# Financial Frictions, Financial Shocks, and Aggregate Volatility

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# Financial Frictions, Financial Shocks, and Aggregate Volatility

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*I revisit the Great Inflation and the Great Moderation for nominal and real variables. I document that while financial price variables follow such a pattern; financial quantity variables experience a continuous immoderation. A model with financial frictions and financial shocks allowing for structural breaks in the size of shocks and the institutional framework is estimated. The paper shows that while the Great Inflation was driven by bad luck, the Great Moderation is mostly due to better financial institutions. Financial shocks arise as relevant drivers of US business cycle fluctuations.*
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Recent economic events suggest a strong interaction between the financial sector and aggregate business cycle fluctuations. Traditionally, the literature has neglected this linkage by assuming that the capital structure irrelevance theorem by Modigliani and Miller (1958) holds. Recently, researchers have focused on understanding the role played by the financial sector in propagating economic shocks originated in other sectors, but little progress has been made in assessing the importance of financial shocks as drivers of business cycle fluctuations. Moreover, while 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 quantity aggregates contemporary with the Great Moderation in real and nominal variables. I aim at evaluating the ability of a state-of-the-art 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 US 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.[1] The Great Moderation stands for the observed slowdown in the volatility of real and nominal variables since the mid-1980s. I show that while the Great Inflation can be described homogeneously for all aggregate variables under analysis, the Great Moderation is a more complex regularity. In particular, I document a dichotomy in the evolution of the volatility in quantities and prices for the financial sector. While financial price variables, such as credit spreads, are less volatile in the recent decades; financial quantity variables, such as business and household wealth, show a continuous immoderation.

To address these patterns in aggregate 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) paradigm. 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 and allowing for structural breaks in a subset of the parameter space. Given that I aim at establishing the role played by the financial sector in aggregate volatility, I not only include financial variables in the observable set; but also proceed to the estimation of the deep parameters of the financial accelerator. My estimation exercise is, to the best of my knowledge, the most complete estimation of the financial accelerator model to date. 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. The immoderation in financial quantities 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 in 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 those 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 agency 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, in

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[1]The *Great Inflation* has traditionally been dated from 1965 to 1982. In my data set, however, the structural breaks in volatility for inflation are in 1970 and 1981. Therefore, I use the term *Great Inflation* to refer to that decade.

order to account for the dynamics of credit spreads, it is crucial to assume that the marginal bankruptcy cost is a drifting parameter.

From variance decompositions, I conclude that financial shocks play a significant role in shaping aggregate volatility. On the one hand, they are the main driver of the variance in financial variables, investment, and the nominal interest rate. On the other hand, they are a solid second on board driving the variance in output, consumption, hours, and inflation. Financial shocks in the model economy provide a foundation for the reduced-form shocks to the marginal efficiency of investment proposed by Justiniano, Primiceri and Tambalotti (2011). They studied two investment-specific technology shocks: one affecting the transformation of consumption into investment goods and another one affecting the transformation of investment goods into capital. I incorporate the former by means of a price shifter affecting the relative price of investment with respect to consumption and the latter is linked to the two financial shocks. As in Justiniano, Primiceri and Tambalotti (2011) and contrary to most of the contributions to the literature, the price shifter plays a negligible role. Therefore, not only shocks originated in the financial sector are important drivers of the US business cycle, but also ignoring them translates into an overstatement of role played by the standard investment-specific technology shock.

This paper relates to two strands of the empirical macro literature. The first strand addresses the study of the Great Moderation and the second one 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 the possible sources of such a mildness in real business cycle fluctuations. Jermann and Quadrini (2008) and De Blas (2009) also explore the role played in the Great Moderation by changes in the financial rigidities faced by firms. I do provide an exhaustive study of the Great Moderation by exploring the behavior of aggregate financial variables. Regarding the estimation of a DSGE model including the financial accelerator, most of the contributions use post-1985 data in order to avoid the structural breaks linked to the Great Moderation. The most complete estimation exercise in the literature is the one by Christiano, Motto and Rostagno (2010). But not only they consider post-1985 data; but also they fix the deep parameters of the financial accelerator model. Therefore, the main contribution of the paper to this strand of the literature is to provide a data-based quantification of the size of the financial accelerator, to document its evolution over time, and the exploration of financial shocks.

The plan of the paper is as follows. Section I presents the empirical evidence that motivates the paper. I describe the model in Section II. I describe the estimation procedure and report the estimation results in Section III. Section IV analyzes the drivers of the divergent patterns in volatility. In Section V, I study the relative importance of each shock and the propagation of financial shocks. Section VI concludes.

## I.    Empirical Motivation

I revisit the two empirical regularities characterizing the US over the 1954-2006 period: the *Great Inflation* and the *Great Moderation*. I consider data until 2006 to avoid distortions due to non-linearities induced by the zero lower bound on the federal funds rate and binding downward nominal rigidities during the 2007-2009 recession. I document that while the volatility of real, nominal, and financial price variables follows the same pattern, financial quantity measures have experienced a sustained immoderation over time. In this section, I consider the following set of variables: output, investment, consumption, inflation, federal funds rate, net worth for firms and households, demand deposits, checkable deposits, net private savings, the Wilshire 5000 index, and three credit spreads: the spread between the Baa corporate rate and the Aaa corporate rate, between Baa and the federal funds rate, and between Baa and the 10-year bond yield.[2]

Following McConnell and Pérez-Quirós (2000), I estimate the timing of the structural breaks in the residual variance in the raw variables and their cyclical counterpart by running an AR(1) model with drift on the variables of interest. Assuming that the error of the AR(1) model, $\varepsilon_t$, follows a normal distribution, I can ensure that $\left[|\widehat{\varepsilon}_t|\sqrt{\pi/2}\right]$ is an unbiased estimator for the residual standard deviation of the variable under analysis. I perform Bai and Perron (1998) tests to estimate the dating and the number of breaks in the standard deviation. The results for the Bai-Perron tests are reported in Table 1. While for the volatility of nominal variables and spreads I can reject the null of parameter constancy for two different dates, I can reject the null only once for real and financial quantity variables. Nominal variables clearly indicate 1970 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 second quarter of 1984 as the start of the *Great Moderation*. Financial quantity measures provide a wide array of dates for the spin-off of their increase in volatility.

In order to economize on the number of parameters to estimate in the structural estimation exercise, I consider two structural breaks in the data set at given dates. In particular, I consider the first break the estimated starting point for the Great Inflation and the second break the estimated beginning of the Great Moderation. In order to determine whether this approach is supported by the data, I run Chow's (1960) tests using 1970:Q1 and 1984:Q2 as the breakpoints. I report the log-likelihood ratio statistic for both raw and cyclical data in the last two columns of Table 1. I conclude that I can reject the null of parameter constancy at both dates for all variables under analysis but household wealth. Therefore, by focusing my analysis on the following three sub-samples 1954:Q4-1971:Q1, 1971:Q2-1984:Q2, and 1984:Q3-2006:Q4, I are not misrepresenting the estimated breaks in raw and cyclical volatilities. One of the novelties of my analysis is the

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[2]See the online Appendix for a full description of the data.

consideration of those two breakpoints when performing the structural estimation exercise.

I report in Table 2 the ratio of standard deviations for raw variables and their cyclical component. To facilitate the analysis, I focus on the evolution of the volatility at business cycle frequencies, that is, the volatility of the cyclical component extracted using the HP filter. Let us start by comparing the standard deviation of the cyclical component in the 1970-1984 sample period with that of the 1954-1970 era. The volatility of real variables is, on average, over 50% greater in the 1970s and early 1980s than in the pre-1970 period. The standard deviation of the cyclical component of all of nominal variables and credit spreads more than doubles in the 1970s and the early 1980s with respect to the 1950s and 1960s. Finally, financial quantity measures are also more volatile over the second sample period. The more dramatic change is the one experienced by demand deposits at commercial banks whose variability quadruples.

When comparing the standard deviations of the cyclical component for the post-1984 period with that of the 1970-1984 sample period, I conclude that the volatility of consumption, investment, and output decreases by about 55%. This slowdown in the volatility of real variables is referred to as the Great Moderation. Nominal variables and credit spreads follow the same pattern as real variables. Financial quantity variables are more volatile in the 1984-2006 sample period. The most significant increases in cyclical variability are the ones for the Wilshire 5000 index, whose volatility is over seven times larger than in the 1970s and early 1980s, and for checkable deposits whose variability more than doubles. Net worth for the nonfarm business sector and net private savings are 45% more volatile in the Great Moderation era than in the Great Inflation period. Jermann and Quadrini (2008) also provide empirical evidence on the increase in the volatility of equity payout and debt repurchase in the nonfarm business sector during the Great Moderation. Given the wide range of financial quantity variables showing increases in volatility, I can ensure that the post mid-1980s are characterized by an *immoderation* of financial quantity variables.

## II.   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 in the US 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 in the workhorse DSGE model, several studies have focused on assessing the empirical relevance of the financial accelerator by com-

paring 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 the analysis on two issues: the role of financial shocks and the model's potential to account for breaks in the second moments of the data. I incorporate in 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 major novelty of this paper.

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

## A.  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, $\lambda_t^p$, is assumed to follow the exogenous stochastic process

(1)
$$\ln(\lambda_t^p) = (1 - \rho_{\lambda^p}) \ln(\lambda_\star^p) + \rho_{\lambda^p} \ln(\lambda_{t-1}^p) + \varepsilon_{\lambda^p,t} - \theta_p \varepsilon_{\lambda^p,t-1}, \qquad \varepsilon_{\lambda^p,t} \sim \mathcal{N}(0, \sigma_{\lambda^p})$$

where $\lambda_\star^p$ stands for the value of the markup at the steady state.

## B.  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.

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

where $\Phi$ 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

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

Thus, I assume that the growth rate of the neutral technological progress follows an AR(1) process where $\Upsilon_z$ 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

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

where $\pi \equiv P_t/P_{t-1}$ is the gross inflation rate and $\pi_\star$ is the inflation rate at 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

$(5)$

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

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

### C.   Capital producers

They are infinitely lived agents operating in a perfectly competitive market. Capital producers produce new physical capital stock, $K_{t+1}$, using a constant returns to scale technology that combines final goods, $I_t$, with currently installed capital, $K_t$, which is repurchased from entrepreneurs. The new capital is sold to entrepreneurs at price $P_t^k$. I assume that one unit of time t investment delivers $\zeta_t$ units of time $t+1$ physical capital. The stochastic process $\zeta_t$ is the investment-specific technology shock along the lines of Greenwood, Hercowitz and Krusell (2000).

$$(6) \qquad \ln(\zeta_t) = \rho_{\zeta,1} \ln(\zeta_{t-1}) + \varepsilon_{\zeta,t} \qquad \varepsilon_{\zeta,t} \sim \mathcal{N}(\sigma_\zeta, 1)$$

Following Christensen and Dib (2008), I assume that capital producers are subject to quadratic capital adjustment costs. The representative capital producer chooses the level of investment that maximizes her profits, which delivers the following expression for the relative price of capital

$$Q_t = \frac{P_t^k}{P_t} = \frac{1}{\zeta_t} \left[ 1 + \xi \left( \frac{I_t}{K_t} - (3_\star - 1 + \delta) \right) \right]$$

, which is the standard Tobin's q equation. In the absence of capital adjustment costs, the relative price for capital, $Q_t$, is equal to the inverse of the investment-specific shock. I assume that the aggregate capital stock of the economy evolves according to $K_t = (1 - \delta) K_t + \zeta_t I_t$.

### D.   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 $H_t = \left[ \int_0^1 H_t(i)^{\frac{1}{1+\lambda_t^w}} \right]^{1+\lambda_t^w}$, where $\lambda_t^w$ is the wage markup that evolves exogenously as

(7)
$$\ln(\lambda_t^w) = (1 - \rho_{\lambda^w}) \ln(\lambda_\star^w) + \rho_{\lambda^w} \ln(\lambda_{t-1}^w) + \varepsilon_{\lambda^w,t} - \theta_w \varepsilon_{\lambda^w,t-1}, \qquad \varepsilon_{\lambda^w,t} \sim \mathcal{N}(0, \sigma_{\lambda^w})$$

In this setup, a wage markup shock is observationally equivalent to a labor supply shock. Profit maximization by the perfectly competitive labor packers implies the following labor demand function

(8)
$$H_t(i) = \left[ \frac{W_t(i)}{W_t} \right]^{-\left( \frac{1+\lambda_t^w}{\lambda_t^w} \right)} H_t$$

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

### E.   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:

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

subject to

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

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, $\nu$ 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, $R_t^n$ 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 from/to 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 due to 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

$$(9) \qquad \ln(b_t) = \rho_b \ln(b_{t-1}) + \varepsilon_{b,t}, \ \ \varepsilon_{b,t} \sim \mathcal{N}(0, \sigma_b)$$

Households set nominal wages for specialized labor services by means of staggered contracts. In any period $t$, a fraction $\xi_p$ of households cannot reoptimize their wages, but follows the indexation rule

$$(10) \qquad W_t(i) = W_{t-1}(i) \left( \pi_{t-1} \mathfrak{Z}_{t-1} \right)^{\iota_w} \left( \pi_\star \mathfrak{Z}_\star \right)^{1-\iota_w}$$

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.

## F.  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, $\omega_t^j$, that affects the productivity of her capital holdings. This idiosyncratic shock is at the center of the informational asymmetry, since it is only freely observed by the entrepreneur. For tractability purposes, I assume $\omega_t^j$, for all $j$, is $i.i.d$ lognormal with $c.d.f.$ $F(\omega)$, parameters $\mu_\omega$ and $\sigma_\omega$, 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

$$(11) \qquad \max_{u_t^j} \left[ u_t^j r_t^{k,j} - a\left( u_t^j \right) \right] \omega_t^j K_t^j$$

where, around the steady state, $a\left(\cdot\right) = 0, a'\left(\cdot\right) > 0, a''\left(\cdot\right) > 0$ 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 returns on holding one unit of capital from $t$ to $t+1$

$$(12) \qquad R_{t+1}^{k,j} = \left[ \frac{r_{t+1}^{k,j} u_{t+1}^j + \omega_{t+1}^j (1-\delta) Q_{t+1}}{Q_t} \right] \frac{P_{t+1}}{P_t}$$

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

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back to capital producers.

An entrepreneur can finance the purchasing of new physical capital 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,$\mu$, is lost in the process of liquidating the firm. In this case, the financial intermediary obtains

$$(13) \qquad (1 - \mu_{t+1}) P_t \omega_{n,t+1}^j R_{n,t+1}^k Q_t K_{t+1}^j$$

where $\mu_{t+1}$ 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

$$(14) \qquad \mathbb{E}_t \frac{R_{t+1}^k}{R_t} \left[ \Gamma(\bar{\omega}_{t+1}) - \mu_{t+1} G(\bar{\omega}_{t+1}) \right] = \left( \frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}} \right)$$

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 $\mu_{t+1} G(\bar{\omega}_{t+1}^j) = \mu_{t+1}$ $\int_0^{\bar{\omega}_{t+1}^j} \omega f(\omega) d\omega$ are the expected monitoring costs. The above 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

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risk free rate, the so-called external finance premium, $\mathbb{E}\left[\frac{R_{t+1}^k}{R_t}\right]$. Equation (14) 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 external finance premium is determined by two channels: the *balance-sheet channel*, through the debt-to-assets ratio, and the *information channel*, through the elasticity of the external finance premium with respect to the leverage ratio. The external finance premium is the key relationship of the financial accelerator, since 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).

Recently, Dib (2009) has explored shocks to the elasticity of the risk premium with respect to the entrepreneurial leverage ratio. He solves the model discarding the contribution of the dynamics of the idiosyncratic productivity threshold to the dynamics of the remaining variables.[3] Hence, those shocks can refer to shocks to the standard deviation of the entrepreneurial distribution, to agency costs paid by financial intermediaries to monitor entrepreneurs, and/or to the entrepreneurial default threshold. He cannot, however, discriminate among the sources of the shock. Christiano, Motto and Rostagno (2010) solve the model completely so that they can introduce a specific type of shock affecting the efficiency of the lending activity. In particular, they propose riskiness shocks affecting the standard deviation of the entrepreneurial distribution. 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.

I introduce exogenous disturbances affecting the elasticity of the premium with respect to the leverage ratio by assuming the marginal bankruptcy cost is time-variant. The information channel, therefore, establishes that the external finance premium is a positive function of the severity of the agency problem measured by the marginal bankruptcy cost, $\mu_t$. An increase in the level of financial rigidity implies an enlargement of the informational asymmetry rents, which translates

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[3]BGG perform simulation exercises under a parameterization that implied a negligible contribution of the dynamics of the cutoff. However, most of the contributions to the financial accelerator literature have adopted this result as a feature of the model. Therefore, they proceed by setting those dynamics to zero.

into a higher premium on external funds. To the best of my knowledge, only Levin, Natalucci and Zakrajšek (2004) have explored time variation along this margin. They estimate a partial equilibrium version of the BGG model using a panel of 900 US nonfinancial firms over the period 1997:1 to 2003:3. They find evidence of significant time variation in the marginal bankruptcy cost. In particular, they conclude that time variation in the parameter of interest is the main driver of the swings in the model-implied external finance premium. I assume that the shock to the marginal bankruptcy cost follows

$$(15) \qquad \ln(\mu_t) = (1 - \rho_\mu) \ln(\mu^\star) + \rho_\mu \ln(\mu_{t-1}) + \varepsilon_{\mu,t}, \quad \varepsilon_{\mu,t} \sim \mathcal{N}(0, \sigma_\mu)$$

The unconditional mean of the process governing the agency problem between borrowers and lenders, $\mu^\star$, determines the average level of financial rigidity in the model economy. This parameter governs, then, the size of the financial accelerator. In particular, $\mu^\star$ stands for the steady-state level of the marginal bankruptcy cost.

In the estimation exercise, I consider as an additional parameter the unconditional mean of the external finance premium. Note that both the unconditional mean of the premium and of the size of the financial accelerator completely describe the characteristics of the financial sector in the model economy at the steady state. On the one hand, a larger average marginal bankruptcy cost translates into a harder access to external financing. On the other hand, a higher average for the external finance premium implies that, on average, external financing is more expensive. Therefore, the flexibility of the financial system at the steady state in the model economy is a negative function of the unconditional means for the marginal bankruptcy cost and the external finance premium.

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

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

where $\gamma$ 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, $\mu_t G\left(\bar{\omega}_t\right) R_t^k Q_{t-1} K_t$ is the gross return lost in case of bankruptcy, and $x_t$ is the wealth shock, which is assumed to be

$$(16) \qquad \qquad \ln(x_t) = \rho_x \ln(x_{t-1}) + \varepsilon_{x,t}, \quad \varepsilon_{x,t} \sim \mathcal{N}(0, \sigma_x),$$

Wealth shocks can be interpreted as shocks to the stock market that generate asset price movements that cannot be accounted for by fundamentals. Christiano, Motto and Rostagno (2003) suggest that shocks to entrepreneurial wealth capture the so-called irrational exuberance. I can also consider wealth shocks as a reduced form for changes in fiscal policy that have redistributive effects between firms and households. 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

(17) $$Trans_t = N_{t+1} - \gamma V_t - W_t^e = \gamma V_t (x_t - 1)$$

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

### G.   Government

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

(18) $$NB_{t+1} + P_t T_t = P_t G_t + R_{t-1}^n NB_t$$

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 the authority adjusts the short-term nominal interest rate responding to deviations of inflation and output growth from the target, i.e., their steady-state values.

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

with $\rho_R > 0, (1 - \rho_R)\psi_\pi > 0, (1 - \rho_R)\psi_y > 0$, and $\varepsilon_{R,t} \sim \mathcal{N}(0, \sigma_R)$.

### H.   Market clearing

The final goods market clearing condition (total resources constraint)

(20) $$Y_t = C_t + I_t + G_t + a(u_t) K_t + \mu_t G(\bar{\omega}_t) R_t^k Q_{t-1} K_t$$

and the credit market clearing condition

(21) $$\frac{D_{t+1}}{P_t} = \frac{B_{t+1}}{P_t} = Q_t K_{t+1} - N_{t+1}$$

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### III.    Bayesian Inference

#### A.    Data

I estimate the model with Bayesian estimation techniques using nine macroeconomic quarterly US time series as observable variables: the growth rate of real per capita net worth in the nonfarm business sector, 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 nondurable consumption 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 federal funds rate. A complete description of the data set is given in the online Appendix. The model is estimated over the full sample period from 1954.4 to 2006.4.

All the series enumerated above except net worth in the nonfarm business sector and the credit spread are standard in the data sets used in the empirical macro literature. I discuss in further detail the inclusion of such financial variables in the set of observable variables. The theoretical framework describes the evolution of three financial series: entrepreneurial wealth, debt, and the external finance premium. Therefore, the estimation exercise could aim to match the behavior of all of those. However, the informational content of debt is already included in the series for net worth by definition. Net worth for a firm is generally defined as total assets minus total liabilities. However, in order to be consistent with the model, I define net worth as tangible assets minus credit market liabilities. First, the model is a model of tangible assets purchased by firms so that it has nothing to say about financial assets held by entrepreneurs. Second, external financing in the model relates only to that obtained in credit markets. Hence, I do not consider trade and taxes payable nor miscellaneous liabilities provided in the Flow of Funds Accounts. An alternative measure for entrepreneurial wealth used by Christiano, Motto and Rostagno (2010) is stock market data. In particular, they use the Wilshire 5000 index. This measure contains information only for publicly traded firms, which are a smaller set of firms than the one linked to the aggregate macroeconomic variables of the data set. Moreover, this series is only available from 1971, which makes it unattractive for studying the Great Inflation period in comparison to the 1950s-1960s.

In order to proxy the external finance premium, BGG suggest considering the spread between the prime lending rate and the 6-month Treasury bill rate. Christiano, Motto and Rostagno (2003) define the external finance premium as the premium on the US industrial Baa corporate bond over the federal funds rate and Christiano, Motto and Rostagno (2010) use the US Industrial Bbb corporate bond yield, backcasted using Baa corporate bond yields, minus the federal funds rate. Recently, Gilchrist, Ortiz and Zakrajšek (2009) use as a proxy for the external finance premium a corporate credit spread index constructed using

individual security-level data. I proceed by defining my proxy for the external finance premium as the spread between the US industrial Baa corporate bond yields and the federal funds rate since, conceptually, it is the closest measure to the model-implied external finance premium.

## B.   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 parameters characterizing the financial system, which are the unconditional means of the marginal bankruptcy cost and the external finance premium. I perform the estimation exercise by using the full sample information to estimate the parameters that are constant across sub-samples and the corresponding sub-sample information to estimate those parameters that are subject to structural breaks. I use a relatively naïve approach in treating structural breaks. I assume economic agents do not face an inference problem to learn endogenously about the regimes. When forming rational expectations about the dynamic economy, they take regime changes as completely exogenous events and assume that the current regime will last forever. Thus, once a structural break in parameters happens, agents learn about it immediately and conveniently readjust their choices. This simplifying assumption facilitates the estimation when, as in this case, breaks in the steady state of the economy are allowed. However, the econometrician must make sure she is using the same information set as the economic agent when conducting the estimation exercise. In the remainder of this section, I provide an overview of the approach taken in the estimation of the model.

Let $\varrho$ be the subvector of structural parameters that is constant across sub-samples and $\tau$ be the subvector subject to structural breaks. The system of log-linearized equilibrium conditions[4] can be represented as

$$(22) \qquad \Gamma_0\left(\varrho,\tau\right)\widetilde{s}_t = \Gamma_1\left(\varrho,\tau\right)\widetilde{s}_{t-1} + \Psi\left(\varrho,\tau\right)\varepsilon_t + \Pi\left(\varrho,\tau\right)\eta_t$$

where $\widetilde{s}_t$ is a vector of model variables expressed in deviations from steady state, $\varepsilon_t$ is a vector of exogenous shocks, and $\eta_t$ is a vector of rational expectations errors with elements $\eta_t^x = \widetilde{x}_t - \mathbb{E}_{t-1}\left[\widetilde{x}_t\right]$. Given that the system is linear and I have assumed that $\varepsilon_t \sim \mathcal{N}\left(0,\Sigma\right)$, I can evaluate the likelihood function using the Kalman filter. I deviate from the standard approach in the literature by casting the solution to the LRE model in state space form for the variables in log-levels

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[4]The log-linearized system is available in the online Appendix.

instead of in log-deviations from the steady state.

$$Transition\ equations: \quad s_t = [I - \Phi(\varrho, \tau)]\,\bar{s} + \Phi(\varrho, \tau)s_{t-1} + \Phi_\varepsilon(\varrho, \tau)\varepsilon_t$$
$$Measurement\ equations: \quad y_t = B(\varrho, \tau)s_t$$

where $s_t$ is the state vector in log-levels, that is, $s_t = \tilde{s}_t + \bar{s}$, and $\bar{s}$ is the log of the state vector evaluated in the steady state.

From the above, it is obvious that structural breaks in any parameter affect the system matrices of the filter. The Kalman filter is a very flexible environment that can accommodate any of these modifications. But the econometrician must handle with special care breaks in parameters that affect the steady state of the economy since she has to take into account the change in the information set used by economic agents. Note that while breaks in the size of shocks shift only $\Phi_\varepsilon(\varrho, \tau)$ and breaks in monetary policy coefficients affect $\Phi(\varrho, \tau)$, breaks in parameters defining the steady-state of the economy translate into changes in $\Phi(\varrho, \tau)$ and $\bar{s}$. In the analysis, I am allowing for structural breaks in two parameters governing the steady state of the economy: the unconditional mean of the marginal bankruptcy cost and the steady state value of the external finance premium. I propose the following modification of the forecasting step in the Kalman filter to accommodate for breaks in the steady state of the economy. Suppose that at $t = t^\star$, the steady state of the economy shifts from $\bar{s}_1$ to $\bar{s}_2$. Then, for $t < t^\star$, the forecasting of the states is given by $\hat{s}_{t|t-1} = [I - \Phi(\varrho, \tau_1)]\,\bar{s}_1 + \Phi(\varrho, \tau_1)\hat{s}_{t-1|t-1}$. At $t = t^\star$, I have $\hat{s}_{t|t-1} = [I - \Phi(\varrho, \tau_2)]\,\bar{s}_2 + \Phi(\varrho, \tau_2)\,[\bar{s}_2 - \bar{s}_1] + \Phi(\varrho, \tau_2)\hat{s}_{t-1|t-1}$. If $t > t^\star$, then $\hat{s}_{t|t-1} = [I - \Phi(\varrho, \tau_2)]\,\bar{s}_2 + \Phi(\varrho, \tau_2)\hat{s}_{t-1|t-1}$.

### C. Prior distribution

The prior information on the parameters used in the estimation exercise is available in the first three columns of Tables 3 and 4. My choices for standard parameters are along the lines of the recent literature. There have been few attempts, however, to estimate the parameters governing the financial accelerator. Thus, I provide here a description of the prior for those parameters. Regarding the subvector of parameters subject to structural breaks, I assume identical priors across sub-samples.

The parameters governing the financial accelerator are the default probability, $F(\bar{\omega})$, the variance in the idiosyncratic productivity shock, $\sigma_\omega^2$, the survival probability, $\gamma$, the unconditional mean of the marginal bankruptcy cost, $\mu_\star$, the external finance premium at the steady state, $R_\star^k/R_\star$, and the size of financial shocks. Following the literature, I use degenerate priors for the default probability and the size of the idiosyncratic productivity shock. In particular, I set $F(\bar{\omega})$ equal to the average of the historical default rates for US bonds over the period 1971-2005 reported by Altman and Pasternack (2006). I fix the idiosyncratic productivity variance equal to 0.24.

I choose a Beta distribution for the survival probability, $\gamma$. The location pa-

rameter 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. The prior distribution for the unconditional mean of the external finance premium, $R_\star^k/R_\star$, is Gaussian with location parameter equal to the sample average.

Regarding the steady-state value of the marginal bankruptcy cost, $\mu^\star$, to the best of my knowledge, there has not been an attempt to estimate such a parameter using aggregate data. I use a Beta distribution for this parameter since 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 11-17% 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 period 1982-1993 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 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 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.

## D.   Posterior estimates of the parameters

The last two columns of Tables 3 and 4 report the posterior median and the 95% credible intervals of a chain of 250,000 posterior draws with a burn-in period of 20%.[5] I first analyze Table 3, which contains those parameters not allowed to change over time. The survival probability of entrepreneurs is estimated to be about 98% per quarter which implies a median life for entrepreneurs of about 12 years. The estimated degree of price and wage stickiness is relatively smaller than the estimates available in the macro literature. In particular, the Calvo parameter for prices is 66% and for wages only 27%. These results are due to the fact that the amplification and propagation mechanism usually captured by nominal rigidities is taken care of by the financial rigidity embedded in the model.

Table 4 reports the estimates for those parameters allowed to change in 1970:Q1 and 1984:Q2. First, I analyze the estimated breaks in the parameters governing

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[5]I have generated two additional chains of 250,000 posterior draws. The results reported in the paper are almost identical across chains.

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 during the Great Moderation. In particular, during Burns-Miller mandate the response to inflation was 20% lower. Volcker-Greenspan period is characterized by a resuscitation of Martin's recipes regarding the response to inflation. The response of the monetary authority to the real side of the economy has been tighter over time. There has been a 20% cumulative increase in the response to deviations of output growth from the target.

Second, I consider the two parameters characterizing the conditions of access to credit. The steady-state value of the external finance premium has been increasing over time, which implies that external credit has become more expensive over the last 50 years. In particular, the estimated model-implied increase in the unconditional mean of the cost of external financing is 50% in the 1970s. Such cost more than quadruples during the Great Moderation.

These increases in the cost of external financing have been paired up with a higher level of financial rigidity during the Great Inflation and an almost frictionless financial framework since the mid-1980s. The unconditional mean of the marginal bankruptcy cost, which accounts for the easiness of access to external financing, is 60% larger in the 1970s. While in the 1950s-1960s financial intermediaries were able to recover 87% of the value of the firm in the event of bankruptcy, they recovered only 79% of the value after liquidation in the 1970s. The enlargement of the marginal bankruptcy cost may be related to the additional difficulty of extracting information about borrowers in periods of turbulence in the aggregate economy. For the Great Moderation period, the estimated average marginal bankruptcy cost is equal to 5%, which implies a recovery value of 95%. 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 these factors define the level of financial rigidity in terms of the model economy. The contemporaneous reduction in the average level of financial rigidity and increase in the unconditional mean of the credit spread are reconcilable under the premise that the former translates into an enlargement of the pool of borrowers, that is, more entrepreneurs in the tails of the distribution are able to leverage up their investments. Consequently, financial intermediaries request a higher average premium to compensate for the larger average default risk undertaken when signing a debt contract.

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 is 33% larger in the 1970s and it increases an additional 92% during the Great Moderation.

Larger balance-sheet shocks affecting the model economy reflect the increasing sensitivity of the system to asset price movements. Note that the US data have been characterized by several price "bubbles" over the last few decades: the dramatic rise in US stock prices during the late 1990s or the housing bubble during the early 2000s, for example. The size of the shock to the marginal bankruptcy cost more than doubles in the 1970s and increases an additional 41% in the mid-1980s. Therefore, on the one hand, the unconditional average of the process governing the level of financial rigidity, $\mu_\star$, is smaller over time; on the other hand, the variability of the disturbance to the process is larger. These two results can be reconciled by noting that a reduction in $\mu^\star$ increases the average recovery rate for financial intermediaries. Hence, intermediaries are willing to enlarge their exposure to risk, which is captured by the increase in $\sigma_\mu$.

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 30%, that of the price and wage markup shocks by 45% and 30%, respectively, the size of the intertemporal preference shock is 57% larger and that of the monetary policy shock almost doubles. The size of all nonfinancial shocks decreases during the Great Moderation by a minimum of 11% for the investment-specific technology shock and a maximum of 55% for the monetary policy shock.

## E.  Model evaluation

I study the model fit of the data performing posterior predictive checks. I focus on analyzing the performance of the model at 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 from the sampler. I HP filter the data in log-levels obtained from the simulation and compute the standard deviation of the cyclical component. Table 5 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 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 and financial price variables 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. However, while the magnitude of the moderation in real variables and inflation is smaller than the

observed one, the model-implied slowdown for interest rates and financial price variables is larger than that in the data. The posterior predictive check is successful at generating the divergent patterns in volatility for financial quantity and price measures. While the volatility of the credit spread is over 60% smaller during the Great Moderation, the cyclical volatility of net worth is about 35% larger.

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 US business cycle properties for real, nominal, and financial variables.

## IV.    Assessing the Drivers of the Financial Immoderation and the Great Moderation

In this section, I analyze the contribution to the model-implied changes in business cycle properties of each of the potential candidates. To do so, I perform two sets of counterfactual exercises. In *Counterfactuals 1-8*, I explore the sources of the Great Inflation. I analyze the model drivers of the Great Moderation and the dichotomy in the volatility of financial variables in *Counterfactuals 9-16*. In *Counterfactuals 1* and *9*, I analyze the role played by the estimated changes in the response of the monetary authority to deviations of inflation and output growth from the target. I study the relative importance of changes in the unconditional mean for the marginal bankruptcy cost in *Counterfactuals 2* and  *10*. *Counterfactuals 3* and *11* report the role played by the estimated breaks in the steady-state value for the external finance premium. I assess the relevance of changes in the financial system by simulating the model economy when both the unconditional means of the level of financial rigidity and of the external finance premium change across sub-samples in *Counterfactuals 4* and *12*. I determine the relevance of changes in both financial institutions and the monetary policy stance in *Counterfactuals 5* and *13* and the relevance of the luck hypothesis in *Counterfactuals 6* and *14*. I establish the relative role played by only financial shocks in *Counterfactuals 7* and *15* and by the remaining shocks in *Counterfactuals 8* and *16*.

For illustration purposes, let us consider *Counterfactual 1*. 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 1954-1970 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 1970-1984 sample period. Obtain the cyclical component.

3) Compute the ratio of standard deviations.

4) Simulate the model economy for 200 periods (after a burn-in of 1000 observations) using the parameter vector characterizing the 1954-1970 period but with the monetary policy coefficients of the 1970-1984 parameter vector. Obtain the cyclical component.

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

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

Table 6 reports 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. In *Counterfactual 1*, I analyze the role played by the estimated changes in 1970 in the response of the monetary authority to deviations of inflation and output growth from the target. The estimated loosening of the response to inflation and the tightening in the response to output account for the following percentages of the model-implied increase in cyclical volatility: 29% for inflation, 9% for the nominal interest rate, and 2% for net worth.

*Counterfactual 2* shows that the estimated 60% increase in the level of financial rigidity accounts for an average of 14% of the model-implied increase in the volatility of the cyclical component of output, investment, consumption, and net worth. It accounts for 22% of the immoderation in interest rates and 26% of that in credit spreads. But, it accounts for only 3% of the increase in inflation volatility. From *Counterfactual 3*, I conclude that the estimated increase in the unconditional mean of the external finance premium accounts for 5% of the model-implied immoderation for investment and net worth but it implies a slowdown in the cyclical volatility of the remaining variables. Therefore, as compiled in *Counterfactual 4*, the relative role played by changes in financial institutions in the Great Inflation is relegated to account for an average of 15% of the model-implied immoderation in investment, consumption, net worth, and the nominal interest rate; 26% of that in credit spreads; and less than 5% for output and inflation.

Comparing the rows for *Counterfactuals 5* and *6*, I conclude that the Great Inflation was mostly due to bad luck. While the institutional change is needed to replicate the model-implied increase in the volatility of nominal variables, financial variables, and investment, it only accounts for about 20% of the model-implied increase in variability. The remaining 80% is accounted for by the larger shocks hitting the US economy during the 1970s. The immoderation in output and consumption can only be explained by the estimated change in the size of exogenous shocks. The conclusion is quite different when analyzing the main source of the Great Moderation. *Counterfactuals 13* and *14* show that the slowdown in cyclical volatility characterizing the post-1984 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 22% of the smoothing in consumption, 46% of the reduction in inflation volatility, and generate an immoderation in business wealth almost twice as large as the one needed. The effect on the remaining variables is at odds with the observed evolution of cyclical volatility. The estimated institutional changes, however, account for about 40% of the model-implied moderation in output and inflation; 48% of the reduction in investment volatility; 13% of that in consumption; and 94% of the smoothing of interest rate variability. The new institutional framework overestimates the moderation of credit spreads by about 15%. *Counterfactuals 9* and *12* state that the bulk of the role of institutions in accounting for the Great Moderation is due to the estimation reduction in the average level of financial rigidity.

## V. Economic Implications

### A. Variance decomposition

Table 7 provides the variance decomposition at business cycle frequencies. 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. I report the median variance decomposition.

First, I conclude that financial shocks are an important source of business cycle fluctuations. In particular, they are the main source of the variance in investment, the nominal interest rate, the credit spread, and business wealth. Financial shocks explain up to 62% of investment variance in the 1970s. During the Great Moderation, the improvement of financial institutions translates into a reduction in the relative role of financial shocks accounting for 38% of investment variance. Financial shocks account for 80% of the variation in nominal interest rates during the Great Inflation and for 60% in the other sub-periods. These shocks are the soloists orchestrating the variance in financial variables. While the wealth shock is the main driver of business cycle fluctuations in business wealth, the shock to the marginal bankruptcy cost accounts for most of the variation in credit spreads. On their estimation of a partial equilibrium version of the BGG model using micro data, Levin, Natalucci and Zakrajšek (2004) also obtained the result that exogenous disturbances in the marginal bankruptcy cost are the main driver of the external finance premium. Therefore, I conclude that models with the financial accelerator that aim to provide empirically plausible swings in the cost of external financing should explore time variation in the level of financial rigidity.

Financial shocks also play a non-negligible secondary role as drivers of output, consumption, hours, and inflation. Their relative contribution to the variance of

these variables more than doubles during the Great Inflation. For example, financial shocks become the main driver of the variance at business cycle frequencies of output and hours worked. In particular, financial shocks account for 30% of the volatility in output and 36% of that in hours.

Second, in contrast to the standard results in the literature, the estimates deliver a negligible role for the investment-specific technology shock as driver of the business cycle. Once financial frictions and financial shocks are at play, the I-shock is just a shifter of the relative price of capital goods. Therefore, it is relegated to account for a small fraction of the variance in nominal variables and business wealth. Justiniano, Primiceri and Tambalotti (2011) consider two types of investment shocks: investment-specific technology shocks affecting the transformation of consumption into investment goods and shocks to the marginal efficiency of investment, which ultimately affect the transformation of investment goods into productive capital. They conclude that the relative importance of the former is negligible, but the latter is the main driver of the real business cycle. They state that shocks to the marginal efficiency of investment are a proxy for disturbances to the financial system. My results confirm their conclusions since *(i)* financial shocks play a significant role as drivers of real and nominal cycles and *(ii)* the price shifter is not relevant. In contrast to Justiniano, Primiceri and Tambalotti (2011), I do not use a one-to-one identification of the investment technology shock with the observed relative price of investment. This difference can account for the discrepancy in the relative role played by such shocks as drivers of nominal variables.

Third, business cycle fluctuations in output and consumption are mostly driven by the neutral technology shock and markup shocks. The relative importance of the former is along the same lines as in the literature. The large role played by markup shocks is due to the fact that they are the main driver of the variance in hours. Given that the estimated labor share of output is very large, the drivers of fluctuations in hours at business cycle frequencies play a significant role in output variance.

Finally, the Great Inflation is characterized by a large relative importance of monetary policy shocks. On the one hand, monetary policy shocks account for 41% of the variation at business cycle frequencies in inflation, which translates into monetary policy shocks being the main driver of the variation in inflation. On the other hand, these shocks are the second most important driver of output, investment, and hours worked accounting for about 20% of their variation. Therefore, changes in the conduct of monetary policy translated into a higher sensitivity of the economy to unexpected monetary policy disturbances.

### B.   Impulse response functions

The propagation of real and nominal shocks in the context of a model of the financial accelerator has already been studied in the literature. Therefore, in this section, I focus only on the study of the propagation dynamics of financial shocks.

For both the wealth shock and the innovation to the marginal bankruptcy cost, I plot the responses in the first 40 quarters in terms of percentage deviations with respect to the steady state. Each plot contains three impulse response functions (IRFs). The dotted line is the IRF computed using the parameter vector characterizing the 1954:Q4-1970:Q1 sample period. The dashed line is the IRF for the 1970s and early 1980s. The solid line is the IRF for the post-1984 period.

## Wealth shock

Figure 1 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 pre-Great Inflation era. The size of the shock generating such a response upon impact is 0.65. I use the same shock across sub-samples to facilitate the comparison. The main messages from the figure are *(i)* the responses upon impact are a positive function of the size of the financial rigidity; and *(ii)* the persistence of the responses is a negative function of the unconditional average of the marginal bankruptcy cost.

Let us first analyze the impulse response functions for net worth. The response upon impact of net worth is 16% larger during the Great Inflation and 22% smaller during the Great Moderation. The IRFs associated with lower unconditional averages for the marginal bankruptcy cost cross the ones for higher levels of financial rigidity from below within the first 9 quarters to lie above them for over 200 periods. This can be easily reconciled from the definition of aggregate net worth. Lower average agency costs alleviate the deadweight loss associated with bankruptcy, $\mu_t G(\bar{\omega}_t) P_{t-1} R_t^k Q_{t-1} K_t$, which implies that for the same initial increase in wealth, the effects are more long-lasting, since more resources are accumulated from period to period. Higher persistence induced by the lower dependence on the financial accelerator mechanism translates into more persistent responses for all variables.

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. Therefore, the response of the external finance premium upon impact is negative. This immediate improvement in credit markets has a significant amplification effect on investment so that the response of investment upon impact exceeds significantly the initial increase in net worth. The response upon impact of the external finance premium is smaller, in absolute terms, over time due to the fact that lower levels of credit market imperfections reduce the elasticity of the external finance premium with respect to the leverage ratio. This implies that the amplification effect linked to the improvement in credit market conditions is more muted. Therefore, the responses upon impact for investment and the remaining variables are a positive function of the average level of financial rigidities.

The initial response of output is positive but smaller than the boost in investment because consumption decreases upon impact and the total resources constraint needs to be satisfied. 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. This is due to the fact that other sources of household wealth, such as labor income, react positively to the wealth shock. The positive response of inflation and the nominal interest rate suggests that the wealth shock displays the features of a standard demand shock: quantities and prices move in the same direction, leading to a tightening of monetary policy.

<div align="center">Shock to the marginal bankruptcy cost</div>

Figure 2 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 that generates an increase upon impact in net worth of 1% in the pre-Great Inflation period. The size of such a shock is 120, which is 184 times larger than the wealth shock necessary to generate such a response in net worth. This shows the smaller effect on the economy of shocks to the marginal bankruptcy cost. The persistence of the propagation dynamics of a shock to the marginal bankruptcy cost is also significantly smaller than the persistence of the responses to a wealth shock.

A negative shock to agency costs creates an incentive for entrepreneurs to select contractual terms with a larger debt-to-net worth ratio, since 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 determining entrepreneurial net worth. I label this effect the *default effect*. On the other hand, there is a *mass effect* that stays for the increase in capital investment linked to a larger set of resources being available. Larger amounts of capital holdings imply a larger equity value through an increase in total capital returns. While the mass effect dominates the default effect at first, the second becomes the driving force after 6 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. Consumption responds to the expansionary shock negatively due to the fact that the over-investment with respect to the additional net worth available must be financed with higher debt. In the model, financial debt is funded through households' deposits. Therefore, the amount of resources available for household consumption decreases when there is

<div align="center">25</div>

an improvement in the conditions of access to credit for firms.

Given the significant decline in the size of the financial accelerator, the post-1984 impulse response functions are all characterized by smaller responses for all variables.

## VI.    Conclusions

I have estimated a fairly large DSGE model to reexamine the sources of the observed breaks in macroeconomic fluctuations in the US 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. But, in contrast to the widespread view, improvements in the financial system, not changes in the conduct of monetary policy, are the key for the slowdown in fluctuations at business cycle frequencies. Easier access to credit since the mid-1980s has been paired up with a higher average credit spread and larger financial shocks. These latter two are the mechanisms needed by the model in order to be able to replicate the immoderation observed in financial quantity measures.

The exploration of the drivers of the US business cycle delivers the finding that financial shocks play a significant role. In particular, they are the main driver of the variances in financial variables, investment, and the nominal interest rate. Financial shocks play a solid secondary role as drivers of fluctuations at business cycle frequencies for output, consumption, hours, and inflation. They actually are the main driver of output and hours worked during the Great Inflation. My results highlight the irrelevance of the investment-specific technology shock as a driver of the US business cycle once financial rigidities and financial shocks are at play.

My study reaffirms the growing convention in the literature on integrating credit market imperfections in otherwise standard macroeconomic models. I have documented the importance of including financial shocks in the analysis. Moreover, I highlight the relevance of taking into account structural breaks in the data, since the conclusions, in terms of assessing the main drivers of the cycle or characterizing the propagation dynamics of shocks, may differ significantly.

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TABLE 1—ECONOMETRIC TESTS

| | BAI-PERRON | | | | CHOW | |
|---|---|---|---|---|---|---|
| | Raw data | | Cyclical data | | Raw data | Cyclical data |
| Output | 1983:Q4 | | 1984:Q2 | | 33.45*** | 34.60*** |
| Investment | 1983:Q4 | | 1984:Q1 | | 28.37*** | 36.24** |
| Consumption | 1984:Q2 | | 1984:Q2 | | 11.98*** | 19.54*** |
| Inflation | 1970:Q1 | 1981:Q2 | 1970:Q1 | 1981:Q2 | 32.06*** | 42.95** |
| Federal Funds Rate | 1970:Q2 | 1982:Q4 | 1972:Q4 | 1983:Q1 | 54.45** | 44.66*** |
| Net worth (firms) | 1988:Q4 | | 1988:Q4 | | 17.26*** | 13.82*** |
| Net worth (households) | 1997:Q1 | | 1997:Q4 | | 3.05 | 3.59 |
| Net private savings | 1998:Q3 | | 1998:Q4 | | 6.33** | 10.41*** |
| Demand deposits | 1980:Q1 | | 1980:Q1 | | 14.44*** | 16.13*** |
| Checkable deposits | 1997:Q2 | | 1997:Q2 | | 22.27*** | 15.46*** |
| Spread: Baa-Aaa | 1974:Q3 | 1985:Q2 | 1974:Q3 | 1985:Q2 | 42.52*** | 31.98*** |
| Spread: Baa-ffr | 1972:Q4 | 1982:Q3 | 1969:Q1 | 1982:Q3 | 37.87*** | 39.69*** |
| Spread: Baa-10y | 1970:Q1 | 1984:Q2 | 1970:Q1 | 1983:Q4 | 29.36*** | 35.22*** |
| Wilshire 5000 index | 1997:Q2 | | 1997:Q2 | | | |

*Note:* Data on output, consumption, investment, net worth, debt, deposits, and savings are in real per capita terms. Raw data for output, consumption, investment, wages, net worth, debt, demand deposits, net private savings, and Wilshire 5000 Index stand for growth rates. The data range from 1954:Q4 to 2006:Q4 for all variables but demand deposits which is available since 1959 and the Wilshire 5000 index, which is available since 1971:Q1. The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$). The log-likelihood ratio statistic is distributed as $\chi^2$ with $(m-1)k$ degrees of freedom, where $m$ is the number of sub-samples. The critical values when there are two breaks are 4.61 at 10%, 5.99 at 5%, and 9.21 at 1%. If the statistic is above the critical value, the null hypothesis of no structural change can be rejected. The symbol * indicates we can reject the null of parameter constancy at 10%, ** at 5%, and *** at 1%.

TABLE 2—RATIO OF STANDARD DEVIATIONS

| | Raw data | | Cyclical component | |
|---|---|---|---|---|
| | $\frac{1970-1984}{1954-1970}$ | $\frac{1984-2006}{1970-1984}$ | $\frac{1970-1984}{1954-1970}$ | $\frac{1984-2006}{1970-1984}$ |
| Output | 1.10 | 0.42 | 1.58 | 0.42 |
| Investment | 1.05 | 0.42 | 1.53 | 0.43 |
| Consumption | 1.20 | 0.53 | 1.74 | 0.44 |
| Inflation | 2.05 | 0.37 | 2.56 | 0.36 |
| Federal Funds Rate | 2.02 | 0.64 | 2.64 | 0.50 |
| Net worth (firms) | 1.31 | 1.48 | 1.30 | 1.47 |
| Net worth (households) | 1.19 | 1.19 | 1.92 | 1.07 |
| Net private savings | 1.35 | 1.40 | 1.10 | 1.44 |
| Demand deposits | 2.77 | 1.10 | 4.44 | 1.05 |
| Checkable deposits | 1.05 | 1.97 | 1.39 | 2.41 |
| Spread: Baa-Aaa | 3 | 0.58 | 3 | 0.33 |
| Spread: Baa-ffr | 2.50 | 0.60 | 2.65 | 0.47 |
| Spread: Baa-10y | 2.29 | 0.75 | 2.33 | 0.50 |
| Wilshire 5000 index | | 5.68 | | 7.51 |

*Note:* Data on output, consumption, investment, net worth, debt, deposits, and savings are in real per capita terms. Raw data for output, consumption, investment, wages, net worth, debt, demand deposits, net private savings, and Wilshire 5000 Index stand for growth rates. The Wilshire 5000 index which is available since 1971:Q1. The cyclical component is extracted using the Hodrick-Prescott filter for the quarterly frequency ($\lambda = 1600$). The standard deviations have been multiplied by 100.

Table 3—Parameters estimated using the full sample

| | Prior | | | Posterior | |
|---|---|---|---|---|---|
| | **Density** | **Para 1** | **Para 2** | **Median** | **95% CI** |
| $\delta$ | Fixed | 0.025 | | | |
| $\left(\frac{G}{Y}\right)^{\star}$ | Fixed | 0.22 | | | |
| $[F(\bar{\omega})]^{\star}$ | Fixed | 0.0075 | | | |
| $\sigma_{\omega}^2$ | Fixed | 0.24 | | | |
| $100[1/\beta - 1]$ | $\mathcal{G}$ | 0.25 | 0.10 | 0.19 | [0.08, 0.32] |
| $100[1/\gamma - 1]$ | $\mathcal{G}$ | 1.48 | 0.50 | 2.06 | [0.89, 3.31] |
| $\pi_n^{\star}$ | $\mathcal{N}$ | 3.00 | 1.00 | 2.65 | [2.20, 3.11] |
| $100\ln(H^{\star})$ | $\mathcal{N}$ | 0.50 | 0.40 | 0.42 | [-0.39, 1.20] |
| $100\Upsilon_z$ | $\mathcal{N}$ | 0.50 | 1.00 | 0.52 | [0.37, 0.67] |
| $\phi = \Phi/y_{\star}$ | Beta | 0.15 | 0.05 | 0.36 | [0.26, 0.45] |
| $\lambda_p$ | Beta | 0.15 | 0.05 | 0.36 | [0.26,0.47] |
| $\lambda_w$ | Beta | 0.15 | 0.05 | 0.18 | [0.09, 0.29] |
| $\iota_p$ | Beta | 0.50 | 0.15 | 0.09 | [0.02, 0.18] |
| $\iota_w$ | Beta | 0.50 | 0.15 | 0.18 | [0.09, 0.30] |
| $\xi_p$ | Beta | 0.66 | 0.15 | 0.66 | [0.59, 0.72] |
| $\xi_w$ | Beta | 0.66 | 0.15 | 0.27 | [0.16, 0.38] |
| $\theta_p$ | Beta | 0.50 | 0.20 | 0.47 | [0.34, 0.61] |
| $\theta_w$ | Beta | 0.50 | 0.20 | 0.45 | [0.26, 0.61] |
| $\alpha$ | Beta | 0.30 | 0.03 | 0.19 | [0.17, 0.21] |
| $\xi$ | $\mathcal{N}$ | 1.50 | 0.25 | 2.66 | [2.29, 3.00] |
| a" | $\mathcal{G}$ | 0.50 | 0.25 | 0.51 | [0.16, 0.99] |
| $\nu$ | $\mathcal{G}$ | 2.00 | 1.00 | 0.61 | [0.28, 1.01] |
| $h$ | Beta | 0.50 | 0.10 | 0.50 | [0.44, 0.57] |
| $\rho_r$ | Beta | 0.50 | 0.10 | 0.73 | [0.69, 0.78] |
| $\rho_z$ | Beta | 0.40 | 0.10 | 0.15 | [0.08, 0.21] |
| $\rho_\zeta$ | Beta | 0.60 | 0.20 | 0.94 | [0.91, 0.97] |
| $\rho_\mu$ | Beta | 0.60 | 0.20 | 0.84 | [0.79, 0.88] |
| $\rho_x$ | Beta | 0.60 | 0.20 | 0.81 | [0.73, 0.89] |
| $\rho_{\lambda_p}$ | Beta | 0.60 | 0.20 | 0.9972 | [0.9915, 0.9999] |
| $\rho_{\lambda_w}$ | Beta | 0.60 | 0.20 | 0.9919 | [0.9816, 0.9991] |
| $\rho_b$ | Beta | 0.60 | 0.20 | 0.92 | [0.89, 0.95] |
| $\rho_g$ | Beta | 0.60 | 0.20 | 0.99 | [0.98, 0.99] |

*Note:* 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 $\nu$ 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 4—PARAMETERS SUBJECT TO STRUCTURAL BREAKS

| | | Prior | | Posterior | |
|---|---|---|---|---|---|
| | Density | Para 1 | Para 2 | Median | 95% CI |
| $\psi_{\pi_1}$ | $\mathcal{N}$ | 1.50 | 0.50 | 2.47 | [2.12, 2.87] |
| $\psi_{\pi_2}$ | $\mathcal{N}$ | 1.50 | 0.50 | 2.02 | [1.76, 2.34] |
| $\psi_{\pi_3}$ | $\mathcal{N}$ | 1.50 | 0.50 | 2.47 | [2.06, 2.92] |
| $\psi_{y_1}$ | $\mathcal{N}$ | 0.50 | 0.30 | 0.57 | [0.42, 0.72] |
| $\psi_{y_2}$ | $\mathcal{N}$ | 0.50 | 0.30 | 0.65 | [0.50, 0.80] |
| $\psi_{y_3}$ | $\mathcal{N}$ | 0.50 | 0.30 | 0.69 | [0.54, 0.84] |
| $\mu^\star_1$ | Beta | 0.28 | 0.05 | 0.13 | [0.09, 0.18] |
| $\mu^\star_2$ | Beta | 0.28 | 0.05 | 0.21 | [0.15, 0.29] |
| $\mu^\star_3$ | Beta | 0.28 | 0.05 | 0.05 | [0.03, 0.07] |
| $400\left[\left(R^k_\star/R_\star\right)_1 - 1\right]$ | $\mathcal{N}$ | 2.40 | 1.00 | -1.00 | [-1.72, -0.33] |
| $400\left[\left(R^k_\star/R_\star\right)_2 - 1\right]$ | $\mathcal{N}$ | 2.40 | 1.00 | 0.49 | [-0.25, 1.27] |
| $400\left[\left(R^k_\star/R_\star\right)_3 - 1\right]$ | $\mathcal{N}$ | 2.40 | 1.00 | 2.15 | [1.50, 2.83] |
| $\sigma_{\mu_1}$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.33 | [0.21, 0.45] |
| $\sigma_{\mu_2}$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.75 | [0.52, 1.03] |
| $\sigma_{\mu_3}$ | $\mathcal{IG}$ | 1.00 | 5.00 | 1.06 | [0.69, 1.42] |
| $100(\sigma_{x_1})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.45 | [0.36, 0.56] |
| $100(\sigma_{x_2})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.60 | [0.46, 0.76] |
| $100(\sigma_{x_3})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 1.15 | [0.92, 1.42] |
| $100(\sigma_{z_1})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 1.38 | [1.14, 1.65] |
| $100(\sigma_{z_2})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 1.35 | [1.11, 1.61] |
| $100(\sigma_{z_3})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.93 | [0.80, 1.07] |
| $100(\sigma_{\zeta_1})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.64 | [0.51, 0.78] |
| $100(\sigma_{\zeta_2})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.83 | [0.68, 1.01] |
| $100(\sigma_{\zeta_3})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 0.74 | [0.60, 0.91] |
| $100(\sigma_{\lambda^p_1})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 6.08 | [3.76, 8.62] |
| $100(\sigma_{\lambda^p_2})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 8.80 | [5.70, 12.55] |
| $100(\sigma_{\lambda^p_3})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 5.52 | [3.80, 7.86] |
| $100(\sigma_{\lambda^w_1})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 2.87 | [2.00, 4.06] |
| $100(\sigma_{\lambda^w_2})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 3.74 | [2.56, 5.31] |
| $100(\sigma_{\lambda^w_3})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 2.98 | [1.97, 4.27] |
| $100(\sigma_{b_1})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 2.01 | [1.49, 2.68] |
| $100(\sigma_{b_2})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 3.15 | [2.38, 4.02] |
| $100(\sigma_{b_3})$ | $\mathcal{IG}$ | 1.00 | 5.00 | 1.65 | [1.24, 2.10] |
| $100(\sigma_{r_1})$ | $\mathcal{IG}$ | 0.50 | 5.00 | 0.27 | [0.22, 0.34] |
| $100(\sigma_{r_2})$ | $\mathcal{IG}$ | 0.50 | 5.00 | 0.51 | [0.41, 0.62] |
| $100(\sigma_{r_3})$ | $\mathcal{IG}$ | 0.50 | 5.00 | 0.23 | [0.19, 0.27] |
| $100(\sigma_{g_1})$ | $\mathcal{IG}$ | 0.50 | 5.00 | 0.38 | [0.32, 0.46] |
| $100(\sigma_{g_2})$ | $\mathcal{IG}$ | 0.50 | 5.00 | 0.43 | [0.36, 0.52] |
| $100(\sigma_{g_3})$ | $\mathcal{IG}$ | 0.50 | 5.00 | 0.31 | [0.27, 0.36] |

*Note:* Para 1 and Para 1 list s and $\nu$ 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 5—MODEL FIT: RATIO OF STANDARD DEVIATIONS. CYCLICAL COMPONENT.

| Series | $\frac{1970-1984}{1954-1970}$ | | | $\frac{1984-2006}{1970-1984}$ | | |
|---|---|---|---|---|---|---|
| | Data | Model | | Data | Model | |
| | | Median | 90% | | Median | 90% |
| Output | 1.58 | 1.46 | [1.28, 1.63] | 0.42 | 0.58 | [0.52, 0.63] |
| Investment | 1.53 | 1.96 | [1.77, 2.21] | 0.43 | 0.56 | [0.50, 0.61] |
| Consumption | 1.74 | 1.24 | [1.11, 1.39] | 0.44 | 0.68 | [0.62, 0.75] |
| Inflation | 2.56 | 1.91 | [1.66, 2.24] | 0.36 | 0.48 | [0.43, 0.57] |
| Nominal interest rate | 2.64 | 2.76 | [2.33, 3.21] | 0.50 | 0.38 | [0.33, 0.45] |
| Net worth | 1.30 | 1.55 | [1.33, 1.80] | 1.47 | 1.34 | [1.04, 1.55] |
| Spread | 2.65 | 3.48 | [2.84, 4.17] | 0.47 | 0.34 | [0.27, 0.40] |

*Note:* 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 non-stationary data generated by the model.

TABLE 6—COUNTERFACTUALS: PERCENTAGE OF THE MODEL-IMPLIED CHANGE IN CYCLICAL STANDARD DEVIATIONS.

| Counterfactual | Y | I | C | $\pi$ | $R^n$ | N | Spread |
|---|---|---|---|---|---|---|---|
| 1 | – | – | 0 | 29 | 9 | 2 | 0 |
| 2 | 11 | 13 | 17 | 3 | 22 | 15 | 26 |
| 3 | – | 5 | 0 | – | – | 4 | – |
| 4 | 4 | 17 | 13 | 2 | 19 | 15 | 26 |
| 5 | **1** | **17** | **1** | **30** | **29** | **15** | **26** |
| 6 | **83** | **61** | **96** | **53** | **44** | **73** | **45** |
| 7 | 24 | 28 | 21 | 5 | 36 | 55 | 44 |
| 8 | 67 | 40 | 92 | 49 | 13 | 25 | 2 |
| 9 | 10 | 9 | – | 29 | 8 | – | – |
| 10 | 26 | 52 | 9 | 12 | 90 | – | 115 |
| 11 | 8 | – | 3 | 4 | 6 | 6 | 0 |
| 12 | 31 | 43 | 13 | 15 | 87 | – | 115 |
| 13 | **36** | **48** | **13** | **38** | **94** | – | **115** |
| 14 | – | – | **22** | **46** | – | **186** | – |
| 15 | – | – | – | – | – | 194 | – |
| 16 | 57 | 36 | 81 | 67 | 10 | – | 1 |

*Note:* I include a dash (-) when the direction of the counterfactual implied change is at odds with the model-implied changes in volatilities.

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TABLE 7—VARIANCE DECOMPOSITION AT BUSINESS CYCLE FREQUENCIES: MEDIANS

| | Bank. cost | Wealth | Neutral | I-shock | P-Markup | W-markup | Inter | MP | Gov |
|---|---|---|---|---|---|---|---|---|---|
| **Output** | | | | | | | | | |
| Pre-1970 | 3 | 7 | 43 | 1 | 16 | 16 | 4 | 10 | 1 |
| 1970-1984 | 21 | 8 | 19 | 0 | 14 | 13 | 2 | 21 | 1 |
| Post-1984 | 6 | 5 | 27 | 2 | 19 | 27 | 4 | 7 | 1 |
| **Investment** | | | | | | | | | |
| Pre-1970 | 10 | 25 | 14 | 2 | 13 | 2 | 22 | 12 | 1 |
| 1970-1984 | 40 | 22 | 3 | 1 | 7 | 1 | 11 | 17 | 0 |
| Post-1984 | 17 | 21 | 7 | 7 | 15 | 5 | 21 | 8 | 0 |
| **Consumption** | | | | | | | | | |
| Pre-1970 | 1 | 6 | 45 | 0 | 6 | 27 | 12 | 1 | 2 |
| 1970-1984 | 4 | 10 | 29 | 0 | 8 | 29 | 16 | 2 | 2 |
| Post-1984 | 2 | 7 | 30 | 2 | 6 | 38 | 13 | 1 | 2 |
| **Hours** | | | | | | | | | |
| Pre-1970 | 6 | 11 | 4 | 2 | 27 | 27 | 7 | 16 | 3 |
| 1970-1984 | 26 | 10 | 2 | 1 | 16 | 15 | 2 | 25 | 1 |
| Post-1984 | 8 | 8 | 2 | 3 | 25 | 37 | 5 | 10 | 2 |
| **Wage** | | | | | | | | | |
| Pre-1970 | 0 | 1 | 65 | 0 | 25 | 5 | 2 | 2 | 0 |
| 1970-1984 | 1 | 2 | 43 | 0 | 36 | 7 | 4 | 7 | 0 |
| Post-1984 | 0 | 1 | 49 | 0 | 33 | 10 | 3 | 2 | 0 |
| **Inflation** | | | | | | | | | |
| Pre-1970 | 3 | 1 | 28 | 0 | 12 | 12 | 12 | 31 | 0 |
| 1970-1984 | 13 | 2 | 11 | 0 | 9 | 9 | 15 | 41 | 0 |
| Post-1984 | 4 | 1 | 21 | 1 | 16 | 22 | 11 | 25 | 0 |
| **Nominal rate** | | | | | | | | | |
| Pre-1970 | 32 | 28 | 2 | 7 | 2 | 0 | 26 | 1 | 1 |
| 1970-1984 | 63 | 17 | 1 | 1 | 1 | 0 | 17 | 0 | 0 |
| Post-1984 | 47 | 13 | 2 | 16 | 3 | 1 | 17 | 1 | 1 |
| **Net Worth** | | | | | | | | | |
| Pre-1970 | 2 | 72 | 3 | 16 | 2 | 0 | 2 | 3 | 0 |
| 1970-1984 | 16 | 61 | 1 | 12 | 1 | 0 | 1 | 7 | 0 |
| Post-1984 | 1 | 92 | 0 | 4 | 1 | 0 | 1 | 1 | 0 |
| **Spread** | | | | | | | | | |
| Pre-1970 | 71 | 25 | 0 | 1 | 0 | 0 | 2 | 0 | 0 |
| 1970-1984 | 90 | 9 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| Post-1984 | 87 | 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Note:* I use periodic components of cycles between 6 and 32 quarters. I compute the variance decomposition at the posterior median using the spectrum of the model. For output, investment, consumption, wages, and net worth, I use an inverse difference filter in order to report the decomposition for levels. I consider 500 bins for frequencies covering the periodicities of interest.

FIGURE 1. **Impulse Response Functions with respect to a wealth shock**. 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.
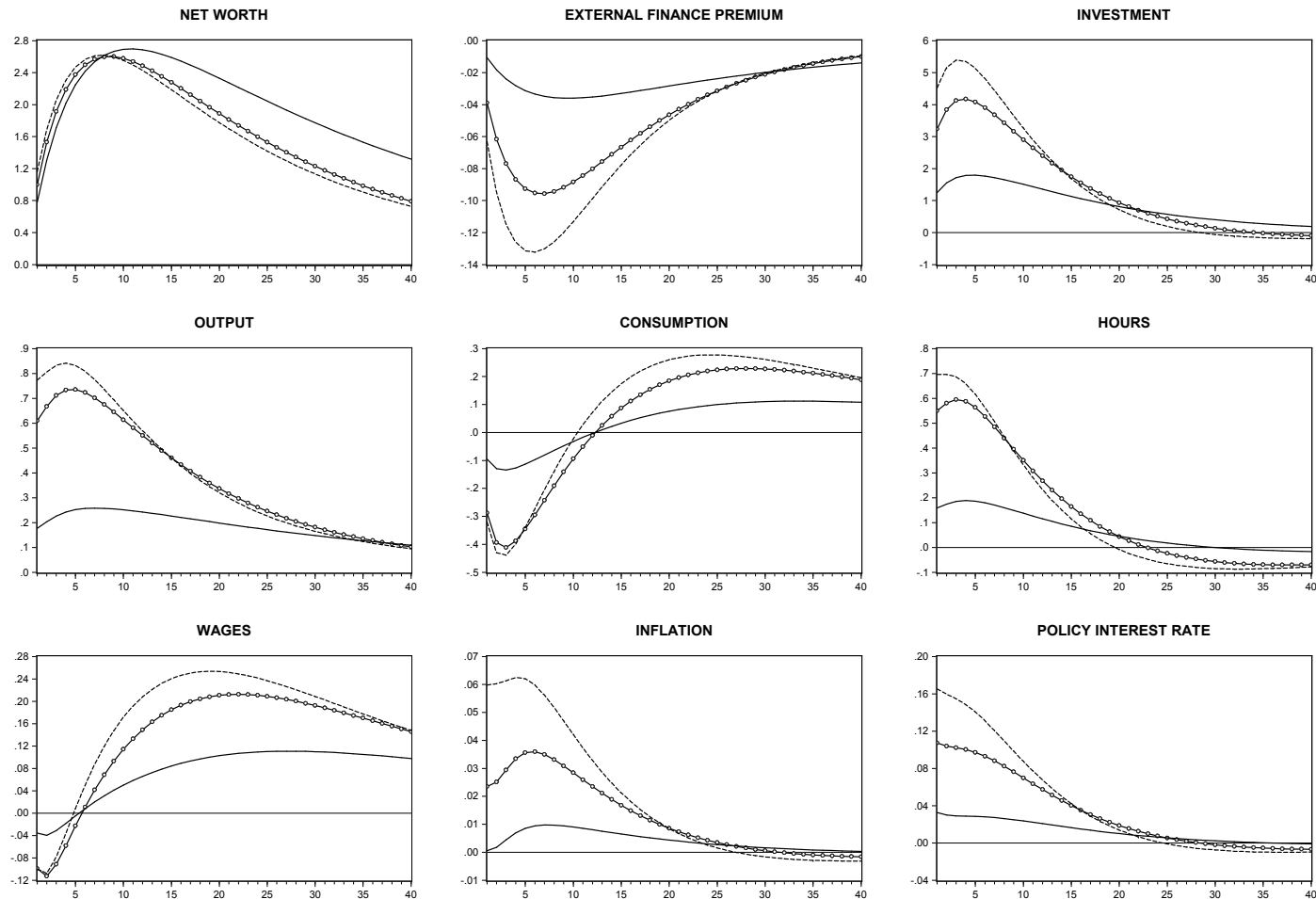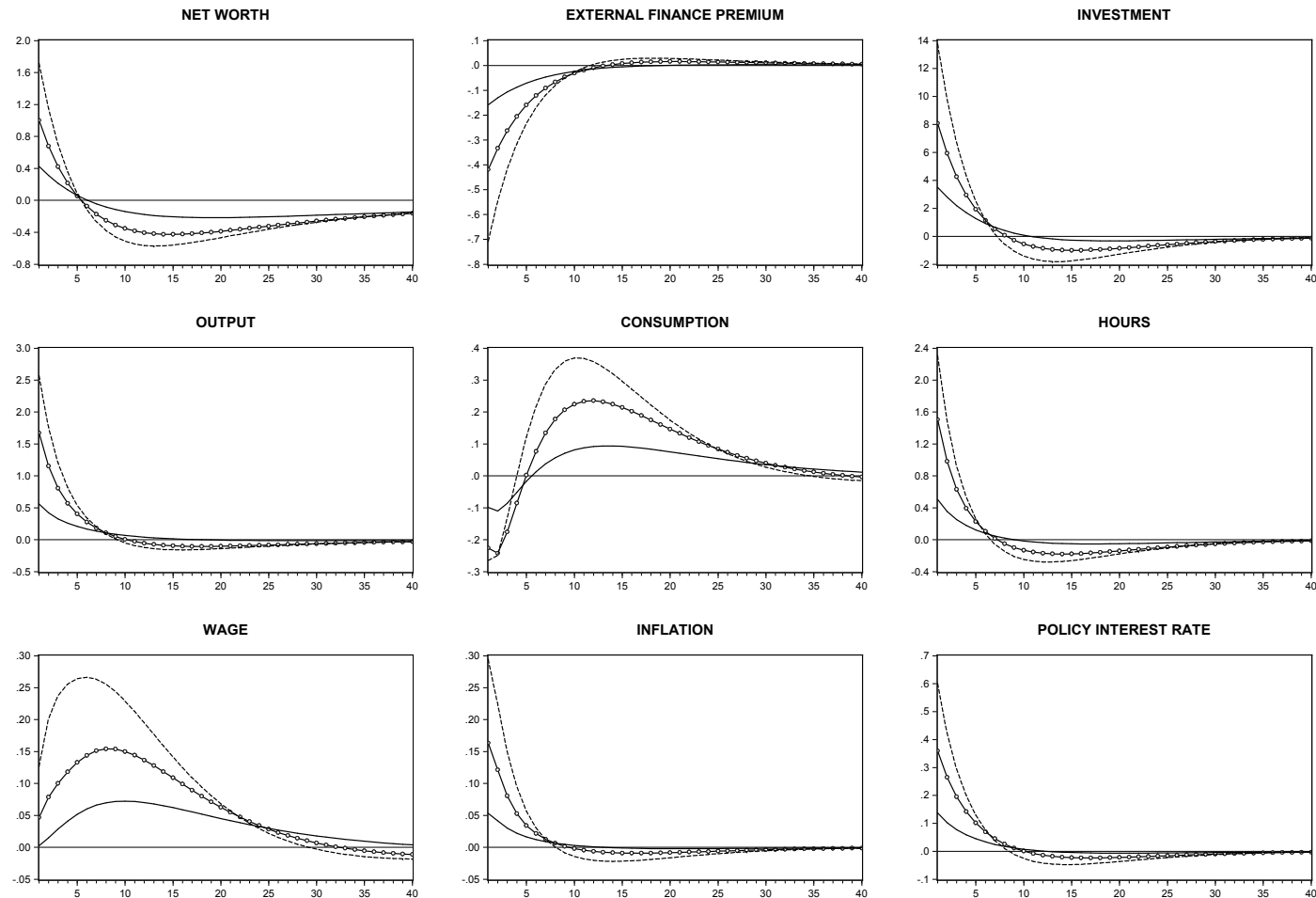
FIGURE 2. **Impulse Response Functions with respect to a shock to the marginal bankruptcy cost**. THE DOTTED LINE IS THE IRF FOR THE 1954:Q4-1970:Q1 PERIOD, THE DASHED LINE IS THE IRF FOR 1970:Q2-1984:Q2, AND THE SOLID LINE IS THE IRF FOR THE POST-1984:Q2 PERIOD.

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<div align="center">Equilibrium conditions</div>

Let $\widetilde{Y}_t = \frac{Y_t}{Z_{a,t}}$ for $C, I, K, G, W/P, B_{t+1}/P_t, NB_{t+1}/P_t, D_{t+1}/P_t, div, T, N_{t+1}$. Let $\widehat{\varsigma} = \log\left(\frac{\varsigma}{\varsigma^\star}\right)$ where $\varsigma^\star$ is the steady state value of the variable $\varsigma$. The following equations can be solved for the 27 variables $w_t, \bar{w}_t, \pi_t, H_t, \Lambda_t, \lambda_t^w, \lambda_t^p, \mathbf{3}_t, R_t, C_t, b_t, Q_t, I_t, K_t, k_t, \zeta_t, G_t, R_t^k, r_t^k, Y_t, u_t, \chi_t, B_{t+1}, \bar{\omega}_t, N_{t+1}, \mu_t, x_t$

The exogenous stochastic processes are

$$\widehat{b}_t = \rho_b \widehat{b}_{t-1} + \varepsilon_{b,t}$$
$$\widehat{\mathbf{3}}_t = \rho_z \widehat{\mathbf{3}}_{t-1} + \varepsilon_{a,t}$$
$$\widehat{\zeta}_t = \rho_\zeta \widehat{\zeta}_{t-1} + \varepsilon_{\zeta,t}$$
$$\widehat{\lambda}_t^p = \rho_{\lambda^p} \widehat{\lambda}_{t-1}^p + \varepsilon_{\lambda^p,t}$$
$$\widehat{\lambda}_t^w = \rho_{\lambda^w} \widehat{\lambda}_{t-1}^w + \varepsilon_{\lambda^w,t}$$
$$\widehat{\mu}_t = \rho_\mu \widehat{\mu}_{t-1} + \varepsilon_{\mu,t}$$
$$\widehat{x}_t = \rho_x \widehat{x}_{t-1} + \varepsilon_{x,t}$$
$$\varepsilon_{R,t}$$

The log-linearized equilibrium conditions are

$$\left(1 + \nu\frac{1+\lambda_w}{\lambda_w}\right)\widehat{\bar{w}}_t + \left(1 + \beta\xi_w\nu\frac{1+\lambda_w}{\lambda_w}\right)\widehat{w}_t = (1 - \beta\xi_w)\left(\widehat{b}_t + \widehat{\theta}_t + \nu\widehat{H}_t - \widehat{\Lambda}_t\right)$$

$$-\beta\xi_w\left(1 + \nu\frac{1+\lambda_w}{\lambda_w}\right)\mathbb{E}_t\left[\iota_w\widehat{\pi}_t + \iota_w\widehat{\mathbf{3}}_t - \widehat{\pi}_{t+1} - \widehat{\mathbf{3}}_{t+1}\right] + \beta\xi_w\left(1 + \nu\frac{1+\lambda_w}{\lambda_w}\right)\mathbb{E}_t\left[\widehat{\bar{w}}_{t+1} + \widehat{w}_{t+1}\right]$$

$$\widehat{w}_t = \widehat{w}_{t-1} - \widehat{\pi}_t - \widehat{\mathbf{3}}_t + \iota_w\widehat{\pi}_{t-1} + \iota_w\widehat{\mathbf{3}}_{t-1} + \frac{1-\xi_w}{\xi_w}\widehat{\bar{w}}_t$$

$$\widehat{\Lambda}_t = \widehat{R}_t + \mathbb{E}_t\left[\widehat{\Lambda}_{t+1} - \widehat{\pi}_{t+1} - \widehat{\mathbf{3}}_{t+1}\right]$$

$$\widehat{\Lambda}_t = \widehat{R}_t^n + \mathbb{E}_t\left[\widehat{\Lambda}_{t+1} - \widehat{\pi}_{t+1} - \widehat{\mathbf{3}}_{t+1}\right]$$

$$\widehat{\Lambda}_t = \left(\frac{\rho_z\beta h \mathbf{3}_\star - \mathbf{3}_\star h}{(\mathbf{3}_\star - \beta h)(\mathbf{3}_\star - h)}\right)\widehat{\mathbf{3}}_t + \left(\frac{\mathbf{3}_\star - \beta h\rho_b}{\mathbf{3}_\star - \beta h}\right)\widehat{b}_t - \left(\frac{\mathbf{3}_\star^2 + \beta h^2}{(\mathbf{3}_\star - \beta h)(\mathbf{3}_\star - h)}\right)\widehat{C}_t$$

$$+\left(\frac{\mathbf{3}_\star h}{(\mathbf{3}_\star - \beta h)(\mathbf{3}_\star - h)}\right)\widehat{C}_{t-1} + \left(\frac{\beta h\mathbf{3}_\star}{(\mathbf{3}_\star - \beta h)(\mathbf{3}_\star - h)}\right)\mathbb{E}_t\widehat{C}_{t+1}$$

$$\widehat{Q}_t = \xi\frac{\widetilde{I}^\star\mathbf{3}^\star}{\widetilde{K}^\star}\left(\widehat{I}_t + \widehat{\mathbf{3}}_t - \widehat{K}_t\right) - \widehat{\zeta}_t$$

$$\widehat{K}_{t+1} = \frac{1-\delta}{\mathbf{3}^\star}\left(\widehat{K}_t - \widehat{\mathbf{3}}_t\right) + \frac{\widetilde{I}^\star}{\widetilde{K}^\star}\left(\widehat{\zeta}_t + \widehat{I}_t\right)$$

<div align="center">37</div>

$$\widehat{\pi}_t = \frac{(1-\xi_p\beta)(1-\xi_p)}{(1+\iota_p\beta)\xi_p}\left[\widehat{\chi}_t + \frac{\lambda^p}{1+\lambda^p}\widehat{\lambda}_t^p\right] + \frac{\iota_p}{1+\iota_p\beta}\widehat{\pi}_{t-1} + \frac{\beta}{1+\iota_p\beta}\mathbb{E}_t\widehat{\pi}_{t+1}$$

$$\widehat{R}_t^n = \rho_R\widehat{R}_{t-1}^n + (1-\rho_R)\rho_\pi\widehat{\pi}_t + (1-\rho_R)\rho_Y\left(\widehat{Y}_t - \widehat{Y}_{t-1} + \widehat{3}_t\right) + \varepsilon_{R,t}$$

$$\widehat{k}_t = \widehat{u}_t + \widehat{K}_t - \widehat{3}_t$$

$$\widehat{r}_t^k = \frac{a_\star''}{r_\star^k}\widehat{u}_t$$

$$\widehat{Y}_t = \alpha\widehat{k}_t + (1-\alpha)\widehat{H}_t$$

$$\widehat{k}_t = \widehat{w}_t - \widehat{r}_t^k + \widehat{H}_t$$

$$\widehat{\chi}_t = (1-\alpha)\widehat{w}_t + \alpha\widehat{r}_t^k$$

$$\widehat{R}_t^k = \frac{\pi_\star r_\star^k}{R_\star^k}\widehat{r}_t^k + \frac{\pi_\star r_\star^k}{R_\star^k}\widehat{u}_t + \frac{(1-\delta)\pi_\star}{R_\star^k}\widehat{Q}_t - \widehat{Q}_{t-1} + \widehat{\pi}_t$$

$$\widehat{Q}_t + \widehat{K}_{t+1} = \frac{\widetilde{B}_\star}{\widetilde{K}_\star}\widehat{B}_{t+1} + \frac{\widetilde{N}_\star}{\widetilde{K}_\star}\widehat{N}_{t+1}$$

$$\widehat{R}_t^k - \widehat{R}_{t-1} = \widehat{B}_t - \widehat{Q}_{t-1} - \widehat{K}_t - \frac{\Gamma_\omega\left(\bar{\omega}_\star\right) - \mu_\star G_\omega\left(\bar{\omega}_\star\right)}{[\Gamma\left(\bar{\omega}_\star\right) - \mu_\star G\left(\bar{\omega}_\star\right)]}\bar{\omega}_\star\widehat{\omega}_t - \frac{G\left(\bar{\omega}_\star\right)}{[\Gamma\left(\bar{\omega}_\star\right) + \mu_\star G\left(\bar{\omega}_\star\right)]}\mu_\star\widehat{\mu}_t$$

$$\widehat{N}_{t+1} = \frac{\gamma}{\pi_\star\widetilde{N}_\star}\left[\left(R_\star^k - R_\star\right)\frac{\widetilde{K}_\star}{3_\star} + R_\star\frac{\widetilde{N}_\star}{3_\star} - \mu_\star R_\star^k\frac{\widetilde{K}_\star}{3_\star}G\left(\omega_\star\right)\right](\widehat{x}_t - \widehat{\pi}_t)$$

$$+\frac{\gamma}{\pi_\star\widetilde{N}_\star}R_\star^k\frac{\widetilde{K}_\star}{3_\star}\left(1 - \mu_\star G\left(\omega_\star\right)\right)\widehat{R}_t^k + \frac{\gamma}{\pi_\star\widetilde{N}_\star}\frac{\widetilde{K}_\star}{3_\star}\left[R_\star^k\left(1 - \mu_\star G\left(\omega_\star\right)\right) - R_\star\right]\left(\widehat{Q}_{t-1} + \widehat{K}_t\right)$$

$$+\frac{\gamma}{\pi_\star\widetilde{N}_\star}\frac{1}{3_\star}\left(\widetilde{K}_\star\left(R_\star - R_\star^k\left(1 - \mu_\star G\left(\omega_\star\right)\right)\right) - R_\star\widetilde{N}_\star\right)\widehat{3}_t + \frac{\gamma}{\pi_\star\widetilde{N}_\star}\frac{\widetilde{R}_\star}{3_\star}\left(\widetilde{N}_\star - \widetilde{K}_\star\right)\widehat{R}_{t-1}$$

$$+\frac{\gamma}{\pi_\star}\frac{R_\star}{3_\star}\widehat{N}_t - \frac{\gamma}{\pi_\star\widetilde{N}_\star}\mu_\star R_\star^k\frac{\widetilde{K}_\star}{3_\star}G\left(\omega_\star\right)\widehat{\mu}_t - \frac{\gamma}{\pi_\star\widetilde{N}_\star}\mu_\star R_\star^k\frac{\widetilde{K}_\star}{3_\star}G_\omega\omega_\star\widehat{\omega}_t$$

$$\frac{1}{g}\widehat{Y}_t - \frac{1}{g}\widehat{g}_t = \frac{\widetilde{C}_\star}{\widetilde{Y}_\star}\widehat{C}_t + \frac{\widetilde{I}_\star}{\widetilde{Y}_\star}\widehat{I}_t + \mu_\star R_\star^k\frac{G\left(\bar{\omega}_\star\right)\widetilde{K}_\star}{\widetilde{Y}_\star 3_\star}\widehat{\mu}_t + r_\star^k\frac{\widetilde{K}_\star}{\widetilde{Y}_\star 3_\star}\widehat{u}_t$$

$$+\frac{\mu_\star G\left(\bar{\omega}_\star\right)R_\star^k\widetilde{K}_\star}{\widetilde{Y}_\star 3_\star}\left[\widehat{R}_t^k + \widehat{Q}_{t-1} + \widehat{K}_t - \widehat{3}_t + \frac{G_\omega(\bar{\omega}^\star)}{G(\bar{\omega}_\star)}\bar{\omega}_\star\widehat{\omega}_t\right]$$

$$\Phi_r\left[\mathbb{E}_t\widehat{R}_{t+1}^k - \widehat{R}_t\right] = \Phi_\omega\bar{\omega}_\star\mathbb{E}_t\widehat{\omega}_{t+1} + \Phi_\mu\mu_\star\mathbb{E}_t\widehat{\mu}_{t+1}$$

where

$$\Phi_r = \left[(1 - \Gamma\left(\bar{\omega}_\star\right)) + \Psi\left(\bar{\omega}_\star, \mu_\star\right)\left(\Gamma\left(\bar{\omega}_\star\right) - \mu_\star G\left(\bar{\omega}_\star\right)\right)\right]\frac{R_\star^k}{R_\star}$$

$$\Phi_\omega = \frac{R_\star^k}{R_\star}\left[\Gamma_\omega(\bar\omega_\star)(1-\Psi(\bar\omega_\star,\mu_\star))-\Psi_\omega(\bar\omega_\star,\mu_\star)(\Gamma(\bar\omega_\star)-\mu_\star G(\bar\omega_\star))+\mu_\star\Psi(\bar\omega_\star,\mu_\star)G_\omega(\bar\omega_\star)\right]$$
$$+\psi_\omega(\bar\omega_\star,\mu_\star)$$

$$\Phi_\mu = \Psi_\mu(\bar\omega_\star,\mu_\star)-\frac{R_\star^k}{R_\star}\left(\Psi_\mu(\bar\omega_\star,\mu_\star)(\Gamma(\bar\omega_\star)-\mu_\star G(\bar\omega_\star))-\Psi(\bar\omega_\star,\mu_\star)G(\bar\omega_\star)\right)$$

$$F(\bar\omega) = \int_0^{\bar\omega}\frac{1}{\omega\sigma_\omega\sqrt{2\pi}}e^{-\frac{\left(\ln(\omega)+0.5\sigma_\omega^2\right)^2}{2\sigma_\omega^2}}d\omega = \Phi\left(\frac{\ln(\bar\omega)+0.5\sigma_\omega^2}{\sigma_\omega}\right)$$

$$F_\omega(\bar\omega) = \frac{1}{\bar\omega\sigma_\omega\sqrt{2\pi}}e^{-\frac{\left(\ln(\bar\omega)+0.5\sigma_\omega^2\right)^2}{2\sigma_\omega^2}}$$

$$F_{\omega\omega}(\bar\omega) = -\frac{1}{\bar\omega}F_\omega(\bar\omega)\left[1+\frac{\ln(\bar\omega)+0.5\sigma_\omega^2}{\sigma_\omega^2}\right]$$

$$G(\bar\omega) = \int_0^{\bar\omega}\omega f(\omega)d\omega = 1-\Phi\left(\frac{0.5\sigma_\omega^2-\ln(\bar\omega)}{\sigma_\omega}\right)$$

$$G_\omega(\bar\omega) = \bar\omega F_\omega(\bar\omega)$$

$$\Gamma(\bar\omega) = \int_0^{\bar\omega}\omega f(\omega)d\omega+\bar\omega\int_{\bar\omega}^{\infty}f(\omega)d\omega = \bar\omega(1-F(\bar\omega))+G(\bar\omega)$$

$$\Gamma_\omega(\bar\omega) = 1-F(\bar\omega)$$

$$\Psi(\bar\omega,\mu) = \frac{\Gamma_\omega(\bar\omega)}{\Gamma_\omega(\bar\omega)-\mu G_\omega(\bar\omega)}$$

$$\Psi_\omega(\bar\omega,\mu) = \frac{-F_\omega(\bar\omega)[1-F(\bar\omega)-\mu\bar\omega F_\omega(\bar\omega)]-[1-F(\bar\omega)][-F_\omega(\bar\omega)-\mu F_\omega(\bar\omega)-\mu\bar\omega F_{\omega\omega}(\bar\omega)]}{(1-F(\bar\omega)-\mu\bar\omega F_\omega(\bar\omega))^2}$$

$$\Psi_\mu(\bar\omega,\mu) = \frac{G_\omega(\bar\omega)\Psi(\bar\omega,\mu)}{\Gamma_\omega(\bar\omega)-\mu G_\omega(\bar\omega)}$$

The state-space representation used in the estimation exercise requires the explicit computation of the steady state for the model economy. Given the parameters, we directly have

$$\mathfrak{Z}_\star = e^{\Upsilon}$$
$$R_\star^n = R_\star = \frac{\mathfrak{Z}_\star\pi_\star}{\beta}$$
$$\varphi_\star = \frac{\ln(\bar\omega_\star)+0.5\sigma_\omega^2}{\sigma_\omega}$$
$$F_\omega(\bar\omega_\star) = \frac{1}{\bar\omega_\star\sigma_\omega\sqrt{2\pi}}e^{-\frac{\left(\ln(\bar\omega_\star)+0.5\sigma_\omega^2\right)^2}{2\sigma_\omega^2}}$$
$$F_{\omega\omega}(\bar\omega_\star) = -\frac{1}{\bar\omega_\star}F_\omega(\bar\omega_\star)\left[1+\frac{\ln(\bar\omega_\star+0.5\sigma_\omega^2)}{\sigma_\omega^2}\right]$$
$$G(\bar\omega_\star) = \Phi(\varphi_\star-\sigma_\omega)$$

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$$
\begin{aligned}
G_\omega(\bar{\omega}_\star) &= \bar{\omega}_\star F_\omega(\bar{\omega}_\star) \\
\Gamma(\bar{\omega}_\star) &= \bar{\omega}_\star \left[1 - F(\bar{\omega}_\star)\right] + G(\bar{\omega}_\star) \\
\Gamma_\omega(\bar{\omega}_\star) &= 1 - F(\bar{\omega}_\star) \\
\chi_\star &= \frac{1}{1 + \lambda_\star^p}
\end{aligned}
$$

Then

$$
\begin{aligned}
R_\star^k &= R_\star \left(\frac{R^k}{R}\right) \\
r_\star^k &= \frac{R_\star^k}{\pi_\star} - (1 - \delta) \\
w_\star &= \left[\frac{\chi_\star \alpha^\alpha (1 - \alpha)^{1-\alpha}}{(r_\star^k)^\alpha}\right]^{\frac{1}{1-\alpha}} \\
\left[\frac{I}{K}\right]_\star &= 1 - \frac{(1 - \delta)}{\mathfrak{Z}_\star} \\
k_\star &= \frac{\alpha}{1 - \alpha} \frac{w_\star}{r_\star^k} H_\star
\end{aligned}
$$

Let us rewrite the latter as $\frac{k_\star}{y_\star} = \frac{\alpha}{1-\alpha} \frac{w_\star}{r_\star^k} \frac{H_\star}{y_\star}$ and let $\phi = \frac{\Phi}{y_\star}$. Then, from the production technology, we have

$$
\frac{k_\star}{Y_\star} = (1 + \phi) \left(\frac{\alpha}{1 - \alpha} \frac{w_\star}{r_\star^k}\right)^{1-\alpha}
$$

and, hence,

$$
\begin{aligned}
\frac{K_\star}{Y_\star} &= \frac{k_\star}{Y_\star} \mathfrak{Z}_\star \\
\frac{I_\star}{Y_\star} &= \frac{I_\star}{K_\star} \frac{K_\star}{Y_\star} \\
\frac{C_\star}{Y_\star} &= \frac{1}{g} - \frac{I_\star}{Y_\star} - \mu_\star G(\bar{\omega}_\star) R_\star^k \frac{K_\star}{\mathfrak{Z}_\star Y_\star}
\end{aligned}
$$

From the zero profit condition in the financial contract, we have

$$
\frac{B_\star}{K_\star} = \frac{R_\star^k}{R_\star} \left[\Gamma(\bar{\omega}_\star) - \mu_\star G(\bar{\omega}_\star)\right]
$$

which implies

$$
B_\star = \frac{B_\star}{K_\star} K_\star
$$

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$$N_\star = K_\star - B_\star$$
$$W_\star^e = N_\star - \gamma \left[ R_\star^k \frac{K_\star}{3_\star} - R_\star \frac{B_\star}{3_\star} - \mu_\star G(\bar{\omega}_\star) R_\star^k \frac{K_\star}{3_\star} \right]$$

As $Y_\star = \frac{k_\star}{k_\star/Y_\star}$, we can compute $X_\star = \frac{X_\star}{Y_\star} Y_\star$ where $X$ stands for consumption, investment, and physical capital. Finally, $\Lambda_\star = \frac{3_\star - \beta h}{C_\star(3_\star - h)}$

DATA

We use US data from NIPA-BEA,CPS-BLS, the FRED database, and the Flow of Funds accounts from the Federal Reserve Board for the period 1954.4-2006.4.

### B1. 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. We have deflated such a series using the implicit price index from Table 1.3.4. We 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 we 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. We 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 business sector in total GDP. Finally, we do the same correction described above to render the investment series in per capita quarterly terms.

- *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. We 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 business sector in total GDP. Finally, we do the same correction described above to have the series in per capita quarterly terms.

- *Growth rate of net worth.* We define net worth as the real per capita weighted average of net worth for the corporate and noncorporate nonfarm business sector. To ensure that the measure of net worth from the data is close enough to the series the model can actually account for, we define net worth as tangible assets minus credit market instruments at market value. On the one hand, we use tangible assets only as a measure for assets because, in our model, collateral is related only to physical capital and inventories;

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that is, there is no role for financial capital. On the other hand, we evaluate net worth at current (market) prices, since such a variable in our theoretical framework stands for the value of the collateral perceived by lenders. Credit market liabilities from the Flow of Funds accounts (the weighted sum of series FL104104005.Q from Table B.102 and series FL114102005.Q from Table B.103) stand for entrepreneurial debt. Tangible assets are given by the weighted sum of series FL102010005.Q from Table B.102 and series FL112010005.Q from Table B.103.

- *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 civilian population over 16 (CE16OV) to a population index. The population index is equal to the ratio of population at the corresponding quarter divided by the population in the third quarter of 2005. This transformation is necessary, since the series on hours is an index with 2005=100.

- *Growth rate of real wages*. Real wages are defined as the real compensation per hour in the nonfarm business sector (COMPRNFB) provided by the BLS.

- *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).

- *Credit spread* is defined as the difference between the Moody's Seasoned Baa Corporate Bond Yield and the federal funds rate. We use the spread in gross quarterly terms and take logs.

### B2.   Data used in the empirical evidence section

In addition to the series described above, we also consider the following ones.

- *Net private savings*: Data on nominal net private savings are available in NIPA Table 5.1. We have deflated such a series using the implicit price index from Table 1.3.4. We 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 we divide by 4 to obtain quarterly values for the measures of interest. We weight the resulting series using the relative significance of the nonfarm business sector in total GDP.

- *Debt in the nonfarm business sector*: We define debt as the real per capita weighted average of credit market liabilities for the corporate and noncorporate nonfarm business sector. Debt is defined as the weighted sum of series FL104104005.Q from Table B.102 and series FL114102005.Q from Table B.103.

- *Net worth of households (and nonprofit organizations)*: It is given by the real per capita transformation of the series FL152090005 from Table B.100 from the Flow of Funds Accounts.

- *Demand deposits*: It stands for real per capita demand deposits at commercial banks provided by the series DEMDEPSL in the FRED database. Data are available from 1959.

- *Corporate bond spread (Baa-Aaa)*: It is defined as the spread of the Moody's Seasoned Baa Corporate Bond Yield and the Moody's Seasoned Aaa Corporate Bond Yield. We consider the log of the gross quarterly counterpart. The data are available in the FRED database.

- *Credit spread (Baa-10y)*: It 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. We consider the log of the gross quarterly counterpart.

- *Wilshire 5000 index*: Wilshire 5000 Total Market Full Cap Index, which includes total market returns (reinvested dividends are included). The series is deflated using the implicit price deflator for the gross value added by the nonfarm business sector. This series is available since 1971:Q1.

### METHODOLOGY

#### C1.   MCMC Algorithm

1) **Posterior Maximization**: The aim of this step is to obtain the parameter vector to initialize our posterior simulator. To obtain the posterior mode, $\widetilde{\varrho}$, we iterate over the following steps:

   a) Fix a vector of structural parameters $\varrho'$.

   b) Solve the DSGE model conditional on $\varrho'$ and compute the system matrices. We restrict ourselves to the determinacy region of the parameter space.

   c) Use the Kalman filter to compute the likelihood of the parameter vector $\varrho'$, $p(Y^T|\varrho')$.

   d) Combine the likelihood function with the prior distribution.

2) Compute the **numerical Hessian** at the posterior mode. Let $\widetilde{\Sigma}$ be the inverse of such a numerical Hessian.

3) Draw the initial parameter vector, $\varrho^{(0)}$, from $\mathcal{N}(\widetilde{\varrho}^{(0)}, c_0^2\widetilde{\Sigma})$ where $c_0$ is a scaling parameter. Otherwise, directly specify a starting value for the posterior simulator.

4) **Posterior Simulator:** for $s = 1, ..., n_{sim}$, draw $\vartheta$ from the proposal distribution $\mathcal{N}\left(\varrho^{(s-1)}, c^2\widetilde{\Sigma}\right)$, where $c$ is a scaling parameter.[6] The jump from $\varrho^{(s-1)}$ is accepted with probability $\min\{1, r\left(\varrho^{(s-1),\vartheta|Y}\right)\}$, and rejected otherwise. Note that

(C1) $$r\left(\varrho^{(s-1),\vartheta|Y}\right) = \frac{\mathcal{L}(\vartheta|Y)p(\vartheta)}{\mathcal{L}(\varrho^{(s-1)}|Y)p(\varrho^{(s-1)})}$$

5) Approximate the expected value of a function $h(\varrho)$ by $\frac{1}{n_{sim}}\sum_{s=1}^{n_{sim}} h(\varrho^{(s)})$.

### C2.    Variance Decomposition

Our data set contains the following series $\Delta Y, \Delta I, \Delta C, \Delta N, \Delta W, \log(H)$, $\log\left(1 + \frac{\pi}{400}\right), \log\left(1 + \frac{R^n}{400}\right), \log\left(1 + \frac{Baa - R^n}{400}\right)$. We are interested, however, in the second moments and dynamic properties of $\log(Y), \log(I), \log(C), \log(N)$, $\log(W), \log(H), \log\left(1 + \frac{\pi}{400}\right), \log\left(1 + \frac{R^n}{400}\right), \log\left(1 + \frac{Baa - R^n}{400}\right)$. Therefore, we use an inverse difference filter for the first five components on the spectrum implied by the DSGE model. The spectral density is obtained using the state-space representation of the DSGE model and 500 bins for frequencies in the range of periodicities of interest. In particular, we compute the variance decomposition at business cycle frequencies, that is, we focus on those periodic components with cycles between 6 and 32 quarters.

Let $X_t$ be univariate data in log-levels and $Y_t = (1 - L) X_t$. Note that

$$X_t = (1 - L)^{-1} Y_t = \sum_{h=0}^{\infty} L^h Y_{t-h} = \sum_{h=0}^{\infty} exp(-i\omega jh)Y_{t-h}$$

Then, the spectral density of $X_t$ is given by

$$s_X(\omega) = \left|\sum_{h=0}^{\infty} exp(-i\omega jh)\right|^2 s_Y(\omega)$$

which can be approximated by

$$s_X(\omega) = \left|\frac{1}{1 - exp(-i\omega jh)}\right|^2 s_Y(\omega)$$

at any frequency but 0.

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[6]The scale factor is set to obtain efficient algorithms. Gelman et al. (2004) argue that the scale coefficient should be set to $c \approx 2.4\sqrt{d}$, where $d$ is the number of parameters to be estimated. However, we will fine tune the scale factor to obtain a rejection rate of about 25%