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Financial Frictions, Financial Shocks, and Aggregate Volatility

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Abstract

I revisit the Great Inflation and the Great Moderation for nominal and real variables. I document an *immoderation* in corporate balance sheet variables so that the Great Moderation is best described as a period of divergent patterns in volatilities for real, nominal and financial variables. A model with time-varying financial frictions and financial shocks allowing for structural breaks in the size of shocks and the institutional framework is estimated. The paper shows that *(i)* while the Great Inflation was driven by bad luck, the Great Moderation was mostly due to better institutions; *(ii)* the slowdown in the volatility of credit spreads is driven by an easier access to credit, while a higher exposure to financial risk determines the *immoderation* of balance sheet variables; and *(iii)* the improvements in the institutional framework during the Great Moderation mitigate the effects of financial disturbances on the U.S. economy.

JEL: E32, E44, C11, C13

Keywords: Great Inflation, Great Moderation, immoderation, financial frictions, financial shocks, structural breaks, Bayesian methods

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Recent economic events suggest a strong interaction between the financial sector and aggregate business cycle fluctuations. While the role played by the financial sector in propagating economic shocks originated in other sectors has been thoroughly examined, the assessment of the importance of financial shocks as drivers of business cycle fluctuations and the documentation of the propagation mechanism of financial shocks are at early stages. In addition, although determining the source of business cycle fluctuations in the real sector is a long-standing question in macroeconomics, understanding the driving forces of financial aggregates has just started to receive some attention. When analyzing the interaction of the financial and real sectors and the relative importance of financial shocks, researchers face an additional challenge: the *immoderation* in financial aggregates contemporary with the Great Moderation in real and nominal variables. In this paper, I aim to evaluate the ability of a DSGE model with financial rigidities and financial shocks to account for the divergent patterns in volatility.

I start by revisiting the evidence on the two main empirical regularities characterizing recent U.S. economic history: the Great Inflation and the Great Moderation. The Great Inflation refers to the decade of high levels of and large volatility in inflation and nominal interest rates that started in 1970. The Great Moderation refers to the observed reduction in the volatility of real and nominal variables since the mid-1980s. I show that while the heightened volatility of the Great Inflation affected homogeneously all aggregate variables, the Great Moderation is a more complex phenomenon. Jermann and Quadrini (2006) provide evidence on the larger magnitude of fluctuations in equity payout and debt repurchases in the U.S. nonfinancial sector during the Great Moderation. I provide further evidence on an increase in the volatility of balance sheet variables in the U.S. nonfinancial corporate sector (an immmoderation) since the mid-1980s, which is contemporaneous to a decline in the volatility of corporate spreads.

To address these patterns in volatility, I build a dynamic stochastic general equilibrium model with an explicit financial sector. In particular, following Christiano, Motto, and Rostagno (2003), I integrate the financial accelerator model of Bernanke, Gertler, and Gilchrist (1999, BGG hereafter) into a version of the standard Smets and Wouters (2007) model. I quantify the relative role played by financial factors, economic shocks, and monetary policy in shaping the evolution of aggregate volatility. To do so, I estimate the model economy using Bayesian methods allowing for structural breaks in a subset of the parameter space. Given that I aim to establish the role played by the financial sector in aggregate volatility, I include not only financial variables in the observable set but also proceed to the estimation of the deep parameters of the financial accelerator. From posterior predictive checks, I conclude that while the Great Inflation was mostly due to bad luck, the smoother business cycle fluctuations since the mid-1980s are the result of higher flexibility in the financial system and a more proactive monetary authority. The immoderation in balance sheet variables is accounted for by larger financial shocks hitting the US economy.

I explore the role of financial shocks as sources of business cycle fluctuations by introducing two financial shocks into the model economy. In the financial accelerator model, the asymmetric information between borrowers and lenders implies that loans are extended at a premium over the risk-free rate. This external finance premium is driven by two channels: the balance sheet channel and the information channel. The balance sheet channel captures the dependence of external financing opportunities on the composition of firms' balance sheets. The information channel implies that the external finance premium is a positive function of the severity of the agency problem. I include financial shocks affecting each of these two channels. Exogenous shocks to the balance sheet channel are introduced in the form of wealth shocks. Shocks to the information channel are modeled as innovations affecting the parameter governing bankruptcy costs. While wealth shocks are included in many studies of the financial accelerator model, time variation in marginal bankruptcy costs has not been explored in the literature. I find that, although the relative role of shocks to marginal bankruptcy cost is smaller than the one played by wealth shocks, it is crucial to assume that the marginal bankruptcy cost is a drifting parameter in order to deliver empirically plausible dynamics in corporate credit spreads. Moreover, the dynamics in the smoothed marginal bankruptcy cost parameter mirror the evolution of empirical measures of financial stress.

The institutional framework plays an important role in shaping the relative contribution of financial shocks in driving business cycle fluctuations for nonfinancial variables. For example, if the dovish monetary policy regime of the 1970s had been in place during the Great Moderation, financial shocks would have accounted for 37% of the variance in inflation and 52% of the variance in the federal funds rate instead of 4% and 23%, respectively. If the conditions of access to credit during the post-1980s were identical to the ones characterizing the 1960s and 1970s, then financial shocks would have explained 75% of the variance of output and 93% of that in investment instead of the actual 8% and 24%, respectively. Thus, I conclude that the institutional changes implemented during the mid-1980s successfully alleviate the dependence of the U.S. economy on financial disturbances.

This paper relates to two strands of the empirical macroeconomic literature. The first addresses the study of the Great Moderation and the second considers the estimation of the financial accelerator model. Since Kim and Nelson (1999) and McConnell and Pérez-Quirós (2000) dated the start of the Great Moderation, there has been a growing literature on dissecting its possible sources. Jermann and Quadrini (2006) and De Blas (2009) also explore the role played in the Great Moderation by changes in the financial rigidities faced by firms. I contribute to this strand of the literature by performing a thorough analysis of the evolution of financial variables, which leads me to document a broader empirical regularity on corporate balance sheet variables. The divergence of financial volatility adds a layer of difficulty to macro models that attempt to account for the observed breaks in volatilities. Regarding the estimation of DSGE models, including the financial accelerator, most of the contributions use post-1985 data in order to avoid the structural breaks linked to the Great Moderation. I address directly the issue of structural breaks while estimating the deep parameters of the financial accelerator. Therefore, relative to this literature, the main contribution of this paper is to provide a data-based quantification of the size of the financial accelerator, to document its evolution over time, and to explore financial shocks.

The organization of the paper is as follows. Section 1 presents the empirical evidence that motivates the paper. I describe the model in section 2. I describe the estimation procedure and report the estimation results in section 3. Section 4 analyzes model evaluation. In section 5, I study the relative importance of each of the potential candidates in accounting for the observed patterns in volatility and the propagation of financial shocks. Section 6 concludes.

1 Empirical Evidence

I revisit the two empirical regularities characterizing the United States over the 1954-2006 period: the Great Inflation and the Great Moderation. The data range covers only until 2006 to avoid distortions caused by nonlinearities induced by the zero lower bound on the federal funds rate, binding downward nominal rigidities and upward pressures on financial volatilities during the recent years.

Following McConnell and Pérez-Quirós (2000), I estimate the timing of the structural breaks in the residual variance of real and nominal variables by running an autoregressive model of order 1 on the cyclical component of these variables. Assuming that the error of the AR(1) model, ε_t, follows a normal distribution, I can ensure that $|\widehat{\varepsilon}_t|\sqrt{\pi/2}$ is an unbiased estimator for the residual standard deviation of the cyclical variable under analysis. I generalize the analysis in McConnell and Pérez-Quirós (2000) allowing for multiple breakpoints at unknown dates using Bai and Perron (1998) tests.[1] The results for these tests are reported in Table 1. While for the volatility of nominal variables I can reject the null of parameter constancy for two different dates, I can reject the null only once for real variables. Nominal variables indicate the early 1970s as the starting point of the Great Inflation and the end of its aftermath in the early 1980s. The break in the volatility of real variables is also quite uniform, pointing to the mid-1980s as the start of the Great Moderation. I also explore the existence and timing of structural breaks using a multivariate approach. Qu and Perron (2007) propose a method to estimate multiple structural changes occurring at unknown dates in a system of equations. I test for multiple structural breaks in the covariance matrix of a VAR model encompassing the cyclical component of the 9 variables used in the estimation of the structural DSGE model described in Section 2. The variables in the information set are: real per capita output, real per capita consumption, real per capita investment, real wages, hours worked, inflation, the nominal policy rate, the credit spread defined as Moody's Baa corporate bond rate over the 10-year Treasury yield, and corporate net worth defined as tangible assets minus credit market liabilities. The Qu and Perron (2007) multivariate test identifies two breaks: 1969:Q4 and 1985:Q1.

Given the relatively wide range for the timing of the structural breaks provided by the univariate and the multivariate tests, I proceed to estimate the structural DSGE model subject to structural breaks in a subset of parameters considering the following range of dates for the Great Inflation: 1968:Q2–1970:Q4; and the following one for the Great Moderation: 1984:Q1–1985:Q4. The marginal data density is maximized for a starting of the Great Inflation in 1970:Q3 and of the Great Moderation in 1985:Q1. Figure 1 provides the log posterior odds of the structural DSGE model for each pair of dates with respect to the fit of the model with the pair 1970:Q3–1985:Q1.[2]

Table 2 reports the ratios of cyclical volatilities for the variables used in the estimation exercise. During the Great Inflation, the volatility of nominal variables more than doubles

[1]Gadea-Rivas, Gómez-Loscos and Pérez-Quirós (2014) show that Bai and Perron (1998) tests present size distortions when only breaks in volatility are tested in non-zero mean series. This criticism does not apply to the Bai and Perron (1998) tests I perform since the time series used are cyclical components whose mean, by construction, is zero.

[2]I consider 300,000 posterior draws to compute the marginal data density for each model. There are two pairs of dates, 1970:Q2–1985:Q1 and 1970:Q3–1984:Q3, with marginal data densities close to the maximum. The prior odds in favor of these alternative dates should be, respectively, 3 and 4 times larger than the prior odds for 1970:Q3–1985:Q1 in order to be selected over the baseline dating.

and that of real variables increases, on average, by 35%. The Great Moderation is characterized by a slowdown in cyclical volatilities of about 50% for real variables and in between 50% and 65% for nominal variables. The credit spread mimics quite closely the evolution in nominal variables: its volatility increases dramatically during the Great Inflation and falls substantially during the Great Moderation. Corporate net worth experienced a continuous immoderation since the early 1970s. The cyclical volatility of net worth increases by 17% during the Great Inflation and doubles during the Great Moderation. This divergent pattern in the cyclical volatility of net worth and credit spread posses a challenge to existing theoretical models.

Finally, I explore further the immoderation in corporate balance-sheet variables. Table 3 reports ratios of cyclical volatilities for a comprehensive set of financial variables for the U.S. nonfinancial corporate sector. The table reports two alternative measures of wealth based on balance sheet data: corporate net worth 1, which is equal to tangible assets minus credit market liabilities, and corporate net worth 2, which is defined as total assets minus total liabilities. The former measure of corporate wealth is the closest to the DSGE model-implied concept of net worth, while the latter is a broader measure of corporate wealth. I use these two measures of net worth to construct the corresponding measures of corporate leverage. I consider two measures of corporate debt flows: the net increase in credit market liabilities and the net increase in corporate bonds[3]. I also explore two standard corporate ratios: Tobin's q and equity q. Tobin's q is defined as the ratio of the sum of the market value of equities and liabilities to total assets; while equity q is defined as the ratio of the market value of corporate equities to corporate net worth. Despite the diversity of relative sizes in the increases in cyclical volatility, we can argue that there is strong evidence of an immoderation in US corporate balance sheet variables not only during the Great Inflation, but, more importantly, also during the Great Moderation.

2 The Model

The theoretical framework features real and nominal rigidities as in Smets and Wouters (2007). In order to assess the role played by financial frictions in the evolution of volatilities

[3]Christiano, Motto, and Rostagno (2014) define credit in the business sector as the credit market instruments component of net increase in liabilities for nonfarm, nonfinancial corporate business and nonfarm, noncorporate business. Levin, Natalucci, and Zakrajšek (2004) use firm-level bond data to construct an empirical counterpart to one-period debt contracts.

in the U.S. economy, I extend the framework including financial rigidities as in BGG. Financial frictions arise because there is asymmetric information between borrowers and lenders. Following Townsend's (1979) costly state verification framework, I assume that while borrowers freely observe the realization of their idiosyncratic risk, lenders must pay monitoring costs to observe an individual borrower's realized return.

Since Christiano, Motto and Rostagno (2003) integrated the financial accelerator mechanism of BGG into the workhorse DSGE model, several studies have focused on assessing the empirical relevance of the financial accelerator by comparing the model fit with that of the workhorse DSGE model or on studying the propagation of real and nominal shocks. In this paper, I focus on analyzing the role of financial shocks and the model's potential to account for breaks in the second moments of the data. I incorporate into the theoretical framework a shock to firms' wealth and a shock to agency costs. While the former has been previously studied, the inclusion of the latter is a novelty of this paper.

The model economy is populated by households, financial intermediaries, entrepreneurs, capital producers, intermediate good firms, retailers, labor packers, and government.

2.1 Retailers

The retail sector is populated by infinitely lived and perfectly competitive firms producing final goods, Y_t, by combining a continuum of intermediate goods, $Y_t(i)$, $i \in [0,1]$, according to a Dixit-Stiglitz aggregator:

$$Y_t = \left[\int_0^1 (Y_t(i))^{\frac{1}{1+\lambda_t^p}} \right]^{1+\lambda_t^p}.$$

As in Smets and Wouters (2007), the price markup, λ_t^p, is assumed to follow the exogenous stochastic process

$$\ln(\lambda_t^p) = (1-\rho_{\lambda_p}) \ln(\lambda_\star^p) + \rho_{\lambda^p} \ln(\lambda_{t-1}^p) + \varepsilon_{\lambda_p,t} - \theta_p \varepsilon_{\lambda_p,t-1}, \tag{1}$$

where $\varepsilon_{\lambda_p,t} \sim \mathcal{N}(0, \sigma_{\lambda_p})$ and $\lambda_\star^p$ stands for the value of the markup in the steady state.

2.2 Intermediate goods sector

There is a continuum of infinitely lived producers of intermediate goods, indexed by $i \in [0,1]$, operating under monopolistic competition. They produce intermediate inputs, $Y_t(i)$, combining labor services, H_t, provided by households and capital services, k_t, provided by entrepreneurs using a Cobb-Douglas technology:

$$Y_t(i) = [Z_{a,t}H_t(i)]^{1-\alpha} k_t(i)^{\alpha} - Z_{a,t}\Phi, \tag{2}$$

where Φ is a fixed cost of production and $Z_{a,t}$ stands for the neutral technology shock. I assume that $Z_{a,t}$ is such that

$$Z_t \equiv \log(\Delta Z_{a,t}) = (1-\rho_z)\Upsilon_z + \rho_z Z_{t-1} + \varepsilon_{Z,t}, \qquad \epsilon_{Z,t} \sim \mathcal{N}(0, \sigma_Z) \tag{3}$$

Thus, I assume that the growth rate of the neutral technological progress follows an AR(1) process where Υ_z is the average growth rate of the economy.

Intermediate goods producers face a pricing problem in a sticky price framework à la Calvo. At any given period, a producer is allowed to reoptimize her price with probability $(1-\xi_p)$. I assume that those firms that do not reoptimize their prices set them using the following indexation rule:

$$P_t(i) = P_{t-1}(i)\pi_{t-1}^{\iota_p}\pi_\star^{1-\iota_p}, \tag{4}$$

where $\pi \equiv P_t/P_{t-1}$ is the gross inflation rate and $\pi_\star$ is the inflation rate in the steady state. When reoptimization is possible, an intermediate firm i will set the price $\widetilde{P}_t$ that maximizes the expected value of the firm as

$$\mathbb{E}_t \sum_{s=0}^{\infty} \xi_p^s \beta^s \frac{\Lambda_{t+s}}{\Lambda_t} \left[\widetilde{P}_t(i) \left(\prod_{l=1}^{s} \pi_{t+l-1}^{\iota_p} \pi_\star^{1-\iota_p} \right) Y_{t+s}(i) - W_{t+s}H_{t+s}(i) - P_{t+s}r_{t+s}^k k_{t+s}(i) \right], \tag{5}$$

subject to its demand function and to cost minimization. In the above expression, Λ_t stands for the stochastic discount factor between t and $t+s$ for households, W_t is the nominal wage, and r^k is the real rate paid on capital services.

2.3 Capital producers

Capital producers are infinitely lived agents operating in a perfectly competitive market. They produce new physical capital stock, K_{t+1}, using the following technology:

$$K_{t+1} = (1-\delta)K_t + \left[1 - \Phi\left(\frac{I_t}{I_{t-1}}\right)\right]\zeta_t I_t, \tag{6}$$

where the function $\Phi(\cdot)$ captures the existence of investment adjustment costs. We assume that $\Phi(\cdot)$ is an increasing and convex function, which, in the steady state, $\Phi(\cdot) = \Phi'(\cdot) = 0$ and $\Phi''(\cdot) \equiv \xi > 0$. The investment-specific technology shock, ζ_t, is assumed to evolve as

$$\ln(\zeta_t) = \rho_{\zeta,1} \ln(\zeta_{t-1}) + \varepsilon_{\zeta,t} \tag{7}$$

with $\varepsilon_{\zeta,t} \sim \mathcal{N}(\sigma_\zeta, 1)$.

2.4 Labor packers

As in Erceg, Henderson and Levin (2000), I assume that a representative labor packer or employment agency combines the differentiated labor services provided by households, $H_t(i)$, according to

$$H_t = \left[\int_0^1 H_t\left(i\right)^{\frac{1}{1+\lambda_t^w}} \right]^{1+\lambda_t^w},$$

where λ_t^w is the wage markup that evolves exogenously as

$$\ln(\lambda_t^w) = (1 - \rho_{\lambda_w}) \ln(\lambda_\star^w) + \rho_{\lambda_w} \ln(\lambda_{t-1}^w) + \varepsilon_{\lambda_w,t} - \theta_w \varepsilon_{\lambda_w,t-1} \tag{8}$$

with $\varepsilon_{\lambda_w,t} \sim \mathcal{N}(0, \sigma_{\lambda_w})$.

Profit maximization by perfectly competitive labor packers implies the following labor demand function:

$$H_t\left(i\right) = \left[\frac{W_t\left(i\right)}{W_t} \right]^{-\left(\frac{1+\lambda_t^w}{\lambda_t^w}\right)} H_t, \tag{9}$$

where $W_t(i)$ is the wage received from the labor packer by the type i household.

2.5 Households

I assume there is a continuum of infinitely lived households, each endowed with a specialized type of labor $i \in [0,1]$. Household i solves the following optimization problem[4]:

$$\mathbb{E}_t \sum_{j=0}^{\infty} \beta^j b_{t+j} \left[\ln(C_{t+j} - hC_{t+j-1}) - \theta \frac{H_{t+j}(i)^{1+\nu}}{1+\nu} \right]$$

subject to

$$C_t + \frac{D_{t+1}}{P_t} + \frac{NB_{t+1}}{P_t} \quad \leq \quad \frac{W_t(i)}{P_t} H_t(i) + R_{t-1}\frac{D_t}{P_t} + R^n_{t-1}\frac{NB_t}{P_t} + div_t - T_t - Trans_t,$$

where C_t stands for consumption, h for the degree of habit formation, D_{t+1} for today's nominal deposits in the financial intermediary, $H_t(i)$ for hours worked, ν for the inverse of the Frisch elasticity of labor, b_t for a shock to the stochastic discount factor, R_t for the risk-free nominal interest rate paid on deposits, R^n_t for the risk-free nominal interest rate paid on government bonds, NB_t for nominal government bonds, T_t for real taxes (subsidies) paid to (received from) the government, div_t for dividends obtained from ownership of firms, and $Trans_t$ for wealth transfers to and from the entrepreneurial sector. The nature of these transfers is described later in this section. Following Erceg, Henderson and Levin (2000), I assume complete markets, which implies that, in equilibrium, all households make the same choice of consumption, deposit holdings, and nominal bond holdings. Hours worked and wages differ across households because of the monopolistic labor supply.

The stochastic discount factor fluctuates endogenously with consumption and exogenously with the intertemporal preferece shock, b_t, which is given by

$$\ln(b_t) = \rho_b \ln(b_{t-1}) + \varepsilon_{b,t}, \quad \varepsilon_{b,t} \sim \mathcal{N}(0, \sigma_b). \tag{10}$$

Households set nominal wages for specialized labor services by means of staggered contracts. In any period t, a fraction ξ_p of households cannot reoptimize their wages, but they

[4] In the context of a financial accelerator model, Chen, Cúdia and Ferrero (2012) suggest to consider constant relative risk aversion preferences in de-trended consumption instead of log-utility to better account for asset pricing. However, the model with unit elasticity of intertemporal substitution outperforms the one with constant relative risk aversion preferences since the log marginal density of the former is 6950, while that of the latter is 6829.

follow the indexation rule

$$W_t(i) = W_{t-1}(i)\left(\pi_{t-1}\mathfrak{z}_{t-1}\right)^{\iota_w}\left(\pi_\star\mathfrak{z}_\star\right)^{1-\iota_w}. \tag{11}$$

A fraction $(1-\xi_w)$ of households are allowed to choose an optimal nominal wage $\overline{W}_t(i)$, by solving

$$\max \mathbb{E}_t \sum_{s=0}^{\infty} \xi_w^s \beta^s \left[-b_{t+s}\theta\frac{H_{t+s}(i)^{1+\nu}}{1+\nu} + \Lambda_{t+s}W_t(j)H_{t+s}(j)\right],$$

subject to the labor demand function.

2.6 Entrepreneurs and financial intermediaries

Entrepreneurs are finitely lived risk-neutral agents who borrow funds captured by financial intermediaries from households. Conditional on survival, an entrepreneur j purchases physical capital, K_{t+1}^j, at relative price Q_t.

At the beginning of the period, an entrepreneur is hit by an idiosyncratic shock, ω_t^j, that affects the productivity of her capital holdings. This idiosyncratic shock is at the center of the informational asymmetry, as it is only freely observed by the entrepreneur. For tractability purposes, I assume ω_t^j, for all j, is *i.i.d* lognormal with *c.d.f.* $F(\omega)$ and parameters μ_ω and σ_ω, such that $\mathbb{E}[\omega^j] = 1$. After observing the realization of the idiosyncratic shock, entrepreneurs choose the capital utilization rate, u_t^j, that solves the following optimization problem

$$\max_{u_t^j} \left[u_t^j r_t^{k,j} - a\left(u_t^j\right)\right]\omega_t^j K_t^j, \tag{12}$$

where, around the steady state, $a(\cdot) = 0, a'(\cdot) > 0, a''(\cdot) > 0$ and $u^\star = 1$. Therefore, capital services, k_t^j, rented to intermediate goods producers are given by $k_t^j = u_t^j\omega_t^j K_t^j$.

The capital demand for entrepreneur j is given by the gross nominal return on holding one unit of capital from t to $t+1$

$$R_{t+1}^{k,j} = \left[\frac{r_{t+1}^{k,j}u_{t+1}^j + \omega_{t+1}^j(1-\delta)Q_{t+1}}{Q_t}\right]\frac{P_{t+1}}{P_t}, \tag{13}$$

where $\omega_{t+1}^j(1-\delta)Q_{t+1}$ is the return to selling the undepreciated capital stock back to capital producers.

An entrepreneur can finance the purchase of new physical capital by investing her own net worth, N_{t+1}^j, and using external financing (in nominal terms), B_{t+1}^j, to leverage her project. Given that the entrepreneur is risk neutral, she offers a debt contract that ensures the lender a return free of aggregate risk. The lender can diversify idiosyncratic risks by holding a perfectly diversified portfolio, which allows her to offer a risk-free rate on deposits to households. Financial intermediaries cannot observe the realized return of a borrower unless they pay an auditing cost. To minimize costs, lenders will audit borrowers only when they report their inability to repay the loan under the terms of the contract. A debt contract is characterized by a triplet consisting of the amount of the loan, B_{t+1}^j, the contractual rate, Z_{t+1}^j, and a schedule of state-contingent threshold values of the idiosyncratic shock, $\bar{\omega}_{n,t+1}^j$, where n refers to the state of nature. For values of the idiosyncratic productivity shock above the threshold, the entrepreneur is able to repay the lender at the contractual rate. For values below the threshold, the borrower defaults, and the lender steps in and seizes the firm's assets. A fraction of the realized entrepreneurial revenue, μ, is lost in the process of liquidating the firm. In this case, the financial intermediary obtains

$$(1-\mu_{t+1})P_t\omega_{n,t+1}^j R_{n,t+1}^k Q_t K_{t+1}^j, \tag{14}$$

where μ_{t+1} stands for the marginal bankruptcy cost. In the literature, the marginal bankruptcy cost is assumed to be a constant parameter. I assume, however, that it is a drifting parameter so that exogenous changes in the level of financial rigidities affect the business cycle properties of the model. Later in this section, I describe in detail the relevance of this assumption and the stochastic specification chosen.

The terms of the debt contract are chosen to maximize expected entrepreneurial profits conditional on the return of the lender, for each possible state of nature, being equal to the riskless rate. That is, the participation constraint is given by the zero profit condition for the financial intermediary from which I can derive the supply for loans:

$$\mathbb{E}_t \frac{R_{t+1}^k}{R_t}\left[\Gamma(\bar{\omega}_{t+1}) - \mu_{t+1}G(\bar{\omega}_{t+1})\right] = \left(\frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}}\right), \tag{15}$$

where

$$\Gamma(\bar{\omega}_{t+1}^j) = \int_0^{\bar{\omega}_{t+1}^j} \omega f(\omega) d\omega + \bar{\omega}_t \int_{\bar{\omega}_{t+1}^j}^{\infty} f(\omega) d\omega$$

is the expected share of gross entrepreneurial earnings going to the lender, and

$$\mu_{t+1} G(\bar{\omega}_{t+1}^j) = \mu_{t+1} \int_0^{\bar{\omega}_{t+1}^j} \omega f(\omega) d\omega$$

is the expected monitoring costs. The previous equation states that financial intermediaries are only willing to provide funds to entrepreneurs if they are compensated by the default risk. That is, lenders charge a premium over the risk-free rate, the so-called external finance premium, $\mathbb{E}\left[R_{t+1}^k / R_t\right]$. Equation (15) provides one of the foundations of the financial accelerator mechanism: a linkage between the entrepreneur's financial position and the cost of external funds, which ultimately affects the demand for capital.

The supply for loans can be rewritten as

$$\mathbb{E}_t \frac{R_{t+1}^k}{R_t} = \mathcal{S}\left(\bar{\omega}_{t+1}, \mu, \sigma_\omega\right) \left(\frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}}\right) \tag{16}$$

The external finance premium is determined by two channels: the *balance sheet channel*, through the debt-to-assets ratio, $\left(\frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}}\right)$, and the *information channel*, through the elasticity of the external finance premium with respect to the leverage ratio, $\mathcal{S}\left(\bar{\omega}_{t+1}, \mu, \sigma_\omega\right)$. The external finance premium is the key relationship of the financial accelerator, as it determines the efficiency of the contractual relationship between borrowers and lenders. I enrich the theoretical framework by assuming that this essential mechanism is affected exogenously by two financial shocks: a wealth shock and a shock to the marginal bankruptcy cost.

The *balance sheet channel* states the negative dependence of the premium on the amount of collateralized net worth, N_{t+1}. The higher the stake of a borrower in the project, the lower the premium over the risk-free rate required by the intermediary. I introduce shocks to this channel through an entrepreneurial equity shifter. These types of wealth shocks were first introduced by Gilchrist and Leahy (2002). Recently, they have been explored by Christiano, Motto and Rostagno (2010); Nolan and Thoenissen (2009); and Gilchrist, Ortiz and Zakrajšek (2009).

The elasticity of the premium with respect to the leverage position of entrepreneurs depends upon the idiosyncratic productivity threshold, $\bar{\omega}_{t+1}$, the marginal bankruptcy cost, μ, and the distribution of the idiosyncratic productivity shocks. Given our assumptions, the latter is fully characterized by the cross-sectional dispersion of productivity across entrepreneurs, σ_ω. Time variation in the elasticity is endogenously driven by fluctuations in the idiosyncratic productivity threshold. Earlier contributions to the literature abstract from the general equilibrium effects generated by fluctuations in the productivity threshold since these were assumed to be negligible in driving the overall dynamics of the model. Therefore, the elasticity of the external finance premium was assumed to be constant. Dib (2010) explores time variation in the elasticity of the premium using a reduced form approach consisting of assuming that the elasticity is driven by a purely exogenous process. More recently, Christiano, Motto and Rostagno (2003) explore the general equilibrium effects of the dynamics of the idiosyncratic productivity threshold, which implies a time-varying elasticity. Moreover, they introduce an additional source of time variation in the *information channel* by assuming that the standard deviation of the idiosyncratic productivity shock is stochastic. A positive shock to the volatility of the idiosyncratic productivity shock widens the distribution so that financial intermediaries find it more difficult to distinguish the quality of entrepreneurs. Therefore, shocks to the standard deviation of the idiosyncratic productivity distribution are labeled risk shocks. In Christiano, Motto and Rostagno (2014), they further explore the role of risk shocks by assuming a news structure with anticipated and unanticipated components embedded in the shock specification. They conclude that risk shocks are the main driver of the US business cycle, with the anticipated component (signals) playing a predominant role.

In this paper, I also exploit the endogenous time variation in the elasticity of the premium with respect to leverage by taking into account the general equilibrium effects of fluctuations in the idiosyncratic productivity threshold, $\bar{\omega}_{t+1}$, and I also introduce a source of exogenous variation in this elasticity. Given that I am at exploring the role played by cyclical variations in financial rigidities in driving business cycle fluctuations and that, in a financial accelerator model, the size of the financial market friction is summarized by the marginal bankruptcy cost parameter, I assume that this parameter is time-varying and driven by an exogenous process. The information channel establishes that the external finance premium is a positive function of the severity of the agency problem measured by the marginal bankruptcy cost, μ_t. An increase in the level of financial rigidity implies an enlargement of the informational asymmetry rents, which translates into a higher premium on external funds. While risk shocks à la Christiano, Motto and Rostagno (2014) capture mean-preserving changes in the cross-sectional dispersion of productivity across entrepreneurs, shocks to marginal bankruptcy costs capture time variation in the strength of financial rigidities. Despite this conceptual difference, both types of shocks translate into similar qualitative effects in the *information channel*. Levin, Natalucci and Zakrajšek (2004) use a partial equilibrium version of the financial accelerator model to obtain time-specific estimates of the bankruptcy parameter using firm-level data over the period 1997-2003. They conclude there is substantial time variation in the magnitude of financial market frictions. They show that most of the variation in the external finance premium in their panel is driven by the variation in the bankruptcy parameter. They conclude that, in their sample, there is little variation in the idiosyncratic volatility across the distribution of firms. Given Levin, Natalucci and Zakrajšek (2004) results, I test the role of time variation in the bankruptcy cost parameter in the context of a general equilibrium framework.[5]

I assume that the marginal bankruptcy cost evolves as follows

$$\begin{aligned} \mu_t &= \frac{1}{1+e^{\varphi_t}} && (17) \\ \ln(\varphi_t) &= (1-\rho_\varphi)\ln(\varphi_\star) + \rho_\varphi \ln(\varphi_{t-1}) + \varepsilon_{\varphi,t}, \quad \varepsilon_{\varphi,t} \sim \mathcal{N}(0,\sigma_\varphi), && (18) \end{aligned}$$

where φ_t is shock to the marginal bankruptcy cost. This specification ensures that the realization of the marginal bankruptcy cost, μ_t, lies between 0 and 1 every period.[6] The unconditional mean of the process governing the agency problem between borrowers and lenders, $\mu^\star = 1/(1+e^{\varphi_\star})$, determines the average level of financial rigidity in the model economy. This parameter governs the size of the financial accelerator. In particular, $\mu^\star$ stands for the steady-state level of the marginal bankruptcy cost.

The other main component of the financial accelerator is the evolution of entrepreneurial wealth. Note that the return on capital and, hence, the demand for capital by entrepreneurs depend on the dynamics of net worth. Let V_t be entrepreneurial equity and W_t^e be the wealth transfers made by exiting firms to the pool of active firms. Then, aggregate entrepreneurial net worth (average net worth across entrepreneurs) is given by the following differential equation

$$\begin{aligned} P_t N_{t+1} &= x_t \gamma V_t + P_t W_t^e \\ &= x_t \gamma \left[P_{t-1} R_t^k Q_{t-1} K_t - R_{t-1} B_t - \mu_t G(\bar{\omega}_t) P_{t-1} R_t^k Q_{t-1} K_t \right] + P_t W_t^e, \end{aligned}$$

where γ is the survival probability, $\left[R_t^k P_{t-1} Q_{t-1} K_t^j - R_{t-1} B_t\right]$ is the nominal gross return on capital net of repayment of loans in the nondefault case, $\mu_t G(\bar{\omega}_t) R_t^k Q_{t-1} K_t$ is the gross

[5] The aggregate data clearly favors the model with time-varying marginal bankruptcy costs over the model with time-varying idiosyncratic risk à la Christiano, Motto and Rostagno (2003). In particular, the marginal data density of the former is 37 log points larger than that of the latter. Recently, Zeke (2016) show that the relative role of idiosyncratic volatility shocks in driving business cycle fluctuations is very sensitive to the cost of default. In particular, for default costs along the lines of the micro empirical evidence, idiosyncratic volatility shocks cannot generate enough aggregate variation.

[6] Alternatively, time variation in the marginal bankruptcy cost can be modeled as $\ln \mu_t = (1-\rho_\mu)\ln \mu_\star + \rho_\mu \ln \mu_{t-1} + \sigma_\mu \epsilon_\mu$, which does not restrict the realization of the marginal bankruptcy cost to lie in the unit interval. However, the posterior odds favor the restricted specification over the unrestricted one.

return lost in case of bankruptcy, and x_t is the wealth shock, which is assumed to be

$$\ln(x_t) = \rho_x \ln(x_{t-1}) + \varepsilon_{x,t}, \quad \varepsilon_{x,t} \sim \mathcal{N}(0, \sigma_x). \tag{19}$$

Exogenously driven changes in the valuation of entrepreneurial equity need to be financed by another sector of the model economy. I assume that the household sector receives (provides) wealth transfers from (to) the entrepreneurial sector, which are defined as

$$Trans_t = N_{t+1} - \gamma V_t - W_t^e = \gamma V_t \left(x_t - 1\right), \tag{20}$$

where $\gamma V_t + W_t^e$ is the value that entrepreneurial equity would have taken if there were no wealth shocks.

2.7 Government

Government spending is financed by government nominal bonds sold to households and by lump-sum taxes:

$$NB_{t+1} + P_t T_t = P_t G_t + R_{t-1}^n NB_t, \tag{21}$$

where the process for public spending G_t is given by $G_t = \left(1 - \frac{1}{g_t}\right) Y_t$, where the government spending shock, g_t, follows the stochastic process:

$$\ln g_t = (1 - \rho_g) \ln g + \rho_g \ln g_{t-1} + \varepsilon_{g,t}, \;\; \varepsilon_{g,t} \sim \mathcal{N}(0, \sigma_g).$$

The monetary authority follows a Taylor-type interest rate rule. I assume that the authority adjusts the short-term nominal interest rate in response to deviations of inflation and output growth from the target—that is, their steady-state values:

$$\left(\frac{R_t^n}{R^{n\star}}\right) = \left(\frac{R_{t-1}^n}{R^{n\star}}\right)^{\rho_R} \left(\frac{\pi_t}{\pi^\star}\right)^{(1-\rho_R)\psi_\pi} \left(\frac{\Delta Y_t}{\Upsilon_z}\right)^{(1-\rho_R)\psi_y} e^{\eta_{mp}} \tag{22}$$

with $\rho_R > 0, (1 - \rho_R)\psi_\pi > 0$, $(1 - \rho_R)\psi_y > 0$, and

$$\eta_{mp,t} = \rho_{mp} \eta_{mp,t-1} + \varepsilon_{R,t}, \;\; \varepsilon_{R,t} \sim \mathcal{N}(0, \sigma_R). \tag{23}$$

3 Bayesian Inference

3.1 Data

I estimate the model with Bayesian estimation techniques using nine macroeconomic quarterly U.S. time series as observable variables: the growth rate of real per-capita net worth in the nonfarm business sector defined as tangible assets minus credit market liabilities, the growth rate of real per-capita gross value added (GVA) by the nonfarm business sector, the growth rate of real per-capita consumption defined as consumption of nondurables and services, the growth rate of real per-capita investment defined as gross private investment, the growth rate of real hourly wages in the nonfarm business sector, log hours worked, the log difference of the GVA deflator, the federal funds rate, and the spread between the Baa corporate bond rate and the 10-year US government bond rate. A complete description of the data set is given in the appendix. The model is estimated over the full sample period from 1954:Q4 to 2006:Q4.

3.2 Structural breaks

I aim to test the relative role played by three theories in accounting for the observed breaks in volatilities: luck, the conduct of monetary policy, and financial institutions. To do so, I allow for breaks in three subsets of parameters: size of shocks, monetary policy coefficients, and the unconditional mean of the marginal bankruptcy cost, which characterizes the financial system[7]. Following Cúrdia and Finocchiaro (2013), I impose the dating of the structural breaks in a subset of parameters but I do not allow economic agents to form expectations about them. These simplifications allow me to proceed within the log-linear framework using small departures in generating the posterior. As in Cúrdia and Finocchiaro (2013), I compute separate equilibria for the same model with only a subset of regime-dependent equations changed and reconnect the rational expectations equilibria via the likelihood function. In this way, a computational bridge can be established between subsamples so that the entire sample can be used to estimate parameters that are constant across regimes and

[7] Allowing for breaks in only one of the parameters characterizing the financial accelerator may seem too simplistic despite being the parameter that conceptually measures the size of the financial rigidity. Table 5 reports the fit of alternative model specifications that allow for breaks in the steady state default probability, $F(\bar{\omega})^{\star}$, the entrepreneurial survival rate, γ, and the volatility of the distribution of idiosyncratic productivity, σ_{ω}. The log posterior odds are clearly in favor of the baseline model in which the only parameter linked to the structure of the financial accelerator subject to structural breaks is the steady state value of the marginal bankruptcy cost.

proceed with the joint estimation of the regimes. Cúrdia and Finocchiaro (2013) develop their approach to estimation for an open economy model with breaks only in the monetary policy coefficients. In this paper, I generalize their estimation method to environments with breaks in parameters governing the steady state of the model economy, which requires to ensure that the econometrician is using the same information set as the economic agent when conducting the estimation exercise.

3.2.1 A simple example

Let us consider an AR(1) process with a time-varying mean:

$$x_t = \rho x_{t-1} + (1-\rho)\,\bar{x}_t + u_t, \tag{24}$$

where $|\rho| < 1$, $\bar{x}_t$ is the time-varying mean, and u_t is a zero-mean iid process. Let us define $\widetilde{x}_t = x_t - \bar{x}_t$—that is, the deviation of x_t with respect to the time-t mean of the process. Note that expression (24) cannot be written as

$$\widetilde{x}_t = \rho\widetilde{x}_{t-1} + u_t$$

as $\widetilde{x}_{t-1} \neq x_{t-1} - \bar{x}_t$. Instead, the model can be expressed as

$$\begin{aligned} x_t - \bar{x}_t &= \rho\,(x_{t-1} - \bar{x}_{t-1}) + \rho\,(\bar{x}_{t-1} - \bar{x}_t) + u_t \\ \widetilde{x}_t &= \rho\widetilde{x}_{t-1} + \rho\,(\bar{x}_{t-1} - \bar{x}_t) + u_t \end{aligned}$$

where $\widetilde{x}_t = x_t - \bar{x}_t$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_{t-1}$.

To illustrate the relevant case for this paper, let us assume that the time-varying mean process is given by

$$\bar{x}_t = \begin{cases} \bar{x}_1 & \text{for } t < t^\star \\ \bar{x}_2 & \text{for } t \geq t^\star \end{cases} \tag{25}$$

Thus, we can represent (24) as follows:

- For $t < t_\star$, $\widetilde{x}_t = \rho\widetilde{x}_{t-1} + u_t$ where $\widetilde{x}_t = x_t - \bar{x}_1$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_1$.
- For $t = t_\star$, $\widetilde{x}_t = \rho\widetilde{x}_{t-1} + \rho\,(\bar{x}_1 - \bar{x}_2) + u_t$ where $\widetilde{x}_t = x_t - \bar{x}_2$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_1$.
- For $t > t_\star$, $\widetilde{x}_t = \rho\widetilde{x}_{t-1} + u_t$ where $\widetilde{x}_t = x_t - \bar{x}_2$ and $\widetilde{x}_{t-1} = x_{t-1} - \bar{x}_2$.

That is,

$$\begin{aligned}
(x_t - \bar{x}_1) &= \rho\,(x_{t-1} - \bar{x}_1) + u_t, & \text{if } t < t_\star, \\
(x_t - \bar{x}_2) &= \rho\,(x_{t-1} - \bar{x}_1) + \rho\,(\bar{x}_1 - \bar{x}_2) + u_t, & \text{if } t = t_\star, \text{and} \\
(x_t - \bar{x}_2) &= \rho\,(x_{t-1} - \bar{x}_2) + u_t, & \text{if } t > t_\star.
\end{aligned}$$

3.2.2 The DSGE model

Let ϱ be the subvector of structural parameters that is constant across subsamples and τ_t be the subvector subject to structural breaks. The system of log-linearized equilibrium conditions can be represented as

$$\Gamma_0\,(\varrho, \tau_t)\,\widetilde{s}_t = \Gamma_1\,(\varrho, \tau_t)\,\widetilde{s}_{t-1} + \Psi\,(\varrho, \tau_t)\,\varepsilon_t + \Pi\,(\varrho, \tau_t)\,\eta_t, \tag{26}$$

where $\widetilde{s}_t$ is a vector of model variables expressed in deviations from the steady state, ε_t is a vector of exogenous shocks, and η_t is a vector of rational expectations errors with elements $\eta_t^x = \widetilde{x}_t - \mathbb{E}_{t-1}[\widetilde{x}_t]$. As in the AR(1) example, $\widetilde{s}_t$ is in log-deviations from $\bar{s}_t$ and $\widetilde{s}_{t-1}$ from $\bar{s}_{t-1}$. The state-space representation of the solution to the LRE model can be written as follows:

$$\begin{aligned}
Transition\ equations: &\quad [s_t - \bar{s}_t] = \Phi(\varrho, \tau_t)\,[s_{t-1} - \bar{s}_{t-1}] + \Phi_\varepsilon(\varrho, \tau_t)\varepsilon_t \text{and} \\
Measurement\ equations: &\quad y_t = B s_t,
\end{aligned}$$

where s_t is the state vector in log-levels. Note that while breaks in the size of shocks shift only $\Phi_\varepsilon(\varrho, \tau_t)$ and breaks in monetary policy coefficients affect $\Phi(\varrho, \tau_t)$, breaks in parameters defining the steady state of the economy translate into changes in $\Phi(\varrho, \tau_t)$ and $\bar{s}$. To evaluate the likelihood function, we only need to modify the forecasting step of the Kalman filter to accommodate for structural breaks as follows:

$$\begin{aligned}
\left[\widehat{s}_{t|t-1} - \bar{s}_1\right] &= \Phi\,(\varrho, \tau_1)\left[\widehat{s}_{t-1|t-1} - \bar{s}_1\right] & \text{if } t < t_\star \\
\left[\widehat{s}_{t|t-1} - \bar{s}_2\right] &= \Phi\,(\varrho, \tau_2)\,[\bar{s}_1 - \bar{s}_2] + \Phi\,(\varrho, \tau_2)\left[\widehat{s}_{t-1|t-1} - \bar{s}_1\right] & \text{if } t = t_\star \\
\left[\widehat{s}_{t|t-1} - \bar{s}_2\right] &= \Phi\,(\varrho, \tau_2)\left[\widehat{s}_{t-1|t-1} - \bar{s}_2\right] & \text{if } t > t_\star.
\end{aligned}$$

3.3 Prior distribution

The prior information on the parameters used in the estimation exercise is available in the first three columns of tables 6 and 7. The parameter space can be partitioned into three sets. The first set contains the *parameters with degenerate priors.* I set the depreciation rate δ to 2.5%, the steady-state value of the government spending to output ratio is equal to 20%, and the steady-state values of the price and wage markup are fixed to 20%. It is well-known that DSGE models have difficulties in matching sample averages of observable variables, which may distort the inference about the parameters governing model dynamics. To overcome this difficulty, I use degenerate priors for the steady-state value of log-hours, $ln(H_{\star})$, and the quarterly growth rate in the model economy, Υ.

The second set of parameters contains the ones being estimated using the *full sample information.* These parameters are reported in the lower panel of table 6. *Parameters subject to structural breaks* are collected in the third set of parameters and shown in table 7. The priors are assumed to be identical across subsamples. My choices for standard parameters are along the lines of those in the recent literature. I provide a further description of the prior choice for the parameters governing the financial accelerator because there have been just a few attempts to estimate them.

For the entrepreneurial default probability, $F(\bar{\omega})$, I choose a Beta distribution with location parameter equal to the average of the historical default rates for U.S. bonds over the 1971–2005 period reported by Altman and Pasternack (2006). I choose a Beta distribution for the survival probability, γ. The location parameter is chosen by solving the steady state for the financial sector when the debt-to-wealth ratio is equal to its historical average. Moreover, the location parameter value implies that firms live, on average, 17 years. This tenure is close to the median tenure reported by Levin, Natalucci and Zakrajšek (2004) from a panel of 900 nonfinancial firms. I impose a Gaussian distribution as the prior for σ_{ω} with a location parameter of 0.28 and dispersion parameter of 0.10. For the steady-state value of the marginal bankruptcy cost, $\mu^{\star}$, I choose a Beta distribution for this parameter as it must lie inside the unit interval. In order to determine the location parameter of the Beta prior distribution, I consider micro evidence on bankruptcy costs. Altman (1984), using data from 26 firms, concludes that bankruptcy costs are about 20% of the firm's value prior to bankruptcy and in the range of 11% to 17% of a firm's value up to three years prior to bankruptcy. Alderson and Betker (1995) analyze 201 firms that completed Chapter 11 bankruptcies during the 1982–1993 period to determine that the mean liquidation costs are 36.5%. Using those two results, Carlstrom and Fuerst (1997) conclude that the interval empirically relevant for the marginal bankruptcy cost parameter is $[0.20, 0.37]$. Levin, Natalucci and Zakrajšek (2004) estimate a partial equilibrium version of the model by BGG using panel data over the period from 1997 to 2003. As a byproduct of their estimation, they obtain the model-implied time series for the marginal bankruptcy cost. Their estimates lie in the range of 7% to 45%. Therefore, I assume that the Beta distribution for the unconditional average level of financial rigidity is centered at 0.28. I choose the diffusion parameter to be equal to 0.05 so that the 95% credible set encompasses most of the values provided in the literature.

3.4 Posterior estimates of the parameters

The last two columns of tables 6 and 7 report the posterior median and the 95% credible intervals of a chain of 500,000 posterior draws with a burn-in period of 20%.[8] I first analyze table 6, which contains those parameters not allowed to change over time. My estimates for standard parameters in DSGE models are along the lines of the estimates available in the literature. The only exception is the investment adjustment cost parameter, ξ, whose posterior median is 0.55. This relatively low value for the adjustment cost parameter suffices to put discipline in investment dynamics, given that the model-implied volatility in investment at business cycle fluctuations is similar to the observed one. I finalize the discussion on the parameters estimated on the full data information by considering the three parameters linked to the financial rigidity: the steady state entrepreneurial default probability, $F(\bar{\omega})^{\star}$, the survival probability of entrepreneurs, γ, and the variance in the idiosyncratic productivity shock, σ_{ω}^{2}. The steady state default probability is estimated to be 0.36%, which is a notch lower than the median default probability in the data set explored by Levin, Natalucci and Zakrajšek (2004) for the period 1997-2003. The survival probability of entrepreneurs is estimated to be about 98% per quarter which implies a median life for entrepreneurs of about 12 years. This value is within the range of the values used in the literature: Bernanke, Gertler and Gilchrist (1999) set $\gamma = 0.973$; Christiano, Motto and Rostagno (2010) propose $\gamma = 0.9762$; and Christiano, Motto and Rostagno (2014) use $\gamma = 0.985$. The variance of the idiosyncratic productivity shock is estimated to be equal to 0.30, which is similar to the 0.24 value set by Christiano, Motto and Rostagno (2010).

Table 7 reports the estimates for those parameters allowed to change in 1970:Q3 and 1985:Q1. First, I analyze the estimated breaks in the *parameters governing the conduct of monetary policy*. As pointed out elsewhere in the literature, the response of the monetary authority to inflation is looser in the 1970s than in the 1950s-1960s and the Great Moderation. In particular, during the Burns-Miller tenure, the response to inflation was about 15% milder than in Martin's mandate. The Volcker-Greenspan period is characterized by a tight response

[8] I have generated two additional chains of 400,000 posterior draws. The results reported across chains are almost identical.

to inflation, which is about 55% larger than during the Great Inflation. The response of the monetary authority to the real side of the economy has steadily been tighter over time, so that during the Great Moderation the response to deviations of output growth from the target is twice as large as the response during the '50s and '60s.

Next, I consider the *parameter characterizing the conditions of access to credit*. The unconditional mean of the marginal bankruptcy cost, which accounts for the easiness of access to external financing, does not change significantly during the Great Inflation. While before the Great Moderation financial intermediaries were able to recover 87% of the value of the firm in the event of bankruptcy, the recovery rate increases to 99% in the mid-1980s. Thus, on average, the most recent period is characterized by an almost frictionless financial environment. The reduction in the average level of financial rigidities accounts not only for the decrease in bankruptcy costs linked to the Bankruptcy Reform Act of 1978 (see White, 1983) but also for other changes in the US financial system. The decades under analysis are characterized by the IT revolution, waves of regulation and deregulation, development of new products, and improvements in the assessment of risk. All of these factors define the level of financial rigidity in terms of the model economy. Thus, the improvements in the conditions of access to credit are reflected by the large reduction in the size of the financial rigidity operating in the model economy.

Finally, I describe the estimated breaks for the *size of exogenous shocks*. The size of financial shocks has increased over time, which implies a higher exposure to financial risk in the model economy. The size of the wealth shock doubles in the 1970s and it more than doubles again during the Great Moderation. Larger balance sheet shocks affecting the model economy reflect the increasing sensitivity of the system to asset price movements. The size of the shock to the marginal bankruptcy cost doubles in the 1970s and it doubles again during the Great Moderation.

The size of the remaining shocks increases in the 1970s and decreases in the mid-1980s. In particular, during the Great Inflation, the size of the investment-specific technology shock increases by 20%; that of the price and wage markup shocks by 50% and 26%, respectively; and the size of the monetary policy shock more than doubles. The size of all nonfinancial shocks decreases during the Great Moderation by a minimum of 15% for the wage markup shock and a maximum of 60% for the monetary policy shock.

4 Model evaluation

In a Bayesian framework, posterior model probabilities can be used for model selection. Table 4 reports the marginal data densities for the baseline model in which I allow for two structural breaks in the parameter vector and for alternative model specifications in which either no breaks are allowed or only one break in either 1970:Q3 or 1985:Q1 is allowed. Log posterior odds clearly favor the specification with two structural breaks. In the remainder of this section, I further study the model fit of the data by performing posterior predictive checks and exploring external validations for the time-varying marginal bankruptcy cost parameter.

4.1 Posterior predictive checks

I focus on analyzing the performance of the model in replicating the observed swings in cyclical volatility. To do so, I generate 1000 samples of 200 observations (after a burn-in period of 1000 observations) from the model economy using every 1000th posterior draw. I filter the data in log-levels obtained from the simulation using the Hodrick-Prescott filter and compute the standard deviation of the cyclical component. Table 8 reports the model-implied ratios of volatilities for the cyclical component. In particular, I report the median and 90% credible intervals, which are due to both parameter and small-sample uncertainty. Given that likelihood-function-based estimation operates by trying to match the entire autocovariance function of the data, there is a tension between matching standard deviations and other second moments of the data. Therefore, the researcher should not expect a perfect accounting of the observed cyclical volatilities. Moreover, in the estimation exercise, I use data in log-levels and first differences instead of cyclical data.

The model successfully generates an enlargement of cyclical volatility for all variables during the Great Inflation. The simulated economy replicates the observed discrepancy in the relative size of the immoderation of nominal variables and credit spreads with respect to the remaining variables. The theoretical framework also delivers the differences in size of the slowdown in the volatility of real variables, nominal outcomes, and the credit spread. The posterior predictive check also delivers that the model is successful at generating the divergent pattern in volatility for balance sheet variables. In particular, the model nearly matches the fact that the cyclical volatility of net worth more than doubles during the Great Moderation. Given that the model is able to replicate to a large extent the empirical evidence at hand, I conclude that the model proposed in this paper is a good candidate for analyzing the U.S. business cycle properties for real, nominal, and financial variables.

4.2 External validation: What does μ_t capture?

I have introduced time variation in the marginal bankruptcy cost parameter arguing that, in this way, I can attempt to capture variations in the conditions of access to credit at business cycle frequencies. Moreover, the marginal bankruptcy cost in the model can be interpreted as the general equilibrium counterpart of the time-specific estimate of the bankruptcy cost parameter in Levin, Natalucci and Zakrajšek (2004). The latter is available for rather a short time span: 1997:Q2-2003:Q3. Figure 2 shows the estimate in Levin, Natalucci and Zakrajšek (2004) (the solid line), based on micro evidence, and the general equilibrium model-implied series (the dashed line). Despite not using micro evidence in the estimation of the general equilibrium model, the two series depict the same dynamics: *(i)* a spike in 1998:Q4, which most likely reflects the turbulence in financial markets after the Russian default and the collapse of the Long-Term Capital Management hedge fund; *(ii)* a run-up in bankruptcy costs linked to the burst of the stock market bubble in 2000; *(iii)* a moderate decline during the 2001 downturn until early 2002; *(iv)* an increase at the end of 2002 capturing the heightened uncertainty generated by the post-Enron scandals; and *(v)* a decline in 2003 reflecting the narrowing of credit spreads as the economy recovers.

Despite the similarities between the model-implied series for marginal bankruptcy costs and the estimated series using micro data by Levin, Natalucci and Zakrajšek (2004), μ_t, in practice, represents much more than just direct default costs. In the context of the model, marginal bankruptcy costs are a summary statistic for the conditions of access to credit. There are several empirical proxies for conditions of access to credit, such as, lending standards and financial stress indexes. Figure 3 shows the quarterly counterpart of the monthly realized stock market volatility provided by Caldara et al. (2016), which is available since 1973. They compute realized equity volatility as the annualized standard deviation of the daily value-weighted total market (log) return from the Center for Research in Security Prices (CRSP) data base. The model-implied marginal bankruptcy cost shows a run-up until the mid-1970s coinciding with the increase in financial uncertainty linked to the oil crises. In the decade from 1975 to 1985, the cost parameter remains relatively stable but high. In 1987, the marginal bankruptcy cost starts a sharp decline, interrupted during the stock market crash in the fourth quarter of 1987, for which both the bankruptcy cost and the financial stress proxy show a sharp spike. The following significant increase in both measures is related to the first Gulf War at the end of 1990. The 1997-2003 period was described earlier. Finally, the model-implied measure of financial conditions does also mimic the sharp decline in financial stress from the end of 2003 until the end of the sample. Figure 4 shows the smoothed series for μ_t against the net percentage of domestic banks tightening standards for commercial and industrial loans to large and middle-market firms, which is available since 1990. The model-implied measure of financial rigidities delivers the sudden tightening in lending standards at the end of 1998 and during 2000-2001 and also mimics the loosening of business lending standards over the 2003-2004 period. Therefore, I conclude that, overall, the model-implied measure of marginal bankruptcy costs seems to be a good summary statistic of the underlying financial stress present in the U.S. economy.

Finally, in the estimation, the shock to the marginal bankruptcy cost arises as the key driver of credit spreads in the model, which is along the lines of what Levin, Natalucci and Zakrajšek (2004) conclude from the micro evidence. Figure 5 reports the credit spread, the blue line measured in the right vertical axis, and the model-implied series for marginal bankruptcy costs, the red line measured in the left vertical axis. As expected, the marginal bankruptcy cost mirrors the observed dynamics for credit spreads. The estimated range of variation for μ_t is quite wide with a minimum of 0% and a maximum of 50%. This range of variation encompasses the ranges estimated using micro evidence. For example, the range of variation for default costs in Andrade and Kaplan (1998) is $10\% - 23\%$; in Levin, Natalucci and Zakrajšek (2004), it is $7\% - 47\%$; and in Davydenko, Strebulaev and Zhao (2012), the range of variation is $14.7\% - 30.5\%$. Davydenko, Strebulaev and Zhao (2012) estimate the cost of default for an average firm to be 21.7% of the market value of assets, while the average value of μ_t over the entire sample in my model is 19%. Therefore, the estimated smoothed series for marginal bankruptcy costs seems to be consistent with the range of estimates in the empirical corporate finance literature.

5 Results

In this section, I first analyze the contribution to the model-implied changes in business cycle properties of each of the potential candidates by performing counterfactual exercises. Tables 9 and 10 report the percentage of the total increase or decrease in the cyclical standard deviation generated by the model that can be accounted for by the corresponding counterfactual. A dash indicates that the direction of the counterfactual change is at odds with the model-implied changes in volatilities. Appendix B provides a detailed description of the implementation of the counterfactuals.

The model predicts that the Great Inflation was mostly due to bad luck, the Great Moderation is the result of better institutions, and the immoderation in balance-sheet variables is driven by a larger exposure to financial risk. However, the institutional framework characterizing the Great Moderation acts as a buffer for the higher financial risk present in the U.S. economy. During the Great Inflation, the estimated changes in institutions account for an average of 10% of the model-implied increase in the volatility of the cyclical component of all but nominal variables. The dovish monetary policy regime during the 1970s and early 1980s and the almost 20% tightening in the conditions of access to credit deliver almost 30% of the model-implied increase in the volatility of inflation and about 20% of that in the volatility of the nominal interest rate. I conclude that while institutional changes are needed to generate the model-implied increase in the volatility of inflation and the nominal interest rate, the larger volatility of the remaining variables can only be explained by the estimated change in the size of exogenous shocks. In the remainder of this section, I further explore the role of institutional changes in the Great Moderation and the interaction between the institutional framework and financial risk.

5.1 The role of institutions in the Great Moderation

The counterfactuals *all institutions* and *all shocks* in Table 10 show that the slowdown in cyclical volatility characterizing the post-1985 period cannot be explained by the model without the estimated institutional changes. The combined increase in the size of financial shocks and reduction in the size of the remaining shocks can only account for 56% of the smoothing in wages and over-predicts the immoderation in business wealth. The effect on the remaining variables is at odds with the observed evolution of cyclical volatility. However, the estimated institutional changes account for 65% of the model-implied moderation in investment and over 50% of the smoothing in output, hours, inflation, and interest rate variability. The new institutional framework overestimates the moderation of credit spreads by about 30%.

The tightening in the response of the monetary authority to deviations of inflation and output growth from their respective targets accounts for an average of 40% of the model-implied moderation in investment, output, and hours worked. Moreover, the hawkish monetary policy approach delivers half of the slowdown in inflation since the mid-1980s and about

30% of that in nominal interest rates. Changes in the conduct of monetary policy have a negligible role in driving the model-implied changes in volatilities for the other variables.[9] Comparing the counterfactuals *only* ψ_π and *only* ψ_y in Table 10, I conclude that the 54% tightening in the response to deviations of inflation from the target plays a more relevant role in accounting for the volatility slowdown in real and nominal variables than the 77% increase in the response to deviations of output growth. The estimated change in the response to output growth accounts for about 15% of the model-implied slowdown in output, investment, and hours worked but it implies changes in volatility that are at odds with the empirical evidence for the remaining variables. The tighter response to inflation, however, is not only sufficient to account for about 25% of the model implied slowdown in output, investment, and hours worked; but it also delivers over 60% of the model-implied moderation in inflation volatility and about 30% of that in the policy rate.

The improvement in the conditions of access to credit during the Great Moderation is key in accounting for the slowdown in credit spreads. In particular, the estimated reduction in the level of financial rigidities at the steady state is enough to over predict the moderation in credit spreads by 30%. This over prediction is partially overridden by the larger financial shocks the model needs in order to account for the immoderation of balance sheet variables. I further explore this issue in subsection 5.3. The reduction in the size of the financial accelerator at the steady state accounts for about 30% of the slowdown in the volatility of investment and almost 15% of that of output, consumption, and hours worked. More importantly, changes in the financial institutional framework in the model economy are essential in delivering the moderation in nominal variables. In particular, the reduction in $\mu_\star$ accounts for about 40% of the slowdown in the volatility of inflation and the nominal interest rate.

5.2 The role of institutions in the transmission of financial shocks

In this subsection, I first describe the transmission mechanism of financial shocks in the estimated model economy using the 1970s as the baseline. Second, I discuss the effects of changes in the institutional framework during the Great Moderation in the transmission of financial shocks. I report responses to financial shocks in the first 50 quarters in terms of percentage deviations with respect to the steady state. Each plot contains four impulse response functions (IRFs). The solid blue line is the IRF computed using the parameter

[9] This counterfactual generates swings in volatility of about 2-3%, which can be directly attributed to parameter uncertainty.

vector characterizing the 1970:Q4–1985:Q1 sample period. The dashed red line is the IRF for the post-1985 period. The green dotted line is the IRF corresponding to a counterfactual economy characterized by the level of financial rigidity of the Great Inflation era, but with the monetary policy stance of the Great Moderation. The starred black line is the IRF of the counterfactual economy with low levels of financial rigidities as in the Great Moderation but the dovish monetary policy of the 1970s.

5.2.1 Wealth shock

Figure 6 reports the impulse response functions following a wealth shock that, upon impact, induces an increase in entrepreneurial net worth equal to a 1% deviation from its steady-state value in the Great Inflation period. I use the same shock across subsamples and across counterfactuals to facilitate the comparison.

Let us first analyze the impulse response functions for net worth. The response upon impact of net worth is about 50% smaller during the Great Moderation. The IRF associated with the post-1985 period, the black starred line, crosses the IRF of the 1970s, the solid blue line, from below within the first 14 quarters to lie above it for over 200 periods. This can be easily reconciled from the definition of aggregate net worth since the Great Moderation is characterized by a lower unconditional average for the marginal bankruptcy costs. Lower average default costs alleviate the deadweight loss associated with bankruptcy, $\mu_t G(\bar{\omega}_t) P_{t-1} R^k_t Q_{t-1} K_t$, which implies that for the same initial increase in wealth, the effects are more long-lasting, as more resources are accumulated from period to period. The persistent expansionary effects in business wealth of a positive wealth shock are also linked to the deleveraging process induced by these types of shocks. As reported in figure 8, entrepreneurs proceed to readjust their funding portfolio by reducing their dependence on external financing. The contraction in credit reduces even further the deadweight loss associated with bankruptcy in addition to reducing the principal and interest to pay back to lenders. Moreover, the size of the balance sheet adjustment is a negative function of the size of the financial accelerator. Thus, in an environment with low financial rigidities, as the one characterizing the U.S. during the Great Moderation, a deleveraging of the business sector can be induced by taxing households and transferring the proceeds to entrepreneurs.

A positive wealth shock that increases the value of collateral reduces the probability of default so that financial intermediaries are willing to lend at a lower premium. This movement translates into a negative response upon impact for the external finance premium. As entrepreneurs engage in a deleveraging process, financial intermediaries reduce the price of credit even further in subsequent periods. During the Great Inflation, the response of the external finance premium bottoms out about 9 basis points below the steady-state level and stays below the steady-state level for over 100 quarters. The lower price of credit and the availability of additional resources caused by the boost in business wealth translate into persistent favorable economic effects. The expansionary effects in real economic variables of a wealth shock translate into an inflationary episode that triggers a tightening of monetary policy.

As is standard in models with the financial accelerator à la BGG, the initial response of consumption and investment is negatively correlated. The negative response of consumption upon impact is linked to the general equilibrium effects of the model. A nonfundamental increase in entrepreneurial wealth shifts resources from households to the entrepreneurial sector. The reduction in disposable income is not large enough to generate a decrease in consumption of the same magnitude as the increase in entrepreneurial wealth due to the fact that other sources of household wealth, such as labor income, react positively to wealth shocks. In this model, credit supply is funded by deposits so that a reduction in business leverage requires a smaller percentage of household income captured through deposits. Thus, the deleveraging process in the business sector frees up resources for consumption in the household sector, which explains the rebound in consumption several quarters after the shock. The sluggish response of consumption is due to the relatively high degree of habit formation.

The Great Moderation is characterized by a significant reduction in the size of the responses upon impact, a reduction in the overall amplitude of the IRFs, and an increase in the persistence of the responses. Most of these features can be accounted for just by the estimated reduction in the size of the financial accelerator. While the tightening in the monetary policy stance dampens significantly the short-run effects of financial shocks for real and financial variables, it has no impact in their medium- to long-run effects. For example, the response upon impact of investment when only the monetary policy stance changes is half the size of the response during the Great Inflation. However, the counterfactual IRF converges to the one corresponding to the Great Inflation about 15 quarters after the shock. The change in monetary policy coefficients have significant short- and long-run effects in the responses of inflation and the nominal interest rate. The response upon impact of inflation in the counterfactual economy is 4 times smaller than during the Great Inflation and the response of the policy rate is about half of the response in the 1970s. More importantly, the persistence of the responses for both variables increases being very close to the persistence characterizing the responses during the Great Moderation. Therefore, I conclude that while the more flexible financial environment is key in delivering the distinct dynamics in response to wealth shocks during the Great Moderation, the hawkish monetary policy regime contributes in dampening the real effects of wealth shocks in the short run and in shaping the smoother but more persistent response of nominal variables.

5.2.2 Shock to the marginal bankruptcy cost

Figure 7 reports the impulse response functions to shocks to the marginal bankruptcy cost. A negative shock to agency costs reduces the deadweight loss associated with bankruptcy. Thus, as all other defining components of net worth are predetermined, I can conclude that the response upon impact to a shock reducing the agency problem must be positive for business wealth. I focus on a negative shock to bankruptcy costs, generating upon impact an increase in net worth of 1% in the Great Inflation period. To have some perspective about the different size of the shocks under analysis, note that a wealth shock increasing net worth by 1% implies a reduction upon impact in the spread of 3 basis points, while a shock to agency costs that increases net worth 1% upon impact generates an 18 basis point decline in credit spreads. The persistence of the propagation dynamics of a shock to the marginal bankruptcy cost is significantly smaller than the persistence of the responses to a wealth shock. The expansionary effects of a shock that reduces agency costs die out about 5 years after the shock, while the favorable effects of a wealth shock have an "almost permanent" flavor.

An expansionary shock to agency costs creates an incentive for entrepreneurs to select contractual terms with a larger debt-to-net-worth ratio (see Figure 8), as the deadweight loss linked to bankruptcy is smaller. There are two opposing effects operating as a result of higher debt-to-net-worth ratios. On the one hand, both the default probability and the default productivity threshold increase, offsetting the effect of lower bankruptcy costs in the event of default. I label this effect the *default effect*. On the other hand, there is a *mass effect*: There is an increase in capital investment given that a larger set of resources is available. Larger amounts of capital holdings imply a larger equity value through an increase in total capital returns. The impulse response for net worth shows that while the mass effect dominates at first, the default effect becomes the driving force after 10 quarters. The response of investment upon impact is larger than the response I obtained to a wealth shock due to the *mass effect* explained above. Irrespective of the relative dominance of this effect in terms of shaping the response of entrepreneurial wealth, the increase in the pool of resources available for purchasing capital enhances investment activity in the economy.

As stated earlier, the Great Moderation era is characterized by a large reduction in the size of the responses upon impact, a reduction in the amplitude of the responses, and an increase in their persistence. In this case, the easier access to credit during the Great Moderation is not enough to account for the milder responses of real variables. The hawkish monetary policy stance is key in delivering the magnitude of the changes in the short-run dynamics of the transmission of marginal bankruptcy costs.

5.3 The interaction of institutions and financial risk

During the Great Moderation, the U.S. is characterized by a more flexible financial system but a larger exposure to financial risk. While the former is necessary to accommodate the observed slowdown in credit spreads and a relative large fraction of the slowdown in other variables, the latter is the only mechanism the model has to account for the increase in the volatility of net worth. In the model, institutional changes in either the conduct of monetary policy or the strength of the financial rigidity generate changes in the volatility of all variables in the same direction. Similarly, an increase (decrease) in the size of financial shocks implies an increase (decrease) in the volatility of all model variables. The internal dynamics of the model joint with the information in the likelihood function of the data drive the size of shocks and the strength of the financial rigidity in opposite directions so as to accommodate the existing tension in the data regarding the evolution of the volatility of net worth and credit spreads. In the remainder of the section, I analyze the effects of institutions in determining the role of financial shocks in driving U.S. business cycle fluctuations.

Table 11 provides the contribution of financial shocks to the median variance decomposition at business cycle frequencies in the rows labeled "Actual". I compute the spectral density of the observable variables implied by the DSGE model evaluated at each $1000th$ posterior draw and use an inverse difference filter to obtain the spectrum for the level of output, investment, consumption, wages, and net worth. I define business cycle fluctuations as those corresponding to cycles between 6 and 32 quarters and consider 500 bins for frequencies covering these periodicities.

The results state that financial shocks are an important source of business cycle fluctuations. During the Great Inflation, financial shocks are the main source of the variance in investment, hours worked, the policy rate, the credit spread, and business wealth. Financial shocks also play quite a relevant secondary role in driving output. While the relative role played by the shock to the marginal bankruptcy cost is smaller than the one played by the wealth shock for all variables but credit spreads, the shock driving time-variation in the level of financial rigidities is the key driver of the credit spread. Levin, Natalucci and Zakrajšek (2004) estimate a partial equilibrium version of the BGG model using micro data and conclude that exogenous disturbances in the marginal bankruptcy cost are the main driver of the external finance premium. Thus, they provide micro evidence supporting the result presented in this paper using aggregate data and a general equilibrium framework: In order to deliver empirically plausible swings in the cost of external financing in a model with the financial accelerator, time variation in the level of financial rigidity should be incorporated.

The relative role of financial shocks in driving business cycle fluctuations decreases significantly during the Great Moderation. For example, while financial shocks account for about 50% of the variance of investment and the policy rate during the Great Inflation, they only account for about 25% of these variances in the Great Moderation. The most dramatic decline in the contribution to business cycle fluctuations is for inflation: financial shocks accounted for 43% of the volatility of inflation in the 1970s but just for 4% in the post-1985 period. Given the estimated changes in the relative contribution of financial shocks to the variance of nonfinancial variables, I argue that the role played by financial shocks as drivers of business cycle fluctuations is sensitive to the institutional framework characterizing the U.S. economy. To explore this hypothesis, I calculate the variance decomposition in counterfactuals scenarios. On the one hand, I explore the influence of the conduct of monetary policy in the role played by financial shocks in driving business cycle fluctuations. During the Great Inflation, if the monetary authority had reacted to deviations of inflation and output growth from their respective targets as it did during the 1950s and 1960s, the relative role played by financial shocks in driving inflation would have been about 15% smaller. Similarly, if the dovish monetary policy regime in place during the 1970s had been in place during the Great Moderation, financial shocks would have accounted for 37% of the variance in inflation and 52% of the variance in the interest rate instead of 4% and 23%, respectively. Therefore, I conclude that the monetary authority successfully minimized the dependence of its target variable—the inflation rate—on credit market disruptions by implementing a hawkish regime during the Great Moderation.

On the other hand, the conditions of access to credit, summarized by the marginal bankruptcy cost at the steady state, are key in determining the role played by financial shocks as drivers of business cycle fluctuations for all nonfinancial variables under analysis.

While the estimated 18% tightening of the conditions of access to credit during the Great Inflation has a negligible effect in the relative contribution of both financial shocks to the variance of the variables under analysis, the estimated 85% reduction during the Great Moderation has a large impact. If the innovations in the financial sector and regulatory changes had not taken place so that the conditions of access to credit since the mid-1980s were identical to the ones in the 1970s, financial shocks would have been the main source of variability in the U.S. economy. For example, financial shocks would have accounted for 74% of the variance of output instead of the estimated 8% or 93% of the variability in investment rather than the 24% implied by our estimates. Moreover, these shocks would have explained 93% of the variation in the policy rate and 62% in the variance of inflation instead of 23% and 4%, respectively. I conclude that the institutional changes regarding the functioning of credit markets in the United States successfully alleviated the potential excessive dependence of the U.S. economy on financial disturbances.

6 Conclusions

I have estimated a fairly large DSGE model to reexamine the sources of the observed breaks in macroeconomic fluctuations in the U.S. economy. The estimation indicates that while the Great Inflation was mostly due to bad luck, the Great Moderation is the result of changes in the institutional framework. Both improvements in the financial system and changes in the conduct of monetary policy are key for explaining the slowdown in fluctuations at business cycle frequencies since the mid-1980s. The easier access to credit has been paired with higher exposure to financial risk in the form of larger financial shocks hitting the U.S. economy, which is key in accounting for the immoderation observed in financial variables. Despite the increase in the size of financial shocks over time, their relative contribution to the variance of nonfinancial variables has not increased dramatically. This outcome is due to the improvements in the institutional framework characterizing the U.S. economy. Thus, I conclude that the hawkish monetary policy regime and the innovations in the financial intermediation process in the mid-1980s have been a safeguard for the vulnerability of the U.S. economy to financial market disruptions. Moreover, the model does provide a policy intervention to reactivate the economy in the midst of a recession paired with high leverage ratios: a "bailout" of the business sector financed by higher household taxes.

Finally, despite concluding that the relative role played by shocks to marginal bankruptcy costs is along the lines of the contribution of monetary policy shocks, the incorporation of time variation in the parameter that controls the level of financial rigidities is key to *(i)* deliver empirically plausible swings in credit spreads in a model with the financial accelerator, and *(ii)* obtain a model based measure of financial stress that closely mimics the dynamics of empirical proxies of financial stress and lending standards. The latter is relevant to assess the health of the U.S. financial system during periods for which none of the empirical measures are available.

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A Data

I use U.S. data from NIPA-BEA, CPS-BLS, the FRED database, and the Flow of Funds accounts from the Federal Reserve Board for the period 1954:Q4–2006:Q4.

A.1 Data used in estimation

- *Growth rate of real per-capita gross value added by the nonfarm business sector.* Data on nominal gross value added are available in NIPA table 1.3.5. I have deflated such a series using the implicit price index from Table 1.3.4. I divide the new series by the civilian noninstitutional +16 (BLS ID LNU00000000) series to obtain per capita variables. The data provided by the BEA are annualized, so I divide by 4 to obtain quarterly values for the measures of interest.

- *Growth rate of real per-capita investment.* Investment is defined as the sum of personal consumption expenditures of durables and gross private domestic investment from NIPA table 1.1.5. I deflate the nominal variables using the GDP deflator provided by NIPA table 1.1.4. We weight the resulting series using the relative significance of the nonfarm, nonfinancial corporate business sector in total GDP.

- *Growth rate of real per-capita consumption.* Consumption is defined as the sum of personal consumption expenditures of nondurables and services from NIPA table 1.1.5.

- *Growth rate of net worth (net worth 1).* I consider data from the Flow of Funds Accounts data set constructed by the Federal Reserve Board. I define net worth (corporate net worth 2) as tangible assets (table B.102, line 2) minus credit market instruments at market value (table B.102, line 22) in the nonfinancial corporate sector.[10]

- *Hours worked* is defined as the log level of the hours of all persons in the nonfarm business sector provided by the BLS divided by 100 and multiplied by the ratio of the civilian population over 16 (CE16OV) to a population index. The population index is equal to the ratio of population in the corresponding quarter divided by the population in the third quarter of 2005. This transformation is necessary, as the series on hours is an index with 2005=100.

- *Growth rate of real wages.* Real wages are defined as the real per-capita counterpart of compensation of employees provided by NIPA table 1.12. Total compensation is corrected by the relative size of the nonfinancial corporate sector.

- *Inflation* is defined as the log difference of the price index for gross value added by the nonfarm business sector (NIPA table 1.3.4).

- The *federal funds rate* is taken from the Federal Reserve Economic Data (FRED).

[10] The vintage for the Flow of Funds Accounts is March 2014.

- *Credit spread (Baa-10y)* is defined as the spread of the Moody's seasoned Baa corporate bond yield corporate bond rate and the 10-year Treasury constant maturity rate. I consider the log of the gross quarterly counterpart.

A.2 Data used in the empirical evidence section

In addition to the series described previously, I also consider the following:

- *Corporate net worth 2* is defined as total assets (table B.102, line 1 from FOFA) minus total liabilities (table B.102, line 21 from FOFA) in the nonfinancial nonfarm corporate sector in the United States. It is defined in real per-capita terms.
- *Leverage 1* is defined as the ratio of credit market liabilities to corporate net worth 1.
- *Leverage 2* is defined as the ratio of credit market liabilities to corporate net worth 2.
- *Tobin q* is the ratio of the sum of equities (market value of equities outstanding, series with mnemonics FL103164103) and total liabilities to total assets.
- *Equity q* is defined as the equities-to-net-worth (measure 1) ratio.
- *Corporate bonds* is defined in real per-capita terms and it corresponds to line 26 of table B.102.
- *Net increase in credit market liabilities* is given by table F.102, line 40 from FOFA. This is the measure of credit used by Christiano, Motto and Rostagno (2014).
- *Net increase in corporate bonds* is given by line 43 in table F.102.
- *Equity payout*, in Jermann and Quadrini (2012) is defined as net dividends (table F.102, line 3) minus net equity issues (table F.102, line 39) of nonfinancial corporate businesses.

B Counterfactuals

Given the estimated changes in parameters, I perform a battery of counterfactual exercises in order to assess the role played by theses changes in the evolution of volatilities at business cycle frequencies. For illustration purposes, let me study the role played by the estimated changes in the conduct of monetary policy in accounting for the increase in volatility during the 1970s. I proceed by performing 1000 simulations for each 1000th draw in the posterior simulator using the following procedure:

1. Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1954–70 sample period. Obtain the cyclical component.

2. Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1970–85 sample period. Obtain the cyclical component.

3. Compute the ratio of standard deviations of the cyclical components.

4. Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1954–70 period but with the monetary policy coefficients of the 1970–85 parameter vector. Obtain the cyclical component.

5. Compute the ratio of cyclical standard deviations with respect to those obtained in step 1.

6. Compute the percentage of the ratio obtained in step 3 attributable to the ratio in step 5.

I analyze the following counterfactuals:

- *All institutions*: This counterfactual determines the relative importance of changes on both financial institutions and the monetary policy stance.

- *All shocks*: This counterfactual studies the relevance of the luck hypothesis by only having the size of the shocks hitting the U.S. economy changing across subperiods.

- *Monetary policy*: In this counterfactual, I quantify the role played by the estimated changes in the response of the monetary authority to deviations of inflation and output growth from the target.

  – *Only* ψ_π: The only parameter changing across subsamples is the response of the monetary authority to deviations of inflation from its target.

  – *Only* ψ_y: The only parameter changing across subsamples is the response of the monetary authority to deviations of output growth from its target.

- *Financial institutions*: This counterfactual analyzes the relative importance of changes in the unconditional mean for the marginal bankruptcy cost.

- *Financial shocks*: In this counterfactual, I determine the relative role played by only financial shocks.

- *Nonfinancial shocks*: This counterfactual is characterized by the size of all shocks but financial shocks changing across subperiods.

C Tables

Table 1: Econometric tests: cyclical volatility

	BAI-PERRON	
Output	1984:Q2	
Investment	1984:Q1	
Consumption	1984:Q2	
Inflation	1970:Q1	1981:Q2
Federal funds rate	1972:Q4	1983:Q1

Notes: The data range from 1954:Q4 to 2006:Q4 for all variables. The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$).

Table 2: Ratio of standard deviations, cyclical component

Series	$\frac{1970-1985}{1954-1970}$	$\frac{1985-2006}{1970-1985}$
Output	1.35	0.53
Investment	1.44	0.46
Consumption	1.37	0.70
Wage	1.34	0.66
Hours	1.52	0.64
Inflation	2.43	0.35
Nominal interest rate	2.63	0.50
Net worth	1.17	2.03
Spread	2.33	0.51

Notes: The data range from 1954:Q4 to 2006:Q4 for all variables. Net worth is defined as tangible assets minus credit market liabilities and Spread as the Moody's Baa corporate bond rate and the 10-year U.S. government bond rate. The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$).

Table 3: Ratio of standard deviations, cyclical component

	$\frac{1970-1985}{1954-1970}$	$\frac{1985-2006}{1970-1985}$
Corporate net worth 1: Tangible assets minus credit market liabilities	1.17	2.03
Corporate net worth 2: Total assets minus liabilities	1.67	1.74
Credit market liabilities to net worth 1	3.44	1.66
Credit market liabilities to net worth 2	3.36	1.11
Tobin's q	1.26	1.16
Equity q	1.30	1.48
Net increase in credit market liabilities	2.12	1.16
Net increase in corporate bonds	1.69	2.76
Equity payout	2.07	1.83

Notes: The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$).

Table 4: Model fit: MDD comparison

Model	MDD	Log posterior odds
Baseline	6950	0
No breaks	6902	48
One break in 1970:Q3	6892	58
One break in 1985:Q1	6904	46

Table 5: Model fit: MDD and log-posterior odds.

Model	MDD	Posterior odds
Baseline	6950	0
Baseline, breaks in $F(\omega_\star)$	6902	48
Baseline, breaks in γ	6927	23
Baseline, breaks in σ_ω	6897	53
Baseline, breaks in $F(\omega_\star), \gamma$	6907	43
Baseline, breaks in $F(\omega_\star), \sigma_\omega$	6932	18
Baseline, breaks in γ, σ_ω	6922	28
Baseline, breaks in $F(\omega_\star), \gamma, \sigma_\omega$	6913	37
Baseline, constant $\mu_\star$, breaks in $F(\omega_\star)$	6876	74
Baseline, constant $\mu_\star$, breaks in γ	6927	23
Baseline, constant $\mu_\star$, breaks in σ_ω	6907	43
Baseline, constant $\mu_\star$, breaks in $F(\omega_\star), \gamma$	6928	22
Baseline, constant $\mu_\star$, breaks in $F(\omega_\star), \sigma_\omega$	6938	12
Baseline, constant $\mu_\star$, breaks in γ, σ_ω	6896	54
Baseline, constant $\mu_\star$, breaks in $F(\omega_\star), \gamma, \sigma_\omega$	6886	64

Table 6: Parameters estimated using the full sample

	Prior			Posterior	
	Density	**Para 1**	**Para 2**	**Median**	**95% CI**
δ	Fixed	0.03	–	–	–
$(G/Y)^\star$	Fixed	0.22	–	–	–
λ_p	Fixed	0.20	–	–	–
λ_w	Fixed	0.20	–	–	–
$100\ln(H^\star)$	Fixed	0.54	–	–	–
$100\Upsilon_z$	Fixed	0.45	–	–	–
$100[F(\bar{\omega})]^\star$	Beta	0.70	0.37	0.36	[0.10, 0.62]
$100\,[1/\beta-1]$	Beta	0.25	0.10	0.19	[0.10, 0.28]
$100\,[1/\gamma-1]$	Gamma	1.48	0.50	1.87	[0.81, 3.38]
σ_ω	$\mathcal{N}$	0.28	0.10	0.55	[0.47, 0.64]
$\pi_n^\star$	$\mathcal{N}$	3.00	1.00	2.41	[1.97, 2.89]
$400\left[\left(R_\star^k/R_\star\right)-1\right]$	$\mathcal{N}$	1.75	0.50	1.69	[1.26, 2.15]
$\phi=\Phi/y_\star$	Beta	0.35	0.15	0.47	[0.35, 0.59]
ι_p	Beta	0.50	0.15	0.12	[0.03, 0.23]
ι_w	Beta	0.50	0.15	0.06	[0.02, 0.11]
ξ_p	Beta	0.66	0.15	0.75	[0.70, 0.81]
ξ_w	Beta	0.66	0.15	0.55	[0.46, 0.66]
θ_p	Beta	0.50	0.20	0.62	[0.49, 0.76]
θ_w	Beta	0.50	0.20	0.64	[0.41, 0.86]
α	Beta	0.30	0.03	0.17	[0.15, 0.19]
ξ	$\mathcal{N}$	4.00	1.00	0.55	[0.38, 0.80]
a”	Gamma	1.00	0.50	1.10	[0.28, 2.47]
ν	Gamma	2.00	0.75	0.90	[0.36, 1.53]
h	Beta	0.60	0.20	0.81	[0.70, 0.89]
ρ_r	Beta	0.50	0.10	0.74	[0.69, 0.78]
ρ_z	Beta	0.40	0.10	0.39	[0.27, 0.51]
ρ_ζ	Beta	0.60	0.20	0.92	[0.87, 0.96]
ρ_φ	Beta	0.60	0.20	0.94	[0.92, 0.96]
ρ_x	Beta	0.60	0.20	0.94	[0.87, 0.98]
ρ_{λ_p}	Beta	0.60	0.20	0.97	[0.95, 0.99]
ρ_{λ_w}	Beta	0.60	0.20	0.98	[0.97, 0.99]
ρ_b	Beta	0.60	0.20	0.54	[0.30, 0.78]
ρ_g	Beta	0.60	0.20	0.99	[0.98, 0.99]
ρ_{mp}	Beta	0.60	0.20	0.16	[0.07, 0.26]

Notes: Para 1 and Para 2 list the means and the standard deviations for Beta, Gamma, and Normal distributions; the upper and lower bound of the support for the uniform distribution; s and ν for the inverse Gamma distribution, where $p_{IG}(\sigma|\nu,s)\propto\sigma^{-\nu-1}e^{-nus^2/2\sigma^2}$. The effective prior is truncated at the boundary of the determinacy region.

Table 7: Parameters subject to structural breaks

	Prior			Posterior	
	Density	**Para 1**	**Para 2**	**Median**	**95% CI**
ψ_{π_1}	$\mathcal{N}$	1.50	0.50	1.39	[1.22, 1.56]
ψ_{π_2}	$\mathcal{N}$	1.50	0.50	1.20	[1.11, 1.31]
ψ_{π_3}	$\mathcal{N}$	1.50	0.50	1.85	[1.57, 2.18]
ψ_{y_1}	$\mathcal{N}$	0.50	0.30	0.18	[0.11, 0.26]
ψ_{y_2}	$\mathcal{N}$	0.50	0.30	0.22	[0.06, 0.37]
ψ_{y_3}	$\mathcal{N}$	0.50	0.30	0.39	[0.28, 0.51]
$\mu_1^\star$	$\mathcal{N}$	0.28	0.05	0.11	[0.06, 0.20]
$\mu_2^\star$	$\mathcal{N}$	0.28	0.05	0.13	[0.06, 0.20]
$\mu_3^\star$	$\mathcal{N}$	0.28	0.05	0.01	[0.01, 0.03]
σ_{φ_1}	$\mathcal{IG}$	0.001	4.00	0.17	[0.09, 0.35]
σ_{φ_2}	$\mathcal{IG}$	0.001	4.00	0.38	[0.21, 0.85]
σ_{φ_3}	$\mathcal{IG}$	0.001	4.00	0.60	[0.30, 1.41]
$100(\sigma_{x_1})$	$\mathcal{IG}$	0.10	4.00	0.45	[0.32, 0.59]
$100(\sigma_{x_2})$	$\mathcal{IG}$	0.10	4.00	0.83	[0.57, 1.21]
$100(\sigma_{x_3})$	$\mathcal{IG}$	0.10	4.00	2.50	[2.07, 2.94]
$100(\sigma_{z_1})$	$\mathcal{IG}$	0.10	4.00	1.39	[1.15, 1.67]
$100(\sigma_{z_2})$	$\mathcal{IG}$	0.10	4.00	1.30	[1.08, 1.55]
$100(\sigma_{z_3})$	$\mathcal{IG}$	0.10	4.00	0.99	[0.84, 1.15]
$100(\sigma_{\zeta_1})$	$\mathcal{IG}$	0.10	4.00	1.18	[0.89, 1.56]
$100(\sigma_{\zeta_2})$	$\mathcal{IG}$	0.10	4.00	1.41	[1.07, 1.84]
$100(\sigma_{\zeta_3})$	$\mathcal{IG}$	0.10	4.00	0.88	[0.68, 1.11]
$100(\sigma_{\lambda_1^p})$	$\mathcal{IG}$	0.10	4.00	0.18	[0.14, 0.22]
$100(\sigma_{\lambda_2^p})$	$\mathcal{IG}$	0.10	4.00	0.28	[0.22, 0.35]
$100(\sigma_{\lambda_3^p})$	$\mathcal{IG}$	0.10	4.00	0.18	[0.14, 0.22]
$100(\sigma_{\lambda_1^w})$	$\mathcal{IG}$	0.10	4.00	0.23	[0.18, 0.28]
$100(\sigma_{\lambda_2^w})$	$\mathcal{IG}$	0.10	4.00	0.29	[0.22, 0.37]
$100(\sigma_{\lambda_3^w})$	$\mathcal{IG}$	0.10	4.00	0.25	[0.20, 0.30]
$100(\sigma_{b_1})$	$\mathcal{IG}$	0.10	4.00	2.69	[1.48, 4.45]
$100(\sigma_{b_2})$	$\mathcal{IG}$	0.10	4.00	3.05	[1.83, 4.70]
$100(\sigma_{b_3})$	$\mathcal{IG}$	0.10	4.00	2.30	[1.36, 3.71]
$100(\sigma_{r_1})$	$\mathcal{IG}$	0.10	4.00	0.13	[0.11, 0.16]
$100(\sigma_{r_2})$	$\mathcal{IG}$	0.10	4.00	0.38	[0.31, 0.45]
$100(\sigma_{r_3})$	$\mathcal{IG}$	0.10	4.00	0.15	[0.12, 0.18]
$100(\sigma_{g_1})$	$\mathcal{IG}$	0.10	4.00	0.34	[0.28, 0.41]
$100(\sigma_{g_2})$	$\mathcal{IG}$	0.10	4.00	0.41	[0.35, 0.49]
$100(\sigma_{g_3})$	$\mathcal{IG}$	0.10	4.00	0.29	[0.25, 0.34]

Notes: Para 1 and Para 1 list s and ν for the inverse Gamma distribution, where $p_{IG}(\sigma|\nu, s) \propto \sigma^{-\nu-1}e^{-nus^2/2\sigma^2}$. The effective prior is truncated at the boundary of the determinacy region.

Table 8: Model fit: Ratio of standard deviations, cyclical component

Series	$\frac{1970-1985}{1954-1970}$			$\frac{1985-2006}{1970-1985}$		
	Data	Model		Data	Model	
		Median	90%		Median	90%
Output	1.35	1.65	[1.43, 1.89]	0.53	0.56	[0.48, 0.65]
Investment	1.44	1.69	[1.39, 1.91]	0.46	0.54	[0.45, 0.61]
Consumption	1.37	1.14	[0.95, 1.32]	0.70	0.78	[0.68, 0.89]
Wage	1.34	1.32	[1.08, 1.50]	0.66	0.70	[0.59, 0.79]
Hours	1.52	1.64	[1.41, 1.88]	0.64	0.56	[0.48, 0.65]
Inflation	2.43	1.91	[1.56, 2.20]	0.35	0.47	[0.38, 0.55]
Nominal interest rate	2.63	2.11	[1.79, 2.44]	0.50	0.44	[0.36, 0.60]
Net worth	1.17	1.54	[1.17, 1.82]	2.03	2.17	[1.57, 2.70]
Spread	2.33	2.31	[1.76, 2.91]	0.51	0.43	[0.32, 0.53]

Notes: For each 1000th parameter draw, I generate 1000 samples with the same length as the data after discarding 1000 initial observations. I HP filter the nonstationary data generated by the model.

Table 9: Counterfactuals: Percentage of the model-implied change in cyclical standard deviations

GREAT INFLATION									
	Y	**I**	**C**	**H**	**W**	π	R	**N**	$\frac{\mathbb{E}\left(R^k_{t+1}\right)}{R_t}$
All institutions	**8**	**7**	**9**	**9**	**9**	**28**	**18**	**5**	**11**
All shocks	**87**	**89**	**102**	**87**	**93**	**59**	**78**	**94**	**86**
Monetary policy	7	4	7	8	9	22	12	4	1
Financial institutions	3	5	9	3	2	4	6	4	12
Financial shocks	32	50	39	33	8	25	39	81	85
Nonfinancial shocks	65	49	73	64	86	41	50	21	4

Notes: I include a dash (-) when the direction of the counterfactual-implied change is at odds with the model-implied changes in volatilities. Y stands for real output, I for real investment, C for real consumption, H for hours, W for real wages, π for inflation, R for the policy interest rate, N for real net worth, $\mathbb{E}\left(R^k_{t+1}\right)/R_t$ for the external finance premium or credit spread, B for real debt, and B/N for leverage.

Table 10: Counterfactuals: Percentage of the model-implied change in cyclical standard deviations

GREAT MODERATION									
	Y	**I**	**C**	**H**	**W**	π	R	**N**	$\frac{\mathbb{E}\left(R^k_{t+1}\right)}{R_t}$
All institutions	**53**	**65**	**15**	**53**	**8**	**56**	**54**	–	**130**
All shocks	–	–	–	–	**56**	–	–	**117**	–
Monetary policy	43	37	–	44	3	51	33	–	–
Only ψ_π	26	20	–	28	7	62	29	–	–
Only ψ_y	13	15	–	13	–	–	–	1	–
Financial institutions	13	27	13	12	0	39	45	–	130
Financial shocks	–	–	–	–	–	–	–	121	–
Monetary policy and financial shocks	–	–	–	–	–	22	–	114	–
Financial institutions and financial shocks	5	13	6	4	–	28	30	105	100
All institutions and financial shocks	49	47	4	48	6	55	50	105	100
Nonfinancial shocks	49	37	92	48	97	36	32	–	1
All institutions and nonfinancial shocks	107	116	116	106	105	101	107	–	130

Notes: I include a dash (-) when the direction of the counterfactual-implied change is at odds with the model-implied changes in volatilities. Y stands for real output, I for real investment, C for real consumption, H for hours, W for real wages, π for inflation, R for the policy interest rate, N for real net worth, $\mathbb{E}\left(R^k_{t+1}\right)/R_t$ for the external finance premium or credit spread, B for real debt, and B/N for leverage.

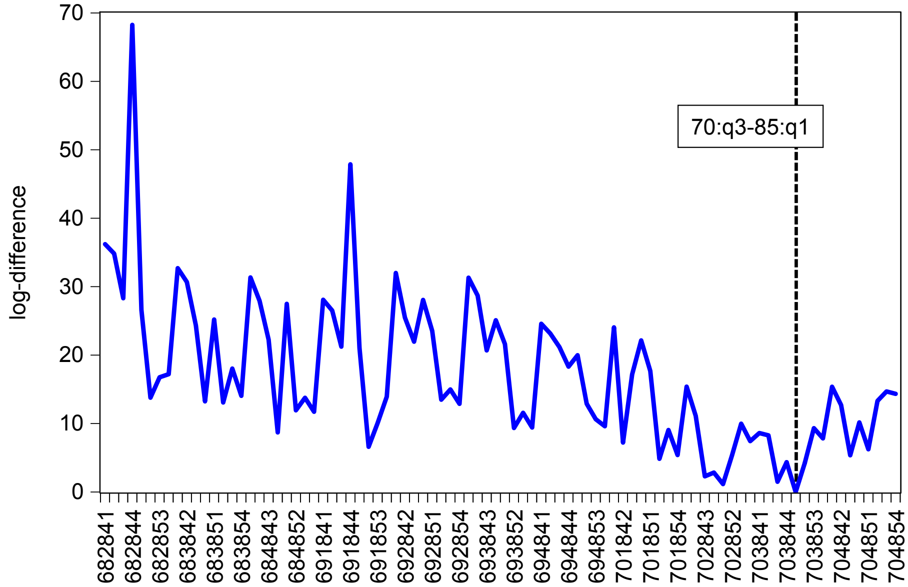
Table 11: Counterfactual variance decomposition: contribution of financial shocks

GREAT INFLATION											
		Y	**I**	**C**	**H**	**W**	π	R^n	**N**	**Spread**
Monetary Policy										
Bankruptcy cost	Actual	6	9	0	8	5	5	8	3	67
	Counter	6	9	0	7	4	7	10	3	66
Wealth	Actual	17	33	8	22	11	38	47	71	28
	Counter	15	32	11	19	8	31	43	71	29
Financial institutions										
Bankruptcy cost	Actual	6	9	0	8	5	5	8	3	67
	Counter	6	10	0	8	5	6	10	3	71
Wealth	Actual	17	33	8	22	11	38	47	71	28
	Counter	15	30	7	19	9	36	47	72	25

GREAT MODERATION										
		Y	**I**	**C**	**H**	**W**	π	R^n	**N**	**Spread**
Monetary Policy										
Bankruptcy cost	Actual	2	4	1	3	1	2	10	0	70
	Counter	4	7	0	5	3	6	10	0	72
Wealth	Actual	6	20	9	9	3	2	13	99	29
	Counter	8	21	7	12	5	31	42	99	28
Financial institutions										
Bankruptcy cost	Actual	2	4	1	3	1	2	10	0	70
	Counter	6	5	1	7	7	11	12	1	35
Wealth	Actual	6	20	9	9	3	2	13	99	29
	Counter	68	88	73	75	49	51	81	98	64

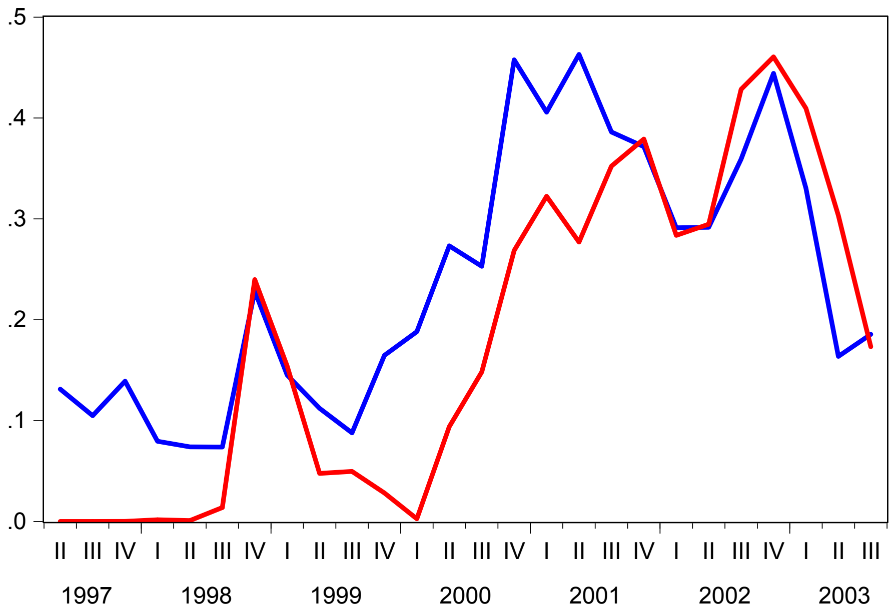
D Figures

Figure 1: Log posterior odds



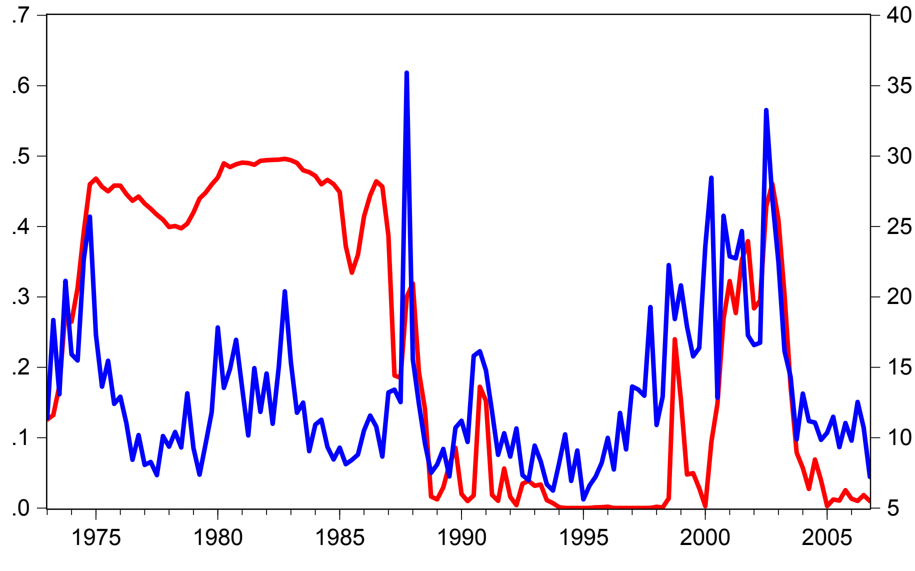
NOTES: The dotted line represents the dating for structural breaks in the model with the largest marginal data density.

Figure 2: Model implied marginal bankruptcy cost and the Bankruptcy cost parameter estimated by Levin, Natalucci and Zakrajšek (2004)



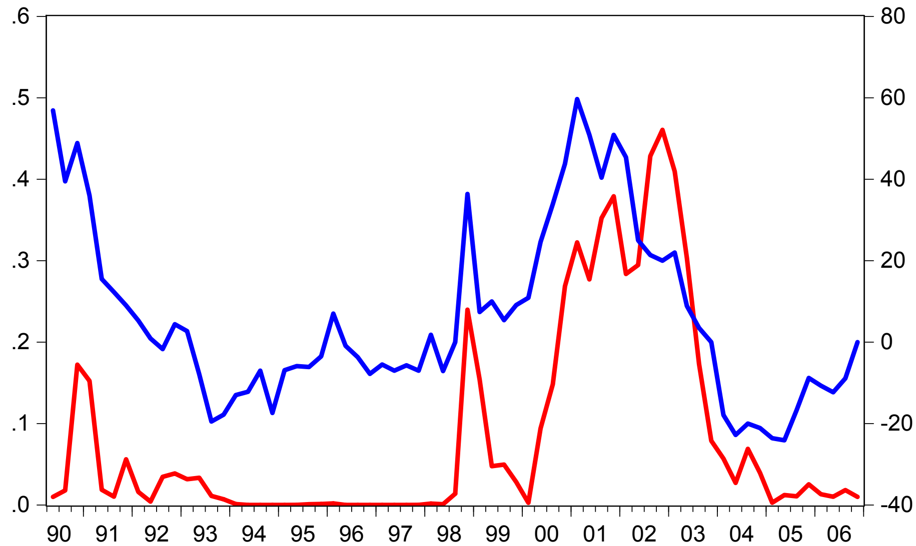
Notes: The blue line represents the time-specific estimate of the bankruptcy cost parameter in Levin, Natalucci and Zakrajšek (2004) and the red line represents the model implied measure of marginal bankruptcy costs.

Figure 3: Model implied marginal bankruptcy cost and financial stress index: realized volatility



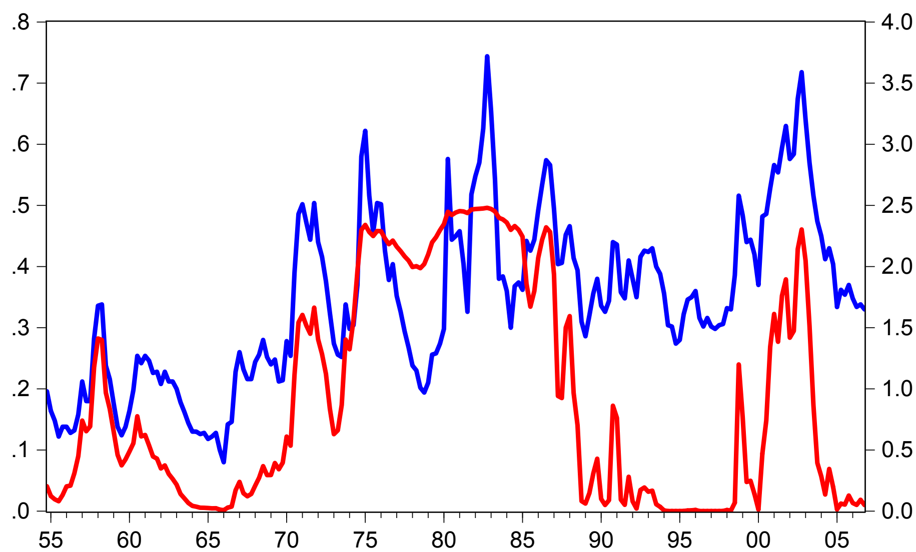
Notes: The solid dashed line represents the model implied measure of marginal bankruptcy costs and it is measured in the left vertical axis. The solid line, which is measured in the right vertical axis, represents realized volatility as computed in Caldara et al. (2016).

Figure 4: Model implied marginal bankruptcy cost and lending standards



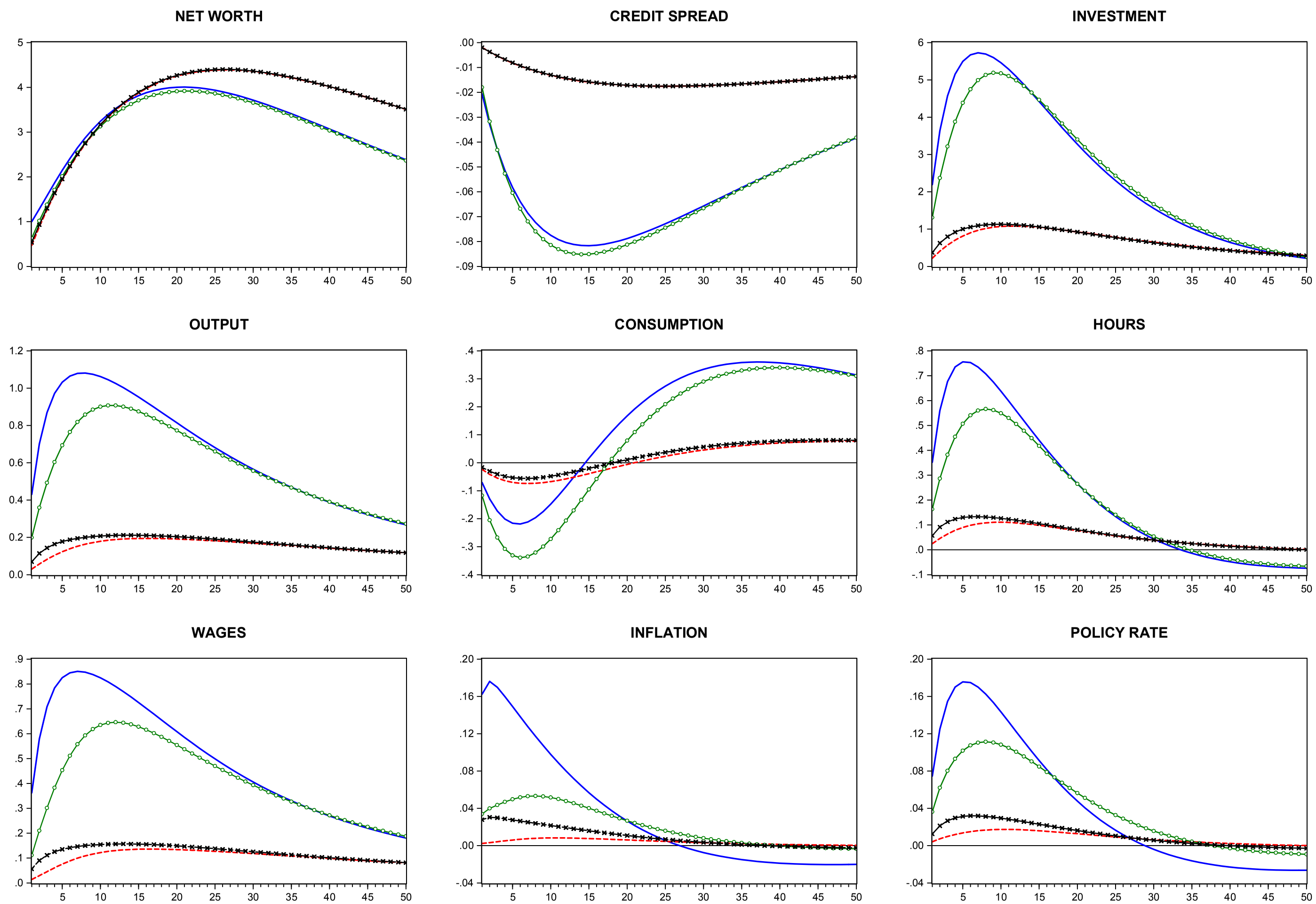
Notes: The solid dashed line represents the model implied measure of marginal bankruptcy costs and it is measured in the left vertical axis. The solid line, which is measured in the right vertical axis, represents the net percentage of domestic banks tightening standards for commercial and industrial loans to large and middle-market firms.

Figure 5: Model implied marginal bankruptcy cost and Spread



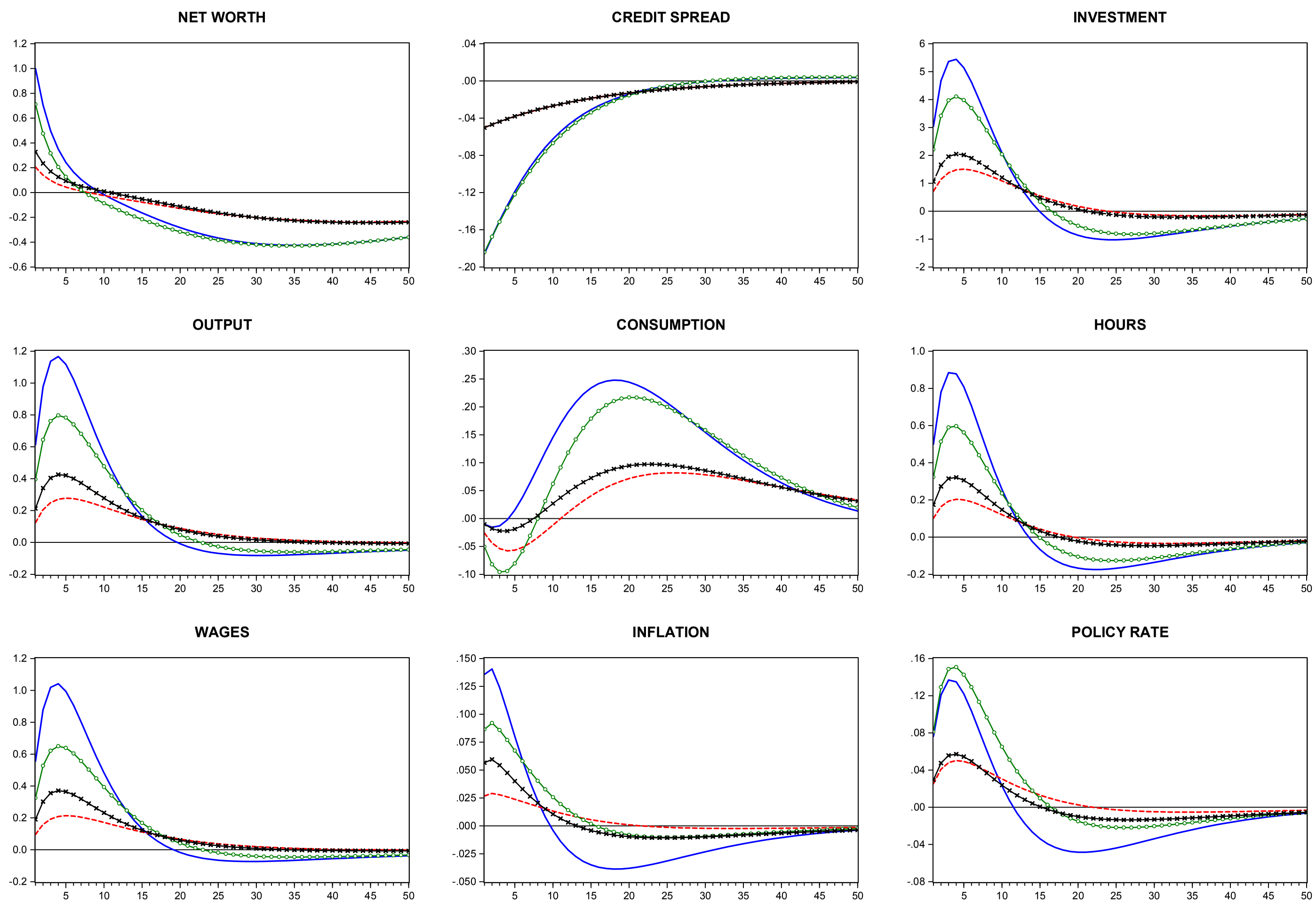
Notes: The blue line represents the credit spread and it is measured in the right vertical axis. The red line, which is measured in the left vertical axis, represents the model implied measure of marginal bankruptcy costs.

Figure 6: Impulse response functions with respect to a wealth shock



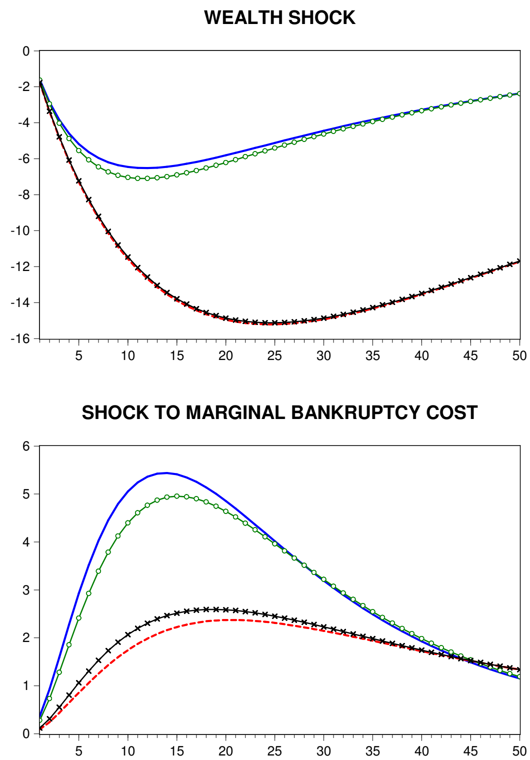
Notes: The solid line is the IRF for 1970:Q4–1985:Q1, the dashed line is the IRF for the post-1985:Q1 period, the dotted line is the IRF when only the monetary policy coefficients change, and the starred line is the IRF when only $\mu_\star$ changes.

Figure 7: Impulse response functions with respect to a shock to the marginal bankruptcy cost



Notes: The solid line is the IRF for 1970:Q4–1985:Q1, the dashed line is the IRF for the post-1985:Q1 period, the dotted line is the IRF when only the monetary policy coefficients change, and the starred line is the IRF when only $\mu_\star$ changes.

Figure 8: Impulse response functions for debt



Notes: The dotted line is the IRF for the 1954:Q4–1970:Q1 period, the dashed line is the IRF for 1970:Q2–1984:Q2, and the solid line is the IRF for the post-1984:Q2 period.