingly, the dividends redistributed to households evolve as:

$$o_t = (1-\gamma)\psi_{t-1}^{V} n_{t-1}. \tag{35}$$

B.2. Retailers

Retailers are monopolistically competitive firms indexed by $j \in [0,1]$. They produce differentiated final goods Y_{jt} using the following linear homogeneous technology:

$$Y_{jt} = Y_{jt}^{E},$$

where Y_{jt}^{E} is the quantity of the intermediate goods used by retailers j as an input and purchased to entrepreneurs in competitive markets at price P_t^E. Assuming Calvo staggered price contracts, $1-\xi_p$ denotes the probability for a retailer to be able to readjust her price each period. Retailers unable to reoptimize their prices follow an indexation rule defined as: $P_{jt} = (\pi)^{\iota_p} (\pi_{t-1})^{1-\iota_p} P_{jt-1}$, where ι_p is a parameter.

B.3. Final Good Producers

A representative final good producer combines intermediate goods Y_{jt} into homogeneous final goods Y_t using the following technology:

$$Y_t = \int_0^1 \left[Y_{jt}^{\frac{1}{\lambda^p}} \right]^{\lambda^p}, \lambda^p > 1,$$

where λ^p is the markup set over the intermediate good price P_t^E. The first order conditions for profit maximization by final goods producers imply the following demand schedule:

$$P_{jt} = P_t \left(\frac{Y_{jt}}{Y_t} \right)^{\frac{\lambda^p}{\lambda^p - 1}}, \quad j \in [0,1],$$

where P_{jt} is the price of good Y_{jt} and where P_t is the price of the final good which satisfies the following relation:

$$P_t = \left[\int_0^1 P_{jt}^{\frac{1}{1-\lambda^p}} dj \right]^{1-\lambda^p}. \tag{36}$$

C. Monetary Authority

The monetary authority sets the nominal interest rate according to a standard Taylor rule expressed in linearized form as:

$$R_t - R = \rho_p (R_{t-1} - R) + (1-\rho_p) \left[\alpha_\pi (E\pi_{t+1} - \pi) + \frac{\alpha_{\Delta y}}{4} g_{y,t} \right] + \frac{1}{400} \epsilon_t^p, \tag{37}$$

where ϵ_t^p is a monetary policy shock expressed in annual percentage points, and ρ_p is a smoothing parameter of the policy rule. Also, $R_t - R$ is the deviation of the net quarterly interest rate, R_t, from its steady-state value R, and α_π and $\alpha_{\Delta y}$ are Taylor rule coefficients for the rate of expected quarterly inflation $E\pi_{t+1} - \pi$ and for the quarterly GDP growth $g_{y,t}$.

D. Aggregates and Cost Functions

The aggregate resource constraint of the economy writes:

$$Y_t = c_t + I_t^k + a(u_t)k_t + y_t^a, \tag{38}$$

where y_t^a corresponds to the resources consumed in monitoring and in bank-specific information acquisition costs:

$$y_t^a = \left[\tau^b s_t^b + \psi_t^m \xi q_t\right] n_t. \tag{39}$$

Here ψ_t^m is the entrepreneur aggregate rate of default defined in section A.II of the appendix. Aggregate funds raised by entrepreneurs are obtained by integrating individual funds over the continuum of entrepreneurs, what yields:

$$x_t = \left[(1-\tau^b)s_t^{bp} + s_t^c\right] \xi n_t. \tag{40}$$

Similarly the aggregate external debt raised by entrepreneurs d_t is given by:

$$d_t = \left[(1-\tau^b)s_t^{bp} + s_t^c\right] (\xi - 1) n_t. \tag{41}$$

The utilization cost function and investment adjustment cost function are taken from Christiano, Motto, and Rostagno (2014). The utilization function is a convex and increasing function defined as:

$$a(u) = r^k \left[exp(\sigma_a(u-1)) - 1\right] \frac{1}{\sigma_a}. \tag{42}$$

This formulation implies a unitary value for the steady-state capital utilization which is independent of the value of the curvature parameter σ_a, where $\sigma_a > 0$. The variable r^k corresponds to the steady-state level of capital rental rate. The investment adjustment cost function writes:

$$S(\eta_t) = \frac{1}{2}\left[\exp\left(\sqrt{S''/2}(\eta_t - \eta)\right) + \exp\left(-\sqrt{S''/2}(\eta_t - \eta)\right) - 2\right],$$

where $\eta_t = \zeta_{I,t} I_t^k / I_{t-1}^k$. Note that this implies $S(\eta) = S'(\eta) = 0$ and $S''(\eta) = S''$ which is a parameter.

E. Shock Processes

The model includes four different shock processes, $A_t, \zeta_t^c, \zeta_t^i$, and ν_t corresponding respectively to technology, preference and marginal efficiency of investment shocks. The shock ν_t is a financial shock affecting the efficiency of banks to limit firm asymmetric information problem and whose properties are discussed later. All shocks follow standard autoregressive processes of degree one. Hence a generic exogenous variable x_t writes as:

$$log\left(\frac{x_t}{x}\right) = \rho_x log\left(\frac{x_{t-1}}{x}\right) + \epsilon_t^x \text{ and } \epsilon_t^x \sim N\left(0, \sigma_x\right).$$

In addition, exogenous shifts in monetary policy are captured by innovations ϵ_t^p which are assumed iid and normally distributed. The model is linearized and simulated locally around its steady state. The next section discusses the calibration of the model.

III. Calibration and Model Properties

This section presents the calibration and static properties of the model and discusses the impulse responses for the different aggregate shocks.

A. Model Calibration

Using a calibrated version of the model, I investigate the evolution of firm debt structure in response to different types of aggregate shocks. There are 25 parameters in total. Most of the parameters are standard in the DSGE literature and are calibrated based on conservative values. Parameter α is set at 0.37 to target a labor share around 60 percent as observed for US non-financial corporate firms in Karabarbounis and Neiman (2014). The depreciation rate δ is set at 0.025 what implies an annual depreciation rate of capital stock around 10 percent. Household discount factor β is set to 0.99 to pin down a policy rate of 4 percent, corresponding to the average annualized federal funds rate since the '80s. Following Christiano, Eichenbaum, and Evans (2005), I set the price and wage markups, λ^p and λ^w respectively to 1.2 and 1.1. The subsidy rate on the purchase of intermediate goods is set at 0.17 to equate the price of the intermediate goods to the price of the final goods.[5] The inverse of the Frisch elasticity σ^L and the labor disutility ψ^L are set respectively to 1 and 0.68 to normalize steady-state hours to unity. Parameters for the Taylor rule coefficients, price and wage stickiness, cost curvature and habit consumption are calibrated so as to lie within posterior densities obtained estimating medium-scale New-Keynesian models for the US over the past thirty years.[6] The calibration for these parameters is summarized in table 1.

Param.	Description	Value
α	Capital share	0.37
β	Discount factor	0.99
δ	Depreciation rate	0.025
λ^p	Price markup	1.2
λ^w	Wage markup	1.1
ψ^L	Labor disutility	0.68
σ^L	Frish elasticity	1
τ^y	Retailers subsidy	0.17
$a_{\Delta y}$	Taylor rule output coefficient	0.3
a_π	Taylor rule inflation coefficient	2
ρ_p	Taylor rule smoothing	0.7
ξ_p	Calvo price stickiness	0.6
ξ_w	Calvo wage stickiness	0.6
σ_a	Utilization cost curvature	2
S''	Invest. adjustment cost curvature	2.5
b	Consumption habit	0.3

Table 1: Calibrated Parameters

Parameters for the financial sector and idiosyncratic productivity distributions are less usual and are calibrated to jointly match the characteristics of intermediated and direct debt for US non-financial corporate firms. Table 3 displays the targeted financial variables and their model counterparts. The calibration for financial parameters is summarized in table 2. These parameters are set to match the loan-to-bond and the debt-to-equity ratios computed using data from the Flow of Funds Accounts for non-financial US corporate firms over the period 1985 to 2018. Their

[5]Because profit maximization for the final good producer under flexible prices yields: $P_t = \lambda^p(1-\tau^y)P_t^E$, this implies $\tau^y = 1 - \frac{1}{\lambda^p}$.

[6]See for instance Smets and Wouters (2007), Justiniano, Primiceri, and Tambalotti (2011), Christiano, Motto, and Rostagno (2014) and Bécard and Gauthier (2018).

average values amount respectively to 0.42 and 0.43 with the ratio of loans over bonds increasing to 0.66 when removing the 2007 crisis period from the sample. The risk premium for loans

Param.	Description	Value
τ^b	Bank intermediation costs	0.0116
ξ	Steady-state leverage	1.98
$1-\gamma$	Dividend rate	0.11
μ^b	Bank monitoring cost	0.131
μ^c	Market monitoring cost	0.111
σ_1	Idiosyncratic shock dispersion	0.136
σ_2	Idiosyncratic shock dispersion	0.113
σ_3	Idiosyncratic shock dispersion	0.357

Table 2: Calibrated Parameters (Financial)

is computed using the Survey on Term Business Lending from the Federal Reserve Board as the spread between the interest rate for commercial and industrial loans over 1 million dollars and the federal funds rate. I find a 1.9 percent annual mean spread over the 1986 to 2017 period. Following De Fiore and Uhlig (2011), I take the average Moody's 12-months default rate for speculative-grade non-financial corporations rated over the period 1999 to 2007 as a proxy for the model bond default rate. The default rate for corporate loans comes from Emery and Cantor (2005) who show that the average default rate for loans has been approximately 20 percent lower than the average default rate for bonds.[7] Except for the ratio of loan-to-bond which is slightly higher than its observed counterpart the model is able to accurately replicate all the above financial facts.

Variable	Description	Model	Data
l/b	Loan-to-bond ratio	0.689	0.42
d/n	Debt-to-equity Ratio	0.437	0.43
Δ^c	Risk premium for bonds	1.36	1.43
Δ^b	Risk premium for loans	1.92	1.88
F^c	Delinquency rate for bonds	5.77	5.37
F^b	Delinquency rate for loans	4.06	4.3

Table 3: Financial Facts - Model vs Data

Note: Default rates and risk premia are expressed in annualized percentage points.

B. Firm Funding Decisions

Before presenting the dynamic implications of the model, I illustrate the relationship between entrepreneurs' expected productivity and their funding decisions in the static model. The upper panel in figure 2 displays expected profits for an entrepreneur conditional on her funding decisions and on the realization of the idiosyncratic shock ε_1. The lower panel displays the density of the idiosyncratic shock ε_1. The grey, orange, and blue areas correspond respectively to the shares of entrepreneurs abstaining from production, contracting with banks and funding from markets.

Entrepreneurs with intermediate expected productivity contract with banks while those with high expected productivity prefer to fund from markets. The reason is that entrepreneurs with low expected productivity have a higher probability of default and prefer to hedge their net worth from processing risks by not producing or by entering into renegotiable contracts with banks. On the other hand, entrepreneurs with high productivity and low risk of default are better off funding

[7] Their study covers the period 1995 to 2003. Their results are confirmed by more recent evidence presented in Lonski (2018).

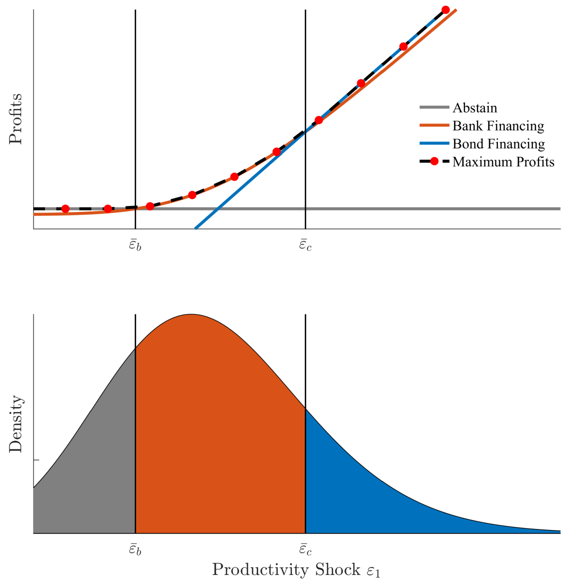

Figure 2: Firm Funding Decisions.

Note: The first panel corresponds to the expected profits of entrepreneurs depending on their funding choices and conditional on the realization of the first idiosyncratic shock ε_1 which density is displayed in the second panel.

from markets and avoiding intermediation costs. This mapping between entrepreneurs' expected productivity and their funding decision is coherent with the evidence presented in Denis and Mihov (2003). Using firm-level data for US corporations, they show that the credit quality of the issuer is the primary determinant of firm debt structure with most productive firms funding from markets and firms with lower credit quality funding from banks.[8] Another important feature of the model is that it rules out the possibility that entrepreneurs fund simultaneously from markets and banks. This is because maximum expected profits are a monotonic function of net worth. This implicit assumption of debt specialization is backed by the evidence presented in Colla, Ippolito, and Li (2013) who show that 85 percent of US-listed firms have recourse only to one type of debt.

C. Model Dynamics and the Debt Structure

This subsection presents the dynamic implications of various macroeconomic shocks. An important result is that only the responses of direct and intermediated debt allow to qualitatively distinguish financial shocks from other macroeconomic shocks.

C.1. The Financial Shock

I start with the presentation of the bank efficiency shock ν_t. Figure 3 displays impulse responses for the main variables. The bank efficiency shock reduces the asymmetric information problem of banks by lowering the share of unknown idiosyncratic productivity for bank-funded entrepreneurs. Because financial contracts in the model imply that financial intermediaries only take on downside risk, a lower dispersion of idiosyncratic productivity for bank-funded entrepreneurs

[8] Adrian, Colla, and Song Shin (2013) also stress the importance of credit quality as a determinant of firms' debt structure.

increases the expected share of output accruing to banks. Due to competition among financial intermediaries resulting in zero profits, bank-funded entrepreneurs can pledge a lower fraction of their profits to banks, what increases their expected payoff. In contrast, the expected payoff for abstaining and market-funded entrepreneurs is unchanged. As a result, entrepreneurs that were indifferent between not producing and contracting with a bank or indifferent between contracting with a bank and borrowing from markets now favor bank finance.

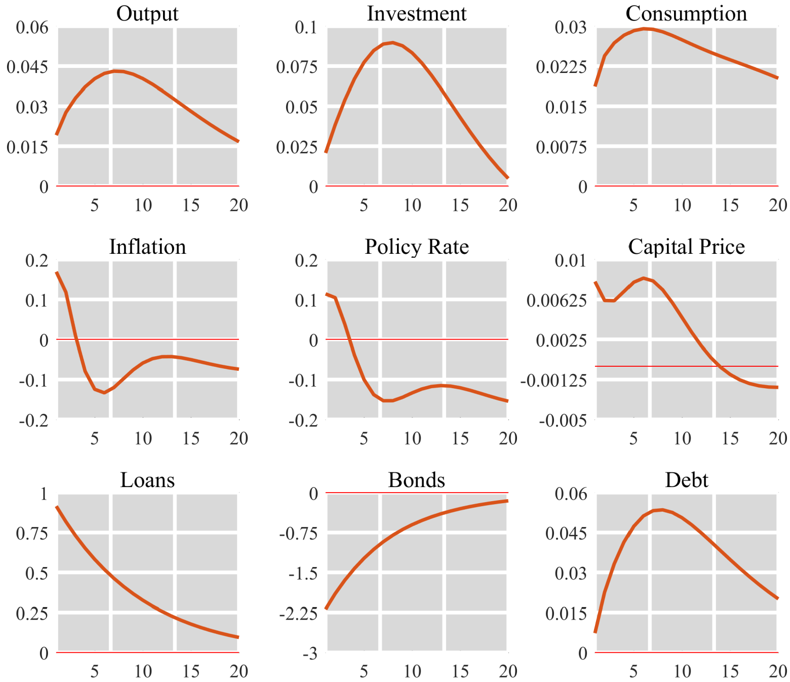

Figure 3: Responses to a Bank Efficiency Shock.

Note: All series are expressed in deviation from steady-state in percentage points. Inflation and the policy rate responses are expressed in basis points.

With the share of market-funded entrepreneurs decreasing and the share of entrepreneurs funding with bank loan rising - the extreme case being if none of the entrepreneurs switching to bank finance decide to proceed with their loan, the financial shock generates opposite movements in the shares of bank and bond-funded entrepreneurs. Because net worth is a predetermined variable, the initial change in the total level of debt of an entrepreneur can only be accounted for by changes in their debt composition. Overall, the total level of debt increases as the proportion of abstaining entrepreneurs switching to bank finance and proceeding with their loan outweigh the share of entrepreneurs switching from market finance to bank finance and *not* proceeding with their loan. As funds available to entrepreneurs move up, demand for labor and capital inputs increases along with wages and the capital rental rate. The marginal cost of production goes up. Output, investment, consumption and hours increase along with the capital price, inflation, and the policy rate. Upward shifts in the policy rate and in the marginal cost of production dampen the debt increase as it pushes up funding and production costs. On the other hand, because entrepreneurs' aggregate profits react positively to the fall in aggregate uncertainty triggered by the financial shock, aggregate net worth accumulates, feeding up next period borrowing through the leverage constraint. Following the reduction in the risk of bank-funded entrepreneurs, the risk borne by bond holders also declines as only the least productive of market-funded entrepreneurs switch to bank funding. This leads to a fall in risk premia for the two types of debt. Overall the financial shock pushes firms to substitute loans for bonds and triggers a rise in output and in debt.[9]

C.2. Macroeconomic Shocks

Without detailing impulse responses for other shocks, it is important to notice that non-financial shocks transmit differently to entrepreneur funding decisions in comparison to financial shocks. Figure 4 presents impulse responses following technology, preference, investment, and monetary shocks. First, notice that the introduction of debt arbitrage in the NK framework does not modify its qualitative implications. The signs of the impulse responses for non-financial shocks correspond to those described in Peersman and Straub (2006). A common feature of these different shocks is that they all generate co-movement in output, loans, and bonds. Two effects are at play. Because all these shocks imply a fall in entrepreneurs' marginal cost of production, their profitability increases. This pushes up net worth and increases entrepreneur demand for the two types of debt. Loans and bonds increase altogether. On the other hand, the decline in the marginal cost of production reduces entrepreneurs processing risk and modifies their funding decisions. Some entrepreneurs abstaining from production are better off producing after the shock is realized. Hence, the shares of entrepreneurs abstaining from production or not proceeding with bank loan decrease. On the other hand, some entrepreneurs that were contracting with a bank prior to the shock now prefer to avoid intermediation costs and switch to market finance. Overall the share of abstaining entrepreneurs decreases and both the share of market-funded entrepreneurs and the share of entrepreneurs proceeding with bank loans increase. Following non-financial shocks, both bond and loan volumes co-move with output.

Section A.III of the appendix presents impulse responses from the model calibrated with different combinations of parameters. The signs of the responses for output, loans and bonds to financial and other aggregate shocks are robust to various parameter specifications. Comparing impulse responses for the different types of shock, it exists no robust qualitative differences between demand and financial shocks other than the response of bonds. The reason is that even with standard parameter values, investment can actually increase in response to a positive preference shock. In that case, investment and preference shocks have the same qualitative characteristics. In the next section, I use the qualitative features implied by the NK model to inform a sign-restriction VAR and identify financial shocks based on loan and bond fluctuations.

[9]Here I focus on a bank efficiency shock ν_t but other financial shocks embedded in the model have similar qualitative implications. This is the case for instance for an exogenous shock to the financial intermediation costs τ^b or to the dividend rate δ. As for a bank efficiency shock, these shocks imply a simultaneous increase in output and loans and a fall in bonds.

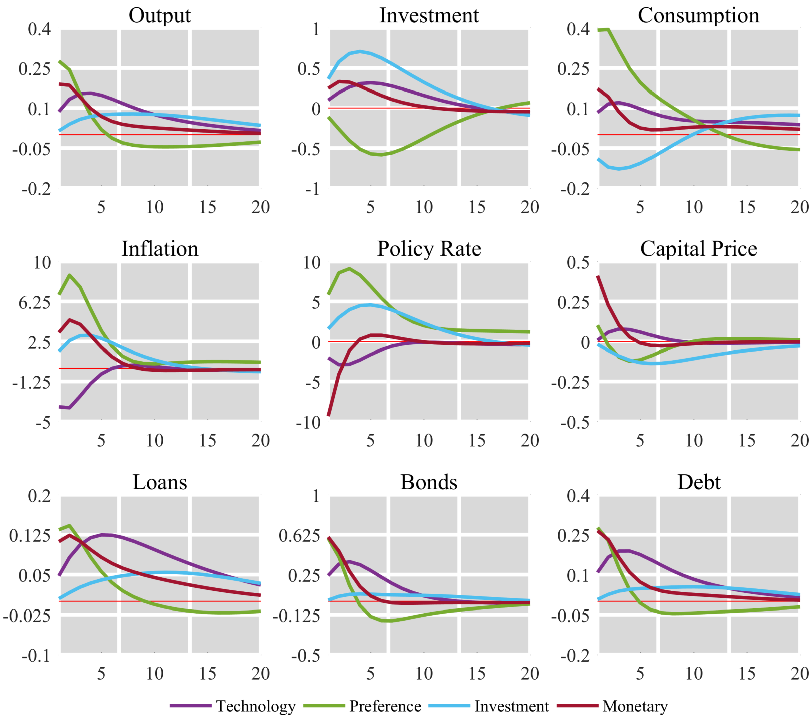

Figure 4: Responses to Non-Financial Shocks.

Note: All series are expressed in deviation from steady-state in percentage points. Inflation and the policy rate responses are expressed in basis points.

IV. Empirical Analysis

This section presents results from a sign-restriction VAR model used to characterize financial shocks and evaluate their business cycle implications.

A. The Sign-Restriction VAR

I implement the qualitative features of the different shocks implied by the modified NK model in a sign-restriction Bayesian VAR estimated with quarterly US data for the period 1985 to 2018. The data set includes the gross domestic product, the ratio of investment-over-GDP, the GDP implicit price deflator and the annualized effective federal funds rate. I take outstanding loan and bond volumes for corporate non-financial firms to track the evolution of firm debt composition. Loan series includes loans from depository institutions and mortgage loans. Bond series includes both bonds and commercial papers. All series are seasonally adjusted and expressed in log-levels except for the federal funds rate. A complete description of the series is provided in section A.I of the appendix. The model is estimated using a lag order of two what minimizes the Bayesian information criterion and the Hannan-Quinn information criterion.[10] The estimation of the model involves two separate steps. The first step is to estimate a reduced form Bayesian VAR model. I then use the algorithm presented in Arias, Rubio-Ram\';irez, and Waggoner (2018) to generate

[10]The model is also estimated with a lag order of four. While impulse responses for the different shocks appear robust to this modification, the share of output and inflation variance explained by demand shocks increases slightly relative to supply shocks.

candidate impulse responses and retain models satisfying the sign-restrictions imposed until a sufficient number of draws are obtained. Section A.I of the appendix contains a more detailed presentation of the econometric methods used to estimate the Bayesian VAR model and retain models that satisfy the imposed sign-restrictions.

	Supply	*Demand*	*Investment*	*Monetary*	*Financial*
GDP	+	+	+	+	+
Prices	-	+	+	+	?
Interest rate	?	+	+	-	?
Investment / Output	?	-	+	?	?
Loans	+	+	+	+	+
Bonds	+	+	+	+	-

Table 4: Sign Restrictions

Note: Sign restrictions imposed for the BVAR estimation. The restrictions are imposed on impact only. The presence of a question mark indicates the absence of restriction.

I consider five types of structural shocks identified based on the signs of the impulse responses on impact for the different variables. A sixth shock is left unrestricted to add a degree of freedom to the estimation. The restrictions imposed and the series used are chosen so as to classify shocks into five broad categories - supply, demand, investment, monetary and financial. These capture most of the shocks found in the business cycle literature as well as the shocks present in the modified NK model.[11] The sign-restrictions imposed are summarized in table 4. Supply shocks are identified as implying opposite movements in output and prices. Demand and investment shocks generate co-movement in output and prices and respectively negative and positive impacts on the investment-to-output ratio. Monetary shocks generate opposite responses in the policy rate and output and prices. Finally, in conformity with the predictions of the NK model, I assume that all these shocks generate co-movements in output, loans, and bonds. The sign-restrictions imposed for financial shocks are less usual. They are identified as the only type of shock that can simultaneously generate co-movements in output and loans and opposite movements in output and bonds. As I do not impose any restrictions on the responses of inflation, interest rate and the investment-to-output ratio conditional to a financial shock, these can be used as a simple test for the overidentifying predictions of the VAR model.

B. Empirical Results

This section presents the results from the VAR model, I focus on the characteristics of financial shocks and how they relate to financial shocks identified with different econometric methods.

B.1. What Financial Shocks Do

Figure 5 displays the median impulse responses following a one standard deviation financial shock. The grayed-area corresponds to the 16th and 84th quantiles. The response of output following a financial shock is short-lived with a duration shorter than 10 quarters before returning

[11] The sign-restrictions imposed also lies in the intervals of robust impulse responses derived by Canova and Paustian (2011) based on a variety of DSGE models. This is true except for the response of interest rate to a supply shock which is left unrestricted. This is to take into account the fact that the sign of the interest rate response to a supply shock hinges on the degree of price stickiness as shown by Peersman and Straub (2009).

to zero. While left unrestricted, the impact of the investment-to-output ratio is positive and twice as strong as for output with a similarly short duration. In comparison, the impact on loans takes more than 15 quarters to fade out and is nearly 5 times stronger than for output. The maximum

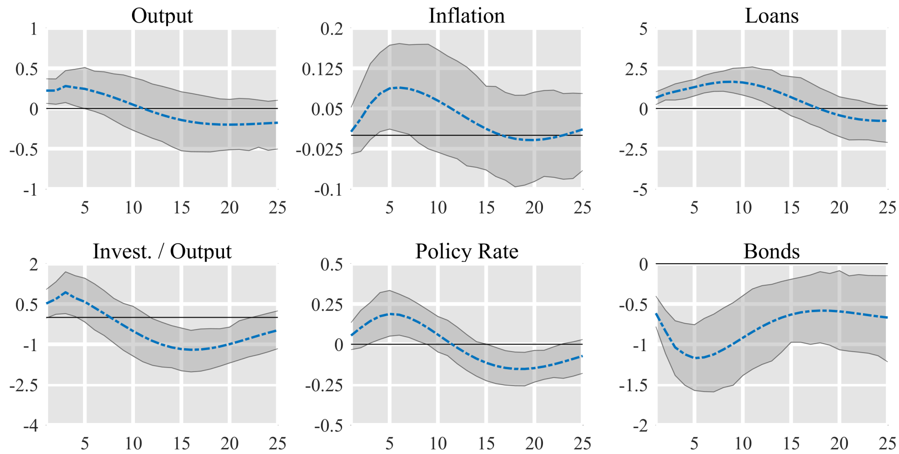

Figure 5: Responses to a Financial Shock.

Note: Median impulse responses to a one standard deviation financial shock. The grey area corresponds to the 16th and 84th quantiles. All series are expressed in percentage points. Inflation and the policy rate are annualized.

impact is reached after 10 quarters with a value close to 2 percent. The fall in bonds is twice weaker than the increase in loans and peaks more rapidly after only 5 quarters. The federal funds rate which is left unrestricted in the estimation exhibits a large positive hump-shaped response which dies out after 10 quarters. I also find the response of inflation to be weak and positive following a financial shock. The responses of the policy rate and inflation are consistent with a large body of empirical and theoretical evidence. Schularick and Taylor (2009) present international evidence of aggressive monetary policy in response to financial shocks during the postwar era. Using a set of estimated DSGE models, Cesa-Bianchi and Sokol (2017) find that the policy rate systematically decreases in response to adverse financial shocks. Gertler and Karadi (2011) also show that expansionary financial shocks relax firms' borrowing constraints what can lead to inflationary pressures.

While financial shocks are identified restricting only responses for output, loans and bonds, the responses of the investment-to-output ratio, the policy rate and inflation match the dynamics implied by financial shocks in most DSGE model.[12] The median impulse responses for the other shocks are displayed in section A.V of the appendix.

B.2. Aggregate Shocks and the Business Cycle

Figure 6 displays the median historical shock decomposition for the output growth rate. Even though financial shocks play the leading role over the whole estimation period, all three recessions contained in the sample are associated with different types of perturbations.

According to the model estimates, the outset of the 90's recession is dominated by a combination of demand and supply shocks increasing from 1990 onward. Walsh (1993) and Blanchard

[12] See for instance Gertler and Kiyotaki (2010), Christiano, Motto, and Rostagno (2014) and Boissay, Collard, and Smets (2016).

(1993) stress the strong role of adverse demand shocks in the early 90's recession.[13] In contrast, the model attributes the fluctuations of output in 1993 and 1998 to financial shocks. Interestingly the two periods coincide with the Japanese bank crisis and the LTCM Russian crisis. These two events are described respectively by Peek and Rosengren (2000) and Chava and Purnanandam (2011) as examples of credit supply shocks affecting non-financial firms via their negative impact on US bank equity. The recession of the early 2000s is also associated with financial as well as monetary and demand factors.[14] Perhaps more surprising, the model attributes only a limited

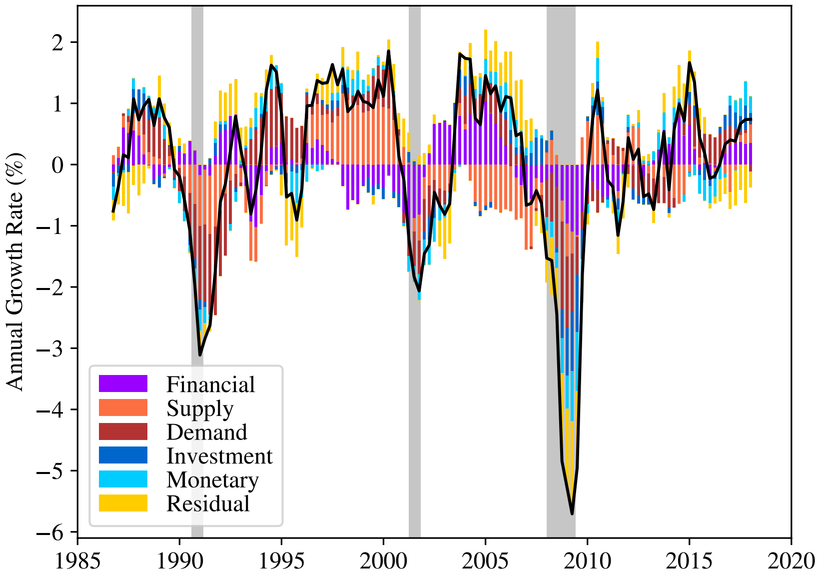

Figure 6: Historical Shock Decomposition for GDP.

Note: Contribution of the different structural shocks to GDP fluctuations expressed in annualized growth rate.

role to financial shocks during the Great Recession. The initial fall in output is attributed mainly to supply-side disturbances with an important role for demand and monetary factors at the core of the recession. This view of the crisis is consistent with the results from Stock and Watson (2012). They estimate a dynamic factor model and find that the Great Recession is best explained by heterogeneous shocks where oil shocks account for the initial slowdown, financial and demand shocks explain the bulk of the recession and a subsequent drag is added by an effectively tight conventional monetary policy arising from the zero lower bound. Here, financial shocks start weighing down on activity by the end of 2008.[15] Overall, the implications of financial shocks for both recessions and expansions contained in the data sample are close to the results from Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) who focus on disentangling financial and uncertainty disturbances.

Figure 7 displays the median variance decomposition for the observables at different horizons. Financial and supply shocks are the most important forces for output fluctuations at short and

[13] The role of oil shocks and the Iraq war in the 90's recession is more controverted. Kilian and Vigfusson (2017) find a significant impact of oil shocks on US activity when using net oil price - the difference of oil price with its peak value over the 12 previous months, instead of a standard linear model. Hamilton (2009) studies the impact of oil shocks on the auto industry between 1990Q1 and 2007Q4. He finds a significant impact of oil shocks during the 90's recession.

[14] With a different econometric approach, Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) find that the fall of industrial production of the early 2000s is entirely attributed to financial exogenous perturbations.

[15] Ivashina and Scharfstein (2010) explain this feature of the crisis. They show that the beginning of the financial crisis was in fact accompanied by an increase in commercial and industrial loans as corporate borrowers drew on their existing credit lines in reaction to the expected financial stress.

long term horizons. Their impact range respectively from a fifth to half of the total output variance and close to half of the loan variance at all frequencies. Nearly all of bonds variance is explained by financial shocks. This can be viewed as evidence that the bond market acts as a substitute for loans when intermediated lending is gripped.[16] Other shocks have limited implications for output. Monetary and investment shocks explain respectively 20 percent of the variance of the policy rate and the investment-to-GDP ratio but have little implications for output fluctuations. The variance of inflation appears disconnected from financial shocks at every frequencies. Papers

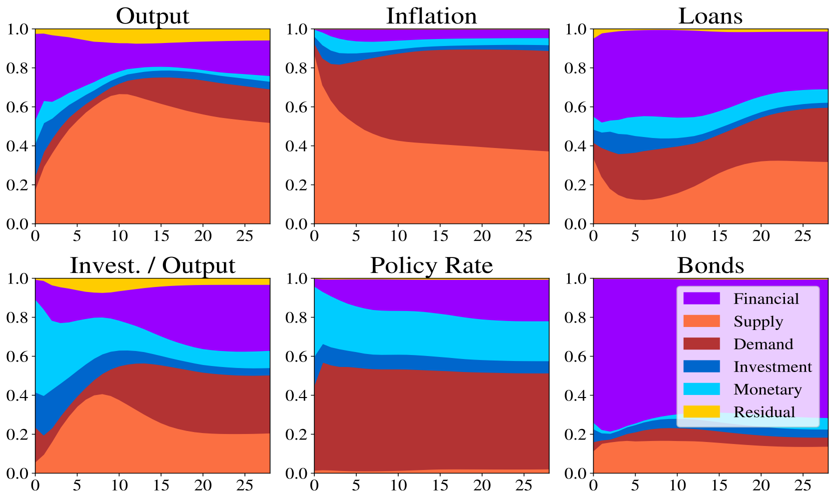

Figure 7: Variance Decomposition.

Note: Median variance decomposition at different horizons for the model observables. The x-axis is expressed in quarters.

using sign-restriction methods to identify financial shocks as Meeks (2012), Fornari and Stracca (2012) and Furlanetto, Ravazzolo, and Sarferaz (2017) find that between a tenth to a third of output fluctuations can be attributed to financial shocks. This is less than results usually obtained from DSGE models estimated with bond spreads such as Justiniano, Primiceri, and Tambalotti (2011), Christiano, Motto, and Rostagno (2014) and Ajello (2016) who find that financial shocks account for close to half of output business cycle fluctuations.

Finally, to make sure the characteristics of the estimated financial shocks do not hinge on sign-restrictions imposed for price, interest rate and investment responses, I re-estimate the VAR model while keeping only the restrictions imposed on GDP, loans and bonds. Section A.IV of the appendix presents the results for this alternative specification. They are identical to what is obtained in the fully specified model. The upshot of this section is that, first, the implications from the model are coherent with results derived using more constrained econometric approaches, and second, that financial shocks are not a systematic component of the business cycle. In the following section, I test the relevance of the identification method.

V. Putting the Model to the Test

In this final section, I use an estimated version of the modified NK model to investigate how financial shocks identified using firm debt composition relate to measures of financial stress such as the corporate bond spread.

[16] In line with the spare tire analogy from Greenspan (1999).

A. Impulse Response Matching

The estimation procedure consists in minimizing the distance between the median impulse responses implied by the structural VAR and by the modified NK model. Denoting θ the vector that contains the estimated parameters listed in table 2 of the appendix, the estimator θ^* is obtained as the solution of:

$$\theta^* = \underset{\theta}{argmin} \left[\hat{\Psi} - \bar{\Psi}(\theta)\right]' V^{-1} \left[\hat{\Psi} - \bar{\Psi}(\theta)\right].$$

Here, $\hat{\Psi}$ is a vector that contains the median impulse responses obtained from the VAR model, $\bar{\Psi}(\theta)$ contains the impulse responses from the NK model and V is a diagonal matrix with the variances of the empirical impulse responses stacked along its main diagonal. I consider an horizon of 25 periods for the five different structural shocks and the six different variables. This implies that $\bar{\Psi}(\theta)$ is a 750 column vector. Figure 8 displays impulse responses to a financial shock for the estimated NK model and the VAR model. The modified NK model is able to reproduce both qualitative and quantitative features of the VAR model for all types shocks with parameter values in line with those obtained from medium-scale DSGE models estimated with US data.[17] Impulse responses for the other shocks are provided in section A.V of the appendix.

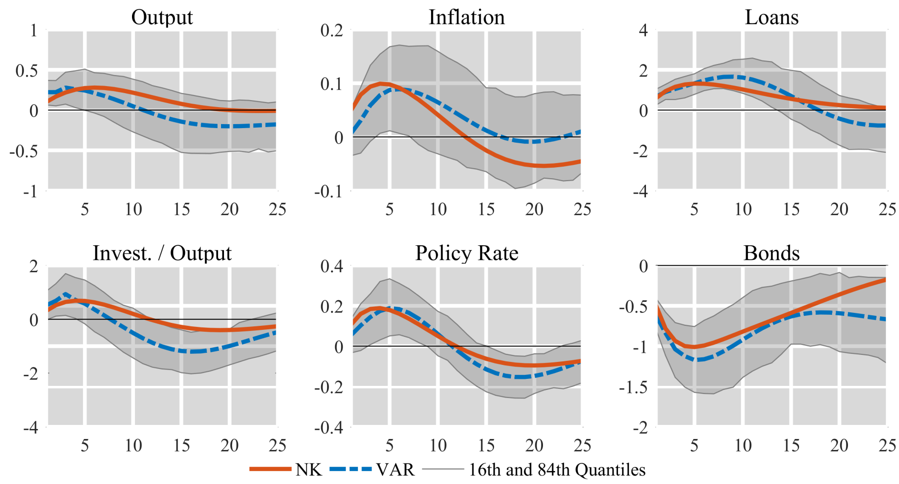

Figure 8: Impacts of a Financial Shock in the VAR and NK Models.

Note: Median impulse responses to a one standard deviation financial shock. The grey area corresponds to the 16th and 84th quantiles for the VAR model. All series are expressed in percentage points. Inflation and the policy rate are annualized.

B. Financial Shocks and the Bond Spread

Going back to the question of whether corporate debt choice can help to identify financial shocks, I investigate the relevance of the identification strategy based on two criteria. First, does the identification method yield financial shocks that resemble measures of financial stress as experienced by non-financial firms? Second, do firm funding decisions help to predict disruptions in the financial system? To address these questions, I proceed as follows. I start by assuming that

[17] See for instance Christiano, Trabandt, and Walentin (2010), Jermann and Quadrini (2012) and Del Negro, Giannoni, and Schorfheide (2015).

the estimated NK model is the true data generating process and use it to recover the structural shocks implied by the data set.[18]

Figure 9 plots the financial shock process ν_t obtained from the modified NK model and Moody's seasoned Baa corporate bond yield minus federal funds rate. The financial shock process resembles the bond spread. The two series are correlated at 0.67 over the whole sample.[19] The proximity between the two series indicates that the modified NK model inherits the quantitative properties of the sign-restriction VAR and most importantly that the identification method can capture financial stress based on aggregate firm funding choices.

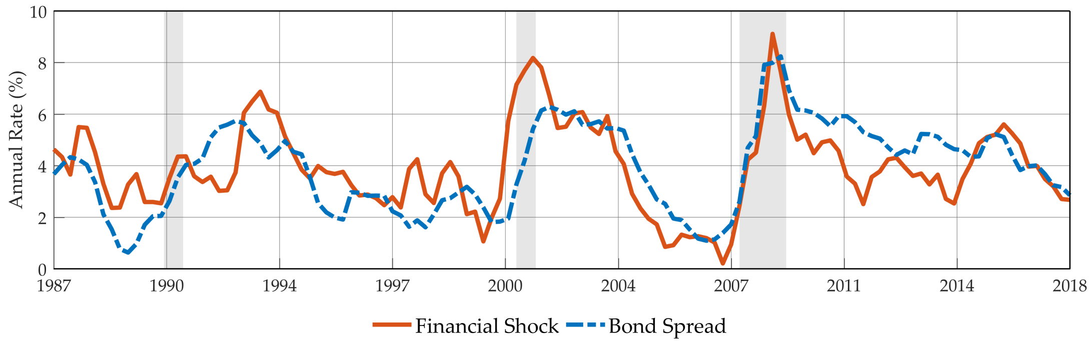

Figure 9: Financial Stress and the Bond Spread.

The orange line corresponds to the opposite of the smoothed ν_t process which is HP-filtered using a smoothing parameter λ of 1600. The blue line corresponds to the Moody's seasoned Baa corporate bond minus federal funds rate. Grey areas correspond to NBER recession dates.

Finally, I investigate whether financial shocks can help to predict the bond spread. Table 5 displays result from Granger-causality tests at different lag orders. The hypothesis that financial shocks do not Granger cause the bond spread is strongly rejected for all specifications. This exercise brings further evidence that firm debt arbitrage can be used to forecast the movements in bond spreads.

H_0: Financial Shocks do not cause Bond Spreads				
Lags	1	2	3	4
P-values	0.000002	0.000044	0.000106	0.000258

Table 5: Granger Causality Tests

Note: Granger causality is inferred based on likelihood-ratio test. The financial shocks correspond to bank efficiency shocks ϵ_t^{ν} obtained using a Kalman filter.

VI. Conclusion

I include a mechanism of debt arbitrage into a New Keynesian model to investigate the evolution of firms' debt structure in response to various macroeconomic shocks. The model implies that only financial shocks produce opposite movements in bonds and loans. In contrast, other

[18]The data used are the same as for the sign-restriction VAR model. Series for output, loans, bonds, and inflation are stationarized using a first-difference filter. Because there are only five types of shocks in the NK model, I assume distinct measurement errors for each of the different series as in Bianchi, Kung, and Morales (2019).

[19]I also find a correlation close to 0.5 when comparing ν_t with the excess bond premium.

macroeconomic shocks generate opposite movements in the two types of debt. I use these results to inform a sign-restrictions VAR model estimated with US data. The financial shocks obtained from the VAR model are consistent with results from various empirical studies based on more constrained identification strategies. I estimate the modified NK model using impulse response matching methods. I find that the NK model can replicate the quantitative implications of the VAR model for all types of shock. The estimated model is used to recover structural shocks in the US over the past thirty years. The financial shocks resemble measures of financial stress and have predictive power for firm credit conditions.

References

Adjemian, Stéphane, Houtan Bastani, Michel Juillard, Ferhat Mihoubi, George Perendia, Marco Ratto, and Sébastien Villemot. 2011. "Dynare: Reference manual, version 4". *Dynare Working Papers Series*.

Adrian, Tobias, Paolo Colla, and Hyun Song Shin. 2013. "Which Financial Frictions? Parsing the Evidence from the Financial Crisis of 2007 to 2009". *NBER Macroeconomics Annual* 27.1, pp. 159–214.

Ajello, Andrea. 2016. "Financial Intermediation, Investment Dynamics, and Business Cycle Fluctuations". *American Economic Review* 106.8, pp. 2256–2303.

Altavilla, Carlo, Matthieu Darracq Pariès, and Giulio Nicoletti. 2015. "Loan supply, credit markets and the euro area financial crisis". *Working Paper Series 1861, European Central Bank.*

Angeletos, George-Marios, Fabrice Collard, and Harris Dellas. 2018. *Business Cycle Anatomy*. Tech. rep. w24875. Cambridge, MA: National Bureau of Economic Research, w24875.

Arias, Jonas E., Juan F. Rubio-Ram\';irez, and Daniel F. Waggoner. 2018. "Inference Based on Structural Vector Autoregressions Identified With Sign and Zero Restrictions: Theory and Applications". *Econometrica* 86.2, pp. 685–720.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. "Measuring Economic Policy Uncertainty". *The Quarterly Journal of Economics* vol. 131.issue 4, pp. 1593–1636.

Bécard, Yvan and David Gauthier. 2018. "Collateral Shocks". *mimeo*.

Becker, Bo and Victoria Ivashina. 2014. "Cyclicality of credit supply: Firm level evidence". *Journal of Monetary Economics* 62, pp. 76–93.

Berlin, Mitchell and Loretta J Mester. 1992. "Debt covenants and renegotiation". *Journal of Financial Intermediation* 2.2, pp. 95–133.

Bernanke, Ben S., Mark Gertler, and Simon Gilchrist. 1999. "The financial accelerator in a quantitative business cycle framework". *Handbook of Macroeconomics* 1, pp. 1341–1393.

Bianchi, Francesco, Howard Kung, and Gonzalo Morales. 2019. "Growth, slowdowns, and recoveries". *Journal of Monetary Economics* 101, pp. 47–63.

Blanchard, Olivier. 1993. "Consumption and the Recession of 1990-1991". *American Economic Review* 83.issue 2, p. 270–74.

Boissay, Frédéric, Fabrice Collard, and Frank Smets. 2016. "Booms and banking crises". *Journal of Political Economy* 124.2, pp. 489–538.

Caldara, Dario, Cristina Fuentes-Albero, Simon Gilchrist, and Egon Zakrajsek. 2016. "The Macroeconomic Impact of Financial and Uncertainty Shocks". *International Finance Discussion Paper* 2016.1166, pp. 1–41.

Canova, Fabio and Matthias Paustian. 2011. "Business cycle measurement with some theory". *Journal of Monetary Economics* 58.4, pp. 345–361.

Cesa-Bianchi, Ambrogio and Andrej Sokol. 2017. "Financial Shocks, Credit Spreads and the International Credit Channel". *SSRN Electronic Journal*.

Chava, Sudheer and Amiyatosh Purnanandam. 2011. "The effect of banking crisis on bank-dependent borrowers". *Journal of Financial Economics* 99.1, pp. 116–135.

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. 2014. "Risk Shocks". *American Economic Review* 104.1, pp. 27–65.

Christiano, Lawrence J, Mathias Trabandt, and Karl Walentin. 2010. "DSGE Models for Monetary Policy", p. 91.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy". *Journal of Political Economy* 113.1, pp. 1–45.

Colla, Paolo, Filippo Ippolito, and Kai Li. 2013. "Debt Specialization". *The Journal of Finance* 68.5, pp. 2117–2141.

Crouzet, Nicolas. 2018. "Aggregate Implications of Corporate Debt Choices". *The Review of Economic Studies* 85.3, pp. 1635–1682.

De Fiore, Fiorella and Harald Uhlig. 2011. "Bank finance versus bond finance". *Journal of Money, Credit and Banking* 43.7, pp. 1399–1421.

De Fiore, Fiorella and Harald Uhlig. 2015. "Corporate Debt Structure and the Financial Crisis". *Journal of Money, Credit and Banking* 47.8, pp. 1571–1598.

Del Negro, Marco, Marc P. Giannoni, and Frank Schorfheide. 2015. "Inflation in the Great Recession and New Keynesian Models". *American Economic Journal: Macroeconomics* 7.1, pp. 168–196.

Denis, David J and Vassil T Mihov. 2003. "The choice among bank debt, non-bank private debt, and public debt: evidence from new corporate borrowings". *Journal of Financial Economics* 70.1, pp. 3–28.

Emery, Kenneth M. and Richard Cantor. 2005. "Relative default rates on corporate loans and bonds". *Journal of Banking & Finance* 29.6, pp. 1575–1584.

Faust, Jon. 1998. "The Robustness of Identified VAR Conclusions About Money". *SSRN Electronic Journal*.

Fornari, Fabio and Livio Stracca. 2012. "What does a financial shock do? First international evidence". *Economic Policy* 27.71, pp. 407–445.

Furlanetto, Francesco, Francesco Ravazzolo, and Samad Sarferaz. 2017. "Identification of Financial Factors in Economic Fluctuations". *The Economic Journal*.

Gali, Jordi. 2010. "Monetary Policy and Unemployment". *Working Paper Series*. National Bureau of Economic Research 15871.

Gertler, Mark and Peter Karadi. 2011. "A model of unconventional monetary policy". *Journal of Monetary Economics* 58.1, pp. 17–34.

Gertler, Mark and Nobuhiro Kiyotaki. 2010. "Financial Intermediation and Credit Policy in Business Cycle Analysis". *Handbook of Monetary Economics*. Vol. 3. Elsevier, pp. 547–599.

Gilchrist, Simon and Egon Zakrajšek. 2012a. "Credit Spreads and Business Cycle Fluctuations". *American Economic Review* 102.4, pp. 1692–1720.

Gilchrist, Simon and Egon Zakrajšek. 2012b. "Credit supply shocks and economic activity in a financial accelerator model". *Rethinking the Financial Crisis*, pp. 37–72.

Gilchrist, Simon, Raphael Schoenle, Jae Sim, and Egon Zakrajšek. 2017. "Inflation Dynamics during the Financial Crisis". *American Economic Review* 107.3, pp. 785–823.

Greenspan, Alan. 1999. *Do efficient financial markets mitigate crises?*

Hamilton, James D. 2009. "Causes and Consequences of the Oil Shock of 2007–08".

Holmstrom, B. and J. Tirole. 1997. "Financial Intermediation, Loanable Funds, and The Real Sector". *The Quarterly Journal of Economics* 112.3, pp. 663–691.

Ivashina, Victoria and David Scharfstein. 2010. "Bank lending during the financial crisis of 2008". *Journal of Financial Economics*, p. 20.

Jermann, Urban and Vincenzo Quadrini. 2012. "Macroeconomic effects of financial shocks". *American Economic Review* 102.1, pp. 238–71.

Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti. 2011. "Investment shocks and the relative price of investment". *Review of Economic Dynamics* 14.1, pp. 102–121.

Karabarbounis, L. and B. Neiman. 2014. "The Global Decline of the Labor Share". *The Quarterly Journal of Economics* 129.1, pp. 61–103.

Kashyap, Anil, Jeremy Stein, and David Wilcox. 1993. "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance". *American Economic Review* 83.1, pp. 78–98.

Kilian, Lutz and Robert J. Vigfusson. 2017. "The Role of Oil Price Shocks in Causing U.S. Recessions". *Journal of Money, Credit and Banking* 49.8, pp. 1747–1776.

Lonski, John. 2018. "Loan Default Rate May Approach Bond Default Rate", p. 30.

Meeks, Roland. 2012. "Do Credit Market Shocks Drive Output Fluctuations? Evidence from Corporate Spreads and Defaults". *Journal of Economic Dynamics and Control*, pp. 568–584.

Mumtaz, Haroon, Gabor Pinter, and Konstantinos Theodoridis. 2018. "What do VARs tell us about the impact of a credit supply shock? Credit supply shocks and SVARs". *International Economic Review* 59.2, pp. 625–646.

Peek, Joe and Eric S. Rosengren. 2000. "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States". *The American Economic Review* 90.1, pp. 30–45.

Peersman, Gert and Roland Straub. 2006. *Putting the New Keynesian model to a test: An SVAR analysis with DSGE priors, manuscript*.

Peersman, Gert and Roland Straub. 2009. "Technology Shocks and Robust Sign Restrictions in a Euro Area SVAR". *International Economic Review* 50.3, pp. 727–750.

Repullo, Rafael and Javier Suarez. 2000. "Entrepreneurial moral hazard and bank monitoring: a model of the credit channel". *European Economic Review* 44.10, pp. 1931–1950.

Romer, Christina D. and David H. Romer. 2017. "New Evidence on the Aftermath of Financial Crises in Advanced Countries". *American Economic Review* 107.10, pp. 3072–3118.

Rubio-Ramirez, Juan F., Daniel F. Waggoner, and Tao Zha. 2010. "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference". *Review of Economic Studies* 77.2, pp. 665–696.

Schularick, Moritz and Alan M. Taylor. 2009. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1870-2008".

Smets, Frank and Rafael Wouters. 2007. "Shocks and frictions in US business cycles: A Bayesian DSGE approach". *American Economic Review* 97.3, pp. 586–606.

Stock, James H. and Mark Watson. 2012. "Disentangling the Channels of the 2007-09 Recession". *Brookings Papers on Economic Activity* 43.1 (Spring), pp. 81–156.

Uhlig, Harald. 2005. "What are the effects of monetary policy on output? Results from an agnostic identification procedure". *Journal of Monetary Economics* 52.2, pp. 381–419.

Walsh, Carl E. 1993. "What Caused the 1990-1991 Recession?" *Economic Review*, pp. 33–48.