Three Essays on Monetary Policy and Macroeconomic Stability

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Abstract

Three Essays on Monetary Policy and Macroeconomic Stability

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The three chapters of the thesis are centered around monetary policy and macroeconomic stability. In the first chapter, a DSGE model is simulated and estimated to evaluate the macroeconomic effect of credit-demand shocks versus credit- supply shocks. The model features two financial shocks originating on the credit-demand side and one shock originating on the credit-supply side. Model simulations show that credit-demand shocks could generate significant macroeconomic fluctuations, up to three times the impact of credit-supply shocks. Bayesian estimation of the parameters of the shocks and variance decomposition show that credit-demand shocks caused 17% of the fluctuation in output. The second paper investigates the role of monetary policy in the rise of household debt in the periods leading to the Great Recession. A Factor-Augmented Vector Autoregression (FAVAR) model is estimated in multiple periods. Tests of stability of the estimated coefficients suggest the existence of a structural break, which is interpreted as a change in the transmission mechanism in periods of low versus high household debt. Monetary policy shocks during both periods are identified by Cholesky decomposition. The paper shows that during the period of higher household debt, the volatility of monetary policy shocks was lower and the impulse responses of output and household debt to monetary policy shocks were stronger. Estimates of monetary policy reaction functions in the two periods suggest the stronger response of output and household debt in the second period might have been due to a combination of a stronger transmission mechanism and a weaker monetary policy reaction. The final chapter of the thesis investigates whether monetary policy surprises affect home equity excess returns, and whether the effect transmits through expected future interest rates, expected future dividends, or expected future excess returns. Home equity excess returns are decomposed into three components using a forecasting VAR model. The three decomposed components are then used to estimate a VAR model where monetary policy shocks are identified by Cholesky decomposition. Analysis of the generated impulse responses shows that, unlike its effect on stock equity returns, the effect of monetary policy surprises on home returns transmits through interest rate and future dividends channels more than through the risk premium channel.

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Chapter 1

The Role of Credit Demand and Credit Supply Shocks in Macroeconomic Fluctuations

Introduction

During the recent financial crisis, the global economy in general and the U.S. economy in particular have experienced the worst financial crisis and the worst recession in decades. A series of dramatic losses left major financial institutions with severe liquidity problems and sent the global economy into a deep recession. The policy response to these events was swift and somewhat successful in containing the damage and in preventing another depression. However, the failure to predict the crisis, the inability to identify the causes of the crisis, and the apparent ineffectiveness of traditional monetary policy to stimulate the economy have raised many questions about our understanding of the interaction between the financial sector and the real economy. Consequently, a new wave of academic research on the monetary transmission mechanism has begun to address some of the shortcomings in the literature and fill in some of the gaps.

The macroeconomic literature views of the role of the financial sector in macroeconomic dynamics have evolved in the past twenty-five years from that of a propagator of real shocks, through many financial frictions, to a sector that in itself is a source of shocks that are able to cause significant fluctuations in real macroeconomic variables. Financial shocks are those that affect the amount of credit in the economy and can be divided into two broad categories: credit demand shocks and credit supply shocks. An emerging strand in the literature has focused on evaluating, theoretically and empirically, the relative importance of the quantitative effect of financial and real shocks on macroeconomic variables. This paper contributes to this emerging strand in two ways. The first is theoretical and it investigates the effect of credit demand shocks through the bank credit channel. The second is empirical, which estimates a dynamic stochastic general equilibrium (DSGE) model by Bayesian methods to evaluate the contribution of a number of real and financial shocks in macroeconomic fluctuations with particular emphasis on the Great Recession. To this end, the paper also belongs to the literature that investigates the causes of the recent financial crisis.

A DSGE model very similar to the one introduced by Meh and Moran (2010) is built and is estimated by Bayesian methods. The model features financial frictions in the form of a double agency problem between banks and entrepreneurs on the one hand and banks and depositors on the other. A financial contract between depositors, banks, and entrepreneurs emerges as a solution to this double agency problem to guarantee that banks always monitor the actions of entrepreneurs and that entrepreneurs always choose the project with the highest probability of success. These financial frictions give rise to what Meh and Moran called the bank capital channel which, according to Meh and Moran (2010), propagates the effect of technological and monetary policy shocks. The model features three financial shocks: bank capital shock, entrepreneurial capital shock, and risk shock. Bank capital shocks affect the supply of credit by increasing the depreciation of bank capital. Entrepreneurial capital shocks affect the demand for credit by affecting the capital of entrepreneurs.

Risk shocks also affect the demand of credit but through altering the return on entrepreneurial projects. The risk shock captures the idiosyncratic risk in actual business ventures which makes it comparable to the risk shock in Christiano, Motto, and Rostagno (2014) which, according to their study, is the most important shock driving the business cycle. In addition, the model features four more shocks; technological shock, monetary policy shock, price mark-up shock, and wage mark-up shock.

The paper first evaluates the effect of credit demand shocks and compare it to the effect of entrepreneurial capital shock and that of the risk shock. Secondly, the DSGE model is estimated by Bayesian methods and variance decomposition of key macroeconomic variables are constructed to uncover the relative importance of the role that real and financial shocks have played in the fluctuations of real macroeconomic variables during the periods leading to the Great Recession.

The paper has two main findings: the first is that although shocks in the financial sector caused significant macroeconomic fluctuations in the periods leading to the great recession, the technological shock still is the leading source. Credit demand shocks, the entrepreneurial risk shock in particular, account for about 17% of fluctuations in output since 1988 compared to more than 80% for technology and mark-up shocks. The second finding is that the macroeconomic effect of credit demand shock is more significant than that of credit supply shock. While the effect of risk shocks is comparable to the effect of bank capital shock, the effect of entrepreneurial capital shocks is more than three times that of bank capital shocks.

The paper is organized as follows: the related literature is reviewed in the following section and the DSGE model is presented in section 1.2. The macroeconomic effect of financial shocks are discussed in section 1.3. The estimation methodology and results are presented in section 1.4 and section 1.5 concludes.

1.1 The Great Recession, Literature Review

The contraction of total lending by financial institutions during downturns might reflect a leftward shift of either the supply of credit or the demand of credit. The role of financial shocks, that affect the demand or supply of credit, in causing the business cycle has been at the center of macroeconomic research since the Great Recession in 2007-2008. The literature can be divided into two broad categories: the first is purely empirical where researchers have used reduced form econometric models to assess and quantify the role of financial shocks. The other is structural in which researchers have either calibrated or estimated DSGE models to evaluate the role of financial shocks in causing the business cycle in general and the Great Recession in particular.

One of the earliest empirical analysis of the Great Recession was performed by Gilchrist, Ortiz, and Zakrajsek (2009) where they analyze the informational content of bond spreads of a large panel of non-financial firms over the period 1990-2008. Using factor-augmented vector autoregression (FAVAR) model they concluded that shocks to credit spreads (i.e. widening of corporate bond spreads) accounts for more than 30% of the variation in economic activity. In a subsequent work and using a larger data set starting from 1970, Gilchrist and Zakrajšek (2012) constructed a high-information credit spreads index and decomposed it into two components: one that captures the systemic movements in default risk and a residual component, which they refer to as excess bond premium. They then estimated a vector auto regression (VAR) model and found that shocks to excess bond premium, interpreted as credit supply shocks due to financial institutions having less appetite for risk, cause significant declines in consumption, investment, and output as well as in equity prices. In a comprehensive study, Stock and Watson (2012) used a high-dimensional dynamic factor model (DFM) and 200 macroeconomic and financial series driven by six macro factors to identify the economic shocks that triggered the Great Recession. They considered six shocks to: oil markets, monetary policy, fiscal policy, productivity, uncertainty, liquidity and financial risk. They found that the Great Recession was initially caused by oil price shocks followed by a large financial and uncertainty shocks.

Although all the three above-mentioned studies have highlighted the important role that financial shocks played in the events leading to the Great Recession, the interpretation of these shocks as credit demand or credit supply shocks is dubious at best. In constructing financial shocks, they used various measures of credit spreads and VIX index of implied volatility of S&P500 Index. For example, if an econometric model is used to identify shocks to a credit spread, it would be impossible to classify the identified shocks as credit supply or credit demand shocks since movements in credit spreads can be a result of changes in either demand or supply of credit. In this case the use of structural model is important. The same is true about shocks identified by implied volatility indices since movements in stock and asset prices simultaneously affect the balance sheet of borrowers and lender.

Applied monetary economists, on the other hand, were unable to tell their version of the story about the causes of the Great Recession, likely due to the fact that only few theoretical models of monetary policy included either an explicit financial sector or financial shocks. Therefore, immediately after the crisis the focus was to develop theoretical models that feature financial sectors and could resemble the kind of dynamics experienced during the crisis.[1]

One of the first quantitative studies of the crisis was conducted by Del Negro et al. (2010) using the same framework proposed by Kiyotaki and Moore (1997b). They assessed whether a liquidity shock could generate fluctuations in macroeconomic

[1] These models were developed during 2008-2010 and the literature is still in its infancy.

and financial variables similar to what was observed during the recession of 2007-2008. In their model, there is no borrowing and lending in their model and the only way of financing a new investment project is by issuing new equity and by selling existing equity holdings. A negative liquidity shock in this context freezes equity holdings and constrained the amount of fund that could be raised to finance a given investment project. Therefore, one can arguably interpret liquidity shocks as credit supply shocks. They concluded that in an economy that exhibits price and wage rigidities, liquidity shocks capture the 2008 US financial crisis.

Within the same theoretical framework of Kiyotaki and Moore (1997b) featuring price and wage rigidities, Mimir (2010) studied the effect of what he called a financial intermediation shock on real macroeconomic variables.[2] With the existence of a financial intermediation sector as equity market maker, financial intermediation shocks affect the cost of selling equities to finance investment projects and, therefore, can be interpreted as credit supply shock. Ajello (2010) estimated the model by Bayesian methods and concluded that financial intermediation shocks account for 40% of variation in the Gross Domestic Product (GDP) and 70% of investment volatility.

In a more complex environment, Christiano, Rostagno, and Motto (2010) built a DSGE model incorporating financial frictions in the form of costly state verification as well as featuring financial intermediaries. The model also features sixteen shocks including two financial shocks, a wealth shock and what they coined a risk shock.[3] Although the two shocks originates in the demand side of the credit market, the entrepreneurial sector, the two shocks simultaneously affect supply and demand for credit.[4] They estimated the model by Bayesian methods and concluded that risk

[2]Identified by using high-yield corporate bond spread as one of the observed variables.

[3]The risk shock is the idiosyncratic shock affecting the riskiness of loans extended to entrepreneurial activities. Its magnitude depends on a time varying standard deviation which is a realization of a stochastic process.

[4]Note that a credit demand shock means that the shock originates in the demand side of the market. However, it can affect credit supply as well.

shocks account for" significant portion of business cycle fluctuations" and that "the full magnitude of the GDP drop in the 2007-2008 recession can be accounted for by the risk shock".

Jermann and Quadrini (2012) used two models and two methodological estimation approaches to evaluate the macroeconomic effects of financial shocks in light of the Great Recession. Financial shocks in this environment affect the demand for credit and they could be interpreted as shocks affecting the liquidity of the firm's assets. In the first part of the paper, they simulated a model exhibiting only two shocks, namely productivity and the financial shock and concluded that financial shocks are important in capturing the dynamics of financial flows and real business cycle variables. They also highlighted the role financial shocks played in limiting firms' ability to borrow during 2008-2009 as a result of the economic downturn that started in 2007. In the second part of the paper, they evaluated the macroeconomic effects of financial shocks relative to other shocks. they did so by estimating a richer DSGE model, exhibiting eight shocks, by Bayesian maximum likelihood.[5] They found that financial shocks contribute to almost 50% of variation in output and about 30% of volatility of working hours.

Iacoviello (2010) estimated a DSGE model featuring a financial intermediary sector and five shocks including three financial shocks: redistribution shocks (transfers of wealth from savers to borrowers that take place in the event of default), credit squeezes (changes in maximum loan-to-value ratios), and asset price shocks (changes in the value of collateral). Redistribution sand asset price shocks originates in the demand side of the credit market while credit squeezes shock is a regulatory shock hitting the supply side. The paper found that more than 50% of the decrease in private GDP during the Great Recession was due to financial shocks. Among the

[5] The number of shocks are larger here because unlike the calibration method, Bayesian estimation is sensitive to number of shocks. Also note that from the eight shocks included in the model, there is only one financial shock which is the same shock included in their first experiment.

three financial shocks, a negative asset price shocks that constraints the ability of entrepreneurs to borrow money seem to have the largest contribution to the drop in output and investment during the great Recession. Furthermore, he emphasized that business cycles are financial rather than real and are mostly caused by a disruption of the flow of resources between agents.

In a slightly different model, Mimir (2010) applied a different methodology by constructing time series of financial shocks using data on credit spread, the leverage ratio, the deposit rate, and net worth. The financial shock in this economy affects the supply of credit, namely the net worth of banks, and constraints the ability of banks to borrow and ultimately affects how much credit banks can extend to firms. The paper found that the U.S. economy was hit hard by negative financial shocks during the Great Recession. Using these constructed time series shocks, the model was able to simulate and generate financial and real dynamics similar to what was observed during the Great Recession.

Although these quantitative studies reached the same conclusion regarding the significance of financial shocks in originating and propagating the downturn experienced in the Great Recession, they differ in terms of identifying the form of the financial shocks and in terms of the transmission channel(s) through which financial shocks affect real macroeconomic variables. Consequently, their conclusions have very different policy implications and different intuitive interpretations about the causes of the Great Recession.

This paper differs from the existing literature by comparing the macroeconomic effect of shocks originating from both sides of the credit market. In other words, the paper investigates the significance of credit demand shocks versus credit supply shocks in macroeconomic fluctuations. The closest work in the literature is the research done by Christiano, Motto, and Rostagno (2014) where they studied the effect of credit demand and credit supply shocks. Their work, however, differs in terms of model features and the specification of financial shocks.

1.2 The Model

The model that is used in this paper is very similar to that proposed by Meh and Moran (2010) and it incorporates the double moral hazard framework of Holmstrom and Tirole (1997) and Chen (2001). In the model, entrepreneurs borrow from banks to undertake entrepreneurial projects. Banks, in turn, finance these loans by receiving uninsured deposits from investors (investors and depositors are used interchangeably throughout the paper). Entrepreneurs can engage in shirking behavior and influence their technology's probability of success. Banks might choose not to monitor entrepreneurs since monitoring is costly. As a result of the first moral hazard, banks require entrepreneurs to invest their own net worth in the projects in order to borrow money. Investors, on the other hand, know that banks have incentives not to monitor and pass the losses to investors since monitoring is costly. As a result of this second moral hazard, investors require banks to invest their own capital in the projects in order to receive funding from investors. Consequently, fluctuation in the net worth of entrepreneurs (entrepreneurs capital channel) and in banks' capital (bank capital channel) would have macroeconomic implications.[6] The endogeneity of bank capital in the model creates what Meh and Moran called bank capital channel through which bank capital influence the business cycle. The model presents a natural way of the lending process extended by banks and therefore, allows for the study of the dynamic interactions between both sides of the credit market on one hand, and real macroeconomic variables on the other. Another key element in the model is the presence of financial contracts between banks and entrepreneurs that

[6]This also captures the financial stress experienced by many banks in the recent financial crisis of 2007-2008. An alternative way to model bank financial stress is by focusing on the liquidity mismatch in the bank's short-term liabilities and long-term assets. This approach was pioneered by Diamond and Dybvig (1983) and applied recently in a DSGE model by Gertler and Kiyotaki (2013)

govern the financing of entrepreneurial projects. The financial contract, explained in detail below, would provide incentives for banks to always choose to monitor entrepreneurs and also provide incentives for entrepreneurs to choose projects with higher probability of success.

1.2.1 Households

The population in the economy is divided into three agents: households (η^h), entrepreneurs (η^e), and bankers (η^b) such as η^h+η^e+$\eta^b = 1$. There is a continuum of households indexed by $i \in (0,\eta^h)$ and have homogeneous preferences. The lifetime expected utility of household i is

$$E_0 \sum_{t=0}^{\infty} \beta^t U^i(c^h_{it} - \gamma c^h_{i(t-1)}, l_{it}, \frac{M^c_{it}}{P_t})$$

where c^h_{it} is consumption in period t, γ measures the degree of habit persistence in consumption, l_{it} is hours worked, and the ratio $\frac{M^c_{it}}{P_t}$ is the real value of currency held.[7] The household i budget constraint is

$$c^h_{it} + q_t i^h_{it} + \frac{M_{i(t+1)}}{P_t} = (1 + r^d_t)\frac{D_{it}}{P_t} + r_t u_t k^h_{it} - v(u_t)k^h_{it} + \frac{W_{it}}{P_t} l_{it} + \Pi_t + \frac{M^c_{it}}{P_t} \quad (1.1)$$

where M_{it} and D_{it} are the money holding and deposits (into banks) at period t respectively. The household receives a lump-sum money transfer from the government (X_t), the sum of government transfer and money holding would be divided between deposits, (D_{it}), and cash, (M^c_{it}), according to the following constraint:

$$M_{it} + X_t = D_{it} + M^c_{it}. \quad (1.2)$$

[7]Note that money-in-utility function approach is used to have money in the economy. Other approaches, such as Cash-in-Advance, could also be used. Also note that habit persistence is added to delay and extend the response of the economy to shocks.

The real wage is given by the ratio $(\frac{W_t}{P_t})$, Π_t is dividends from intermediate good producing firms, r_t is the rental rate of utilized capital, r_t^d is the risk-free rate, and q_i is the price of one unit of new capital good i_{it}^h. Finally, u_t is the capital utilization rate and $v(\cdot)$ is a convex function used to determine the capital utilization cost, $v(u_t)k_{it}^h$.

The capital stock evolves according to the standard law motion of capital:

$$k_{i(t+1)}^h = (1-\delta)k_{it}^h + i_{it}^h. \tag{1.3}$$

Note that the control variables for household are $\{c_{it}^h, M_{it}^c, u_t, M_{i(t+1)}, k_{i(t+1)}^h$, and $l_{it}\}$.

In this economy, the nominal wage is rigid and is modeled following Erceg, Henderson, and Levin (2000) and Christiano, Eichenbaum, and Evans (2005). Aggregate labor is presented by a competitive labor aggregator which assembles individual labor types (l_{it}):

$$H_t = \left(\int_0^{\eta^h} l_{it}^{(\xi_t^w - 1)/\xi_t^w} \, \mathrm{di} \right)^{\xi_t^w / \xi_t^w - 1} \tag{1.4}$$

where ξ_t^w is elasticity of substitution between labor types and it follows the following stochastic process:

$$\xi_t^w = \alpha_w + \rho_w \xi_{t-1}^w + \epsilon_t^w \tag{1.5}$$

where $\rho_w \in (0,1)$ and ϵ_t^w is *i.i.d.* with mean 0 and standard deviation σ_w. Aggregators are competitive and make zero profits which leads to the following demand equation for each labor type:

$$l_{it} = \left(\frac{W_{i,t}}{W_t} \right)^{-\xi_t^w} H_t. \tag{1.6}$$

The above of each labor type is a function of its relative wage ratio ($\frac{W_{i,t}}{W_t}$) and of overall labor supply (H_t). The economy-wide aggregate wage could be defined as:

$$W_t = \left(\int_0^{\eta^h} w_{i,t}^{(1-\xi_t^w)} \mathrm{d}i \right)^{1/(1-\xi_t^w)}. \tag{1.7}$$

Each period, household i receives the signal to reoptimize its nominal wage with probability $(1-\phi)$ while with probability ϕ the household indexes its wage to the inflation rate, π_{t-1}, according to the following equation:

$$W_{it} = \pi_{t-1} W_{i(t-1)}. \tag{1.8}$$

For more details on this wage-setting environment, see Erceg et al (2000) and Christiano et al. (2005).

Production of Final Good

Final output, Y_t, is produced by competitive firms using a continuum of intermediate goods, y_{jt}, indexed by $j \in$(0,1) and using the standard Dixit-Stiglitz aggregator:

$$Y_t = \left(\int_0^1 y_{jt}^{1/\xi_t^p} \, \mathrm{dj} \right)^{\xi_t^p} \tag{1.9}$$

ξ_t^p is the constant elasticity of substitution between intermediate goods, it evolves according to the following process:

$$\xi_t^p = \rho_p \xi_{t-1}^p + \epsilon_t^p \tag{1.10}$$

where $\rho_p \in (0,1)$ and ϵ_t^p is *i.i.d.* with mean 0 and standard deviation σ_p. Profit maximization and the zero-profit assumption leads to the following demand for good (j):

$$y_{jt} = (\frac{p_{j,t}}{P_t})^{-\xi_t^p} Y_t \tag{1.11}$$

Which expresses the demand for good (j) as a function of aggregate production (Y_t) and its relative price ($\frac{p_{j,t}}{P_t}$). final-good price index, P_t:

$$P_t = \left(\int_0^1 \mathrm{p}_{\mathrm{jt}}^{1/(1-,\mathrm{p})} \,\mathrm{dj} \right)^{(1-\xi_p)}. \tag{1.12}$$

Intermediate Goods Production

Firms producing intermediate goods operate in a monopolistically competitive market. Each firm produces an intermediate good, y_{jt}, with the following production technology:

$$y_{jt} = \begin{cases} z_t(k_{jt})^{\theta_k}(h_{jt})^{\theta_h}(h^e_{jt})^{\theta_e}(h^b_{jt})^{\theta_b} - \Theta & \text{if} \quad z_t(k_{jt})^{\theta_k}(h_{jt})^{\theta_h}(h^e_{jt})^{\theta_e}(h^b_{jt})^{\theta_b} \geq \Theta \\ 0 \quad \text{otherwise} \end{cases} \tag{1.13}$$

where k_{jt} and h_{jt} are the amount of capital and labor services used by firm j at time t. h^e_{jt} and h^b_{jt} represents labor services from entrepreneurs and bankers.[8] Finally, $\Theta > 0$ represents the fixed cost of production and z_t is aggregate technological shock evolving according to the following autoregressive process:

$$log(z_t) = \rho_z log(z_{t-1}) + \epsilon_{zt} \tag{1.14}$$

where p_x $\in$(0,1) and ϵ_{zt} is *i.i.d.* with mean 0 and standard deviation σ_z. Similar to the wage determination process, the intermediate goods sector exhibits nominal price rigidities. Each period, a firm receives a signal to reoptimize its price with

[8]Following Carlstrom and Fuerst (1997), these variables were included to guarantee that entrepreneurs and bankers have non-zero wealth to contribute to the financial contract. However, the model calibration renders the influence of these variables on the model's dynamics to be negligible.

probability $1-\phi_p$. Otherwise it indexes, with probability ϕ_p, its price to last period's aggregate inflation. After k periods with no reoptimization, the price of good j will be:

$$p_{jt+k} = \prod_{s=0}^{k-1} \pi_{t+s} p_{jt} \tag{1.15}$$

where $\pi_t = \frac{P_t}{P_{t-1}}$ is the aggregate rate of price inflation.

A reoptimizing firm chooses $\tilde{p}_{jt}, k_{jt}, h_{jt}, h^e_{jt}$, and h^b_{jt} to solve the following optimization problem:

$$\max_{\tilde{p}_{jt},k_{jt},h_{jt},h^e_{jt},h^b_{jt}} E_t \sum_{k=0}^{\infty} (\beta\phi_p)^k \lambda_{t+k} \left[\frac{p_{jt+k} y_{jt+k}}{P_{t+k}} - s_{t+k} y_{jt+k} \right]$$

subject to (1.13) and (1.15). Consequently, in equilibrium $\tilde{p}_{jt}$ follows:

$$\tilde{p}_{jt} = \xi^p_t \frac{E_t \sum_{k=0}^{\infty} (\beta\phi_p)^k \lambda_{t+k} s_{t+k} Y_{t+k} \pi_{t+k}^{\xi^p_t/(\xi^p_t-1)}}{E_t \sum_{k=0}^{\infty} (\beta\phi_w)^k \lambda_{t+k} Y_{t+k} \pi_{t+k}^{1/(\xi^p_t-1)}}. \tag{1.16}$$

where λ_{t+k} is a Lagrange multiplier of the maximization problem associated with (1.16) and s_{t+k} is the Lagrange multiplier of the cost minimization problem associated with (1.13).

1.2.2 Capital Good Production

There are two types of projects available to entrepreneurs, both having the same return R_t when successful and zero when they fail. Each requires an initial investment, i_t, to be determined by the financial contract between the banker and the entrepreneur. The two projects differ, however, in their probability of success. First, the "good" project has a high probability of success denoted by α^g and zero private benefits to the entrepreneur. The second project has a lower probability of success denoted by $\alpha^b < \alpha^g$ and provides the entrepreneur with private benefits proportional to the project size (bi_t, $b > 0$). Entrepreneurs could behave and choose the first project or could deceive and choose the bad project. Banks, on the other hand, have access to a perfect monitoring technology that can detect bad projects. The financial contract between banks and entrepreneurs (discussed below) provides incentives for entrepreneurs to choose the “good" projects and also provide incentives for banks to monitor all the time.

Monitoring entrepreneurs is a costly activity for banks. In order to prevent entrepreneurs from choosing bad projects, banks incur the monitoring cost of μi_t. This private cost is a source of another moral hazard problem in the model between banks and investors (depositors). Depositors require that banks invest their own capital in the entrepreneurial projects to ensure that banks have incentives to adequately monitor the entrepreneurs they finance. This mechanism reassures depositors and help banks attract loanable funds.

1.2.3 Entrepreneurs, Bankers, and Financial Contract

Banks exist to provide external finances to any entrepreneur with net worth (n_t) wishing to undertake a project of size ($i_t > n_t$). To be able to finance entrepreneurs, banks pool their own net worth (a_t) with funds from households (d_t). The distribution of returns from successful projects between entrepreneurs, banks, and households are governed by a financial contract whose terms are discussed below. The inability of households to monitor entrepreneur's activity is a source of one moral hazard problem which is addressed by the existence of banks who are able to monitor entrepreneurs. On the other hand, the financial intermediation of banks is a source of another moral hazard problem because they might not undertake the cost of monitoring since the risk is transferred to investors. The solution to this double moral hazard problem in the model is addressed by requiring entrepreneurs and banks to invest their own net worth in the project along with household investors. This framework allows for dynamic interactions between bank capital, entrepreneurial net worth, economic activity, and monetary policy. There exists a continuum of risk-neutral entrepreneurs and bankers. At the end of each period, a fraction $(1-\tau^e)$ of entrepreneurs and $(1-\tau^b)$ of bankers consume all their net worth, exit the economy, and are replaced by new ones with zero assets. A typical entrepreneur starts period t with holdings k_t^e in capital goods which are rented to intermediate goods producers. The corresponding rental income, r_t, combined with the value of undepreciated capital, q_t, and the small wage received from the intermediate goods producers, w_t^e, constitute the net worth, n_t, which is available to an entrepreneur:

$$n_t = \left[r_t + q_t(1-\delta e^{\zeta_t^e})\right] k_t^e + w_t^e. \tag{1.17}$$

ζ_t^e is a stochastic process evolving according to the following:

$$\zeta_t^e = \rho_e \zeta_{t-1}^e + \epsilon_t^e \tag{1.18}$$

where $\rho_e \in (0,1)$ and ϵ_t^e are *i.i.d.* with mean 0 and standard deviation σ_e.

A banker's net worth, a_t, is determined in a similar way by a banker's holding of capital goods, k_t^b, and the small wage it receives from the intermediate-good producers, w_t^b:

$$a_t = \left[r_t + q_t(1-\delta e^{\zeta_t^b})\right] k_t^b + w_t^b. \tag{1.19}$$

ζ_t^b evolves according to the following process:

$$\zeta_t^b = \rho_b \zeta_{t-1}^b + \epsilon_t^b \tag{1.20}$$

where $\rho_b \in (0,1)$ and ϵ_t^b are *i.i.d.* with mean 0 and standard deviation σ_b.

Each entrepreneur then undertakes a capital-good producing project and invests along with its bank their entire net worth, n_t and a_t in the project. The bank also invests the funds it raised from households, d_t, in the project. If the project fails, both agents receive a zero return and neither consume nor save. If it is successful, entrepreneur receives $R_t^e i_t$, the bank receives $R_t^b i_t$, and the investor household receives $R_t^h i_t$. Successful agents either exit and spend their wealth on final goods, or stay and save their entire return which becomes their next period real assets, k_{t+1}^e and k_{t+1}^b, k_{t+1}^h respectively.[9] The investment size, i_t, is determined by a one period optimal financial contract between the entrepreneurs undertaking the project and their bank.[10] The contract also determines the contributions from the bank (a_t) and the bank's investors (d_t). Finally, the contract determines how the project's return is shared among the entrepreneur ($R_t^e > 0$), the bank ($R_t^b > 0$), and the investors ($R_t^h > 0$). Note that the assumption of limited liability rules out negative returns. Formally, the contract seeks to maximize the expected return to the entrepreneur subject to incentive, participation, and feasibility constraints:

$$\max_{\{i_t, a_t, d_t, R_t^e, R_t^b, R_t^h\}} \quad q_t \alpha^g R_t^e i_t \qquad \text{subject to} \tag{1.21}$$

[9]The exit occur with exogenous probability, which is discussed in section 1.2.3.

[10]This is a result of the assumption of inter-period anonymity as in Carlstrom and Fuerst (1997) and Bernanke, Gertler, and Gilchrist (1999). The assumption is crucial for model tractability, otherwise, we would have to solve repeated games with moral hazard.

$$q_t\alpha^g R^e_t i_t \geq q_t\alpha^b R^e_t i_t + q_t b i_t, \tag{1.22}$$

$$q_t\alpha^g R^b_t i_t - \mu i_t \geq q_t\alpha^b R^b_t i_t, \tag{1.23}$$

$$q_t\alpha^g R^b_t i_t \geq (1 + r^a_t) a_t, \tag{1.24}$$

$$q_t\alpha^g R^h_t i_t \geq (1 + r^d_t) d_t, \tag{1.25}$$

$$a_t + d_t - \mu i_t \geq i_t - n_t, \tag{1.26}$$

$$R^e_t + R^b_t + R^h_t = R_t. \tag{1.27}$$

Condition (1.22) ensures that entrepreneurs have incentives to choose the good project. The left-hand side is the entrepreneur's expected return if they choose the "good" project, which has to be at least as much as what they would receive if they choose the low-deception project (the expected return plus the private benefits). The left-hand side of equation (1.23) is the expected return for the bank in case it monitors the entrepreneur and pay the cost μi_t, which has to be greater than or equal to the bank's expected return if it decides not to monitor. Conditions (1.24) and (1.25) are the participation constraints of the bank and the investing households respectively. The left-hand side in (1.24) is the expected return for the participating bank which has to be at least as high as the return it obtains on its net worth (r^a_t). Similarly, the left-hand side in (1.25) is the expected return for the participating household which has to be at least as high as the return it gets on its deposits (r^d_t). Finally (1.26) and (1.27) are the feasibility constraints. The former states that the bank's loanable funds, net of monitoring, covers the entrepreneur's financing needs. The latter states that the payments distributed among the three agents when the project is successful add up to the total return. R_t is the return on a successful project which follows the following stochastic process:

$$R_t = \alpha_r + \rho_r R_{t-1} + \epsilon^R_t \tag{1.28}$$

where $\rho_R \in (0,1)$ and ϵ_t^R are *i.i.d.* with mean 0 and standard deviation σ_R.[11] In equilibrium, the returns of the three agents are:

$$R_t^e = \frac{b}{\alpha^g - \alpha^b}, \tag{1.29}$$

$$R_t^b = \frac{\mu}{q_t(\alpha^g - \alpha^b)}, \tag{1.30}$$

$$R_t^h = R_t - \frac{b}{\alpha^g - \alpha^b} - \frac{\mu}{q_t(\alpha^g - \alpha^b)}. \tag{1.31}$$

The solution to the maximization problem yield:

$$i_t = \frac{a_t + n_t}{G_t} \quad \text{where} \tag{1.32}$$

$$G_t = 1 + \mu - \frac{q_t \alpha^g}{1 + r_t^d}\left[R_t - \frac{b}{\alpha^g - \alpha^b} - \frac{\mu}{q_t(\alpha^g - \alpha^b)}\right]. \tag{1.33}$$

In (1.32), $\frac{1}{G_t}$ is the leverage achieved by the financial contract over the combined net worth of the bank and the entrepreneur. Note that G_t does not depend on individual characteristics and thus leverage is constant across all contracts in the economy.

Monetary Policy and Aggregation

Monetary policy sets the short-term nominal interest rate, r_t^d according to a "Taylor rule with inertia":

$$r_t^d = (1 - \rho_r) r^d + \rho_r r_{t-1}^d + (1 - \rho_r)[\rho_\pi(\pi_t - \pi) + \rho_y y_t] + \epsilon_t^{mp} \tag{1.34}$$

where r^d is the steady-state interest rate, $\tilde{\pi}$ is the inflation target, $\hat{y}_t$ is the output gap, and ϵ_t^{mp} is an *i.i.d.* monetary policy shock with standard deviation σ^{mp}.

Note that the production function for capital goods is assumed to be linear both

[11] α_r is a drift to be calibrated in order to have a particular non-stochastic steady state value of R_t

in the private benefits accruing to entrepreneurs and in the cost of monitoring facing banks. As a result, the distribution of net worth across entrepreneurs and the distribution of bank capital across banks have no effect on aggregate investment I_t:

$$I_t = \frac{A_t + N_t}{G_t}. \tag{1.35}$$

The aggregate equilibrium return on banks' net worth is given by:

$$1 + r_t^a = \frac{q_t \alpha^g R_t^b I_t}{A_t}. \tag{1.36}$$

Aggregate stocks of capital holdings are:

$$K_t^h = \eta^h k_t^h, \tag{1.37}$$

$$K_t^e = \eta^e k_t^e, \tag{1.38}$$

$$K_t^b = \eta^b k_t^b. \tag{1.39}$$

Recall that η^h, η^e, and η^b are the percentage in the population of households, entrepreneurs, and bankers, respectively. The aggregate level of entrepreneurs' net worth and banks' net worth as well as their respective beginning-of-period asset holdings in (t+1) are:

$$N_t = \left[r_t + q_t (1 - \delta e^{\zeta_t^e}) \right] K_t^e + \eta^e w_t^e, \tag{1.40}$$

$$A_t = \left[r_t + q_t (1 - \delta b^{\zeta_t^b}) \right] K_t^b + \eta^e w_t^b, \tag{1.41}$$

$$K_{t+1}^e = \tau^e \alpha^g R_t^e I_t, \tag{1.42}$$

$$K_{t+1}^b = \tau^b \alpha^g R_t^b I_t. \tag{1.43}$$

Combine (1.40) and (1.42) with (1.41) and (1.43) and substitute for aggregate investment from (1.35) to get the following laws of motion for entrepreneurs' net worth and banks' net worth, N_{t+1} and A_{t+1} respectively :

$$\begin{aligned} N_{t+1} &= [r_{t+1} + q_{t+1}(1 - \delta e^{\zeta_t^e})]\tau^e \alpha^g R_t^e \tfrac{A_t+N_t}{G_t} + \eta^e w_{t+1}^e, && (1.44) \\ A_{t+1} &= [r_{t+1} + q_{t+1}(1 - \delta b^{\zeta_t^b})]\tau^b \alpha^g R_t^b \tfrac{A_t+N_t}{G_t} + \eta^e w_{t+1}^b. && (1.45) \end{aligned}$$

Aggregate consumption for entrepreneurs, banks, and households are:

$$\begin{aligned} C_t^e &= (1 - \tau^e) q_t \alpha^g R_t^e I_t, && (1.46) \\ C_t^b &= (1 - \tau^b) q_t \alpha^g R_t^b I_t, && (1.47) \\ C_t^h &= \eta^h c_t^h. && (1.48) \end{aligned}$$

A competitive equilibrium for the economy consists of:

1. decision rules for c_t^h, i_t^h, W_{ti}, k_{t+1}^h, u_t, M_t^c, D_t, and M_{t+1} that solve household maximization problem,

2. decision rules for $\tilde{p}_{jt}$, k_{jt}, h_{jt}, h_t^e, h_t^b that solve the profit maximization problem of intermediate good producers,

3. decision rules for i_t, R_t, R_t^e, R_t^b, R_t^h, a_t, and d_t that solve the maximization problem associated with the financial contract,

4. the following market-clearing conditions:

$$K_t = K_t^e + K_t^b + K_t^h, \tag{1.49}$$

$$u_t K_t^h + K_t^e + K_t^b = \int_0^1 k_{jt}\, dj, \tag{1.50}$$

$$H_t = \int_0^1 h_{jt}\, dj, \tag{1.51}$$

$$Y_t = C_t^e + C_t^b + C_t^h + (1+\mu) I_t, \tag{1.52}$$

$$K_{t+1} = (1-\delta) K_t + \alpha^g R_t I_t, \tag{1.53}$$

$$\eta^b d_t = \eta^h \frac{D_t}{P_t}, \tag{1.54}$$

$$\bar{M}_t = \eta^h M_t. \tag{1.55}$$

1.2.4 Shocks

The model features real, nominal, financial, and policy shocks. The real and nominal shocks are: technological shock (z_t), price mark-up shock (ξ_t^p), and wage mark-up shock (ξ_t^w). There are also three financial shocks: bank capital shock (ζ_t^b), entrepreneurial capital shock (ζ_t^e), and risk shock (ϵ_t^R). Finally, the seventh shock in the model is a monetary policy shock (ϵ_t^{mp}). Real and nominal shocks as well as monetary policy shock are classical shocks that have received great deal of attention in the literature. In contrast, financial shocks started to feature just recently in the literature and their specifications differ widely across models. Therefore, it is quite important to briefly describe the role of the three financial shocks in the model and to explain the mechanism through which they affect the amount of credit in the model and eventually influence the business cycle.

The credit market in the model is composed of three players: banks and depositors on the supply side of the market and entrepreneurs on the demand side. A key feature of the credit market in the model is the determination of the size of entrepreneurial projects (I) which is given by equations (1.32) and (1.33). Note that the project's size (I) is increasing in banks' net worth, entrepreneurs' net worth, and with the return on entrepreneurial projects. Therefore, total lending can be expressed as a function of aggregate investment needed to finance all projects (I_t) and aggregate net worth of entrepreneurs (N_t):

$$TL_t = I_t - N_t. \tag{1.56}$$

This equation along with equations (1.32) and (1.33) will determine how each financial shock affects total lending in the model. The bank capital shock, ζ_t^b, originates in the supply side of the credit market and it directly affects the depreciation rate of bank capital. This shock could be interpreted to include shocks affecting the balance sheets of banks, changes in asset prices or loan defaults for example. A positive shock to the depreciation rate of bank's capital would lower bank capital and leads to lower bank's net worth, as could be seen in equation (1.40). From equations (1.32) and (1.56), project size and total lending will decrease as net worth of banks decreases. Lower investment would lead to lower output The other two shocks originate in the demand side of the credit market. The entrepreneurial capital shock, ζ_t^e, directly affects the depreciation rate of entrepreneurial capital. An upward movement of the shock would lower the net worth of entrepreneurs and would decrease total lending. Similar to the interpretation of the bank capital shock, the entrepreneurial capital shock can account for factors that affect the balance sheets of entrepreneurs such as movements in asset prices or changes in cash flows. Even though risk shock originates in the demand side of the credit market, it does not directly affect entrepreneurial net worth. Rather, it affects the size of the entrepreneurial project through leverage $\frac{1}{G}$ as can be clearly be seen in equation

(1.33). In particular, an increase in the project's return will increase the amount of investment that the financial contract would commit to the project. This will in turn increase the total lending in the economy.

1.3 The Macroeconomic Effect of Financial Shocks

The model presented in section 1.2 features three financial shocks: bank capital shock, entrepreneurial capital shock, and risk shock. In this section, the model is calibrated to the same values as in Meh and Moran (2010) and the macroeconomic effect of the three financial shocks are evaluated by examining the impulse response functions of key variables in the model to each one of the shocks.

1.3.1 Parameter Values and Functional Forms

A natural starting point for the exercise is to define functional forms as well as to assign numerical values to the parameters of the model. Household's preferences and capital utilization function are given by:

$$u(c_t^h - \gamma c_{t-1}^h, l_{it}, M_t^c/P_t) = log(c_t^h - \gamma c_{t-1}^h) + \psi \left(\frac{l_{it}^{(1+\zeta_l)}}{1+\zeta_l} \right) + \zeta log(M_t^c/P_t) \tag{1.57}$$

$$v(u_t) = \gamma_1(u_t - 1) + \frac{1}{2}\gamma_2(u_t - 1)^2 \tag{1.58}$$

The purpose of the simulation exercise in section 1.3 is to analyse the effect of the three financial shocks. Therefore, the parameters of the model are divided into three categories: the first category includes the standard deviations of technological shock (σ_z), price rigidity shock (σ_p), wage rigidity shock (σ_ω), and monetary policy shock (σ_{mp}). The four standard deviations are set to zero. The second category includes the six parameters governing the persistence and the standard deviation of the three

Param.	Value	Param.	Value	Param.	Value
γ	0.65	θ_k	0.36	μ	0.025
ζ	0.0018	θ_h	0.6399	α_g	0.99
ψ	1.9	θ_e	0.00005	α_b	0.75
β	0.99	θ_b	0.00005	b	0.16
ζ_w	21	η_b	0.03	τ_e	0.78
ϕ_w	0.64	τ_b	0.72	γ_1	0.029908
ζ_p	6	η_h	0.9	γ_2	0.00029908
ϕ_p	0.6	η_e	0.07	$\overline{\pi}$	1.005
ρ_π	1.5	ρ_y	0.1	ρ_r	0.8
δ	0.1	ρ_{bk}	0.9817	ρ_{ek}	0.9625
ρ_R	0.9130	σ_{ek}	4.5944	σ_R	0.0119
σ_{bk}	3.0972				

TABLE 1.1: Parameter Values

financial shocks; the bank capital shock ($\rho_b k$, $\sigma_b k$), the entrepreneurial capital shock ($\rho_e k$, $\sigma_e k$), and the risk shock (ρ_R, σ_R). The values of these parameters are estimated by Bayesian methods, consult section 1.4 for further details on the estimation methods and the data used in the estimation. The third category includes all the remaining parameters of the models whose value were taken directly from Meh and Moran (2010)

Table 1.1 lists the values of the parameters that were taken from Meh and Moran (2010) as well as the values of the six parameters of the three financial shocks that were estimated in section 1.4.

The model is first solved by first-order approximation methods using Dynare. Next, three simulation exercises were conducted: the first hit the economy with one standard deviation shock to bank capital depreciation and generated impulse response functions of key variables in the model. The same was done in the second and third simulation exercises but by hitting the economy with one standard deviation shock to entrepreneurial capital depreciation and to entrepreneurial project return, respectively. The following subsections present the impulse response functions of the three exercises followed by discussions of the dynamics of the propagation of the shocks as well as the relative importance of the shocks in macroeconomic fluctuations.

1.3.2 Bank Capital Shock

Figure 1.1 shows, the effect of a positive shock to bank capital depreciation on number of financial and macroeconomic variables. Remember that a positive bank capital depreciation shock in the model increases the rate of capital depreciation and leads to a decrease in bank's capital. Overall, the shock leads to a recessionary period, with output and investment falling significantly for several periods. The shock also creates some inflationary pressures, which must be confronted with higher short-term rates. In particular, the shock decreases the value of the net worth of banks by about 6% on impact. Recall that the level of bank capital is a determinant of aggregate investment as shown if in (1.1). The decrease in bank capital causes aggregate investment to decrease by about 1% on impact. Intuitively, the decrease in aggregate investment could be seen as a result of stressed entrepreneurial leverage due to the decrease in bank capital. The increased stress on bank capital is evident by the drop in capital adequacy ratio of more than 4.5% which continue to decrease for 40 periods after the initial impact. The pressures on bank capital, entrepreneurial leverage, and aggregate investment caused by the bank capital shock cause earnings of economic agents to decrease which leads to a second-round effects in subsequent periods. As a result, aggregate investment decreases for several periods and bottoms at 11%, 20 periods after the onset of the shock. Similarly, output also bottoms at 2.5%, 20 periods after the initial shock. The disturbances in the financial sector creates inflationary pressures, 1.4%, to which monetary authorities respond by increasing short term rates by 5.6%. Intuitively, a sudden drop of banking net worth

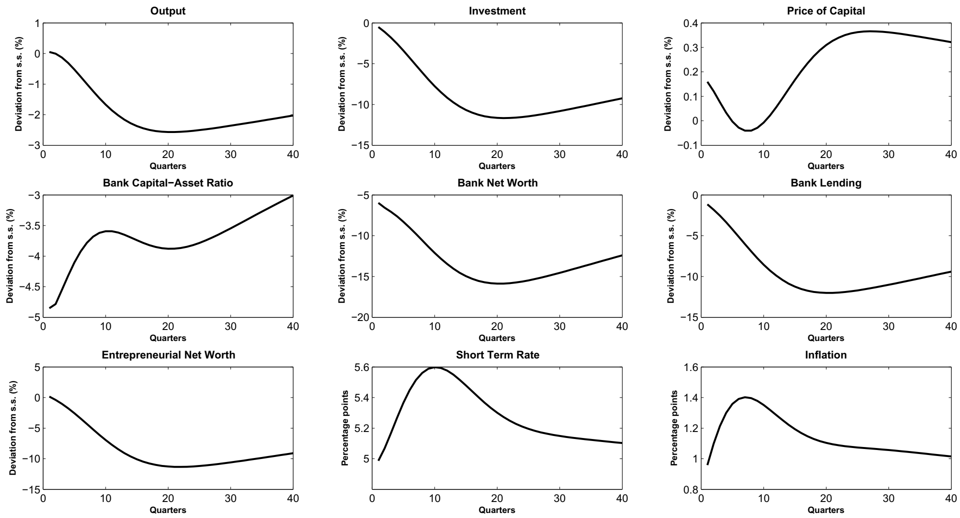


FIGURE 1.1: Impulse response functions of a one standard deviation shock to bank capital.

depresses economic activity and affects the conduct of monetary policy. Although the magnitude of the macroeconomic effect of the bank capital shock is much larger than what was reported in Meh and Moran (2010), the dynamics of the impulse responses to are the same. In Meh and Moran (2010). the bank capital shock decreased bank's net worth by 6% at impact, after which the net worth gradually reverted to its steady state. The bank capital shock in this section, as shown in Figure 1.1, continues to decreases bank net worth for many periods reaching a cumulative decrease of more than 15%. by The difference in magnitude stems from differences in the modelling and parameterization of the shock.

1.3.3 Entrepreneurial Capital Shock

The macroeconomic effect of a positive shock to entrepreneurial capital depreciation is shown in Figure 1.2. Overall, the shock leads to a severe recessionary period that is larger in magnitude than the recessionary period caused by the bank capital shock that was discussed above. Similar to the bank capital shock, output and investment fall significantly for years. The shock also creates some inflationary pressures, which must be confronted with higher short-term rates. In particular, the shock decreases the value of entrepreneurial net worth by 10% on impact. Entrepreneurial capital is also a determinant of aggregate investment. The decrease in entrepreneurial capital causes aggregate investment to decrease by about 5% on impact, more than three times the effect of bank capital shock on aggregate investment. Intuitively, the decrease in aggregate investment could be seen as a direct result of the decrease in entrepreneurial net worth regardless of the abundance of bank capital that was not affected at impact. In fact, bank capital-asset ratio increased at impact due lower loan issuance. The pressure on entrepreneurial capital, and aggregate investment caused by the shock causes earnings of economic agents to decrease which leads to a second-round effects in subsequent periods. As a result, aggregate investment decreases for several periods and bottoms at 60%, 18 periods after the onset of the shock. Similarly, output also bottoms at 13%, 16 periods after the initial shock. The disturbances in the credit demand sector creates a severe inflationary pressure that was significantly larger in magnitude than the recession caused by bank capital shock. The response of monetary authorities by increasing short term rates is also much more significant, an 8% increase in the short-term rates as compared to 5.6%.

1.3.4 Risk Shock

A risk shock in the model is also generated in the demand side of the credit market, similar to the entrepreneurial capital shock. Overall, a negative shock to the return of entrepreneurial projects leads to a mild recessionary period of comparable magnitude to the recessionary period caused by the bank capital shock. Unlike the two other shocks, neither bank capital nor entrepreneurial capital were affected at impact. This is due to the fact that the risk shock does not destroy capital directly. As is seen in Figure 1.3, the risk shock affects the leverage ratio ($1/G$), a decrease in the

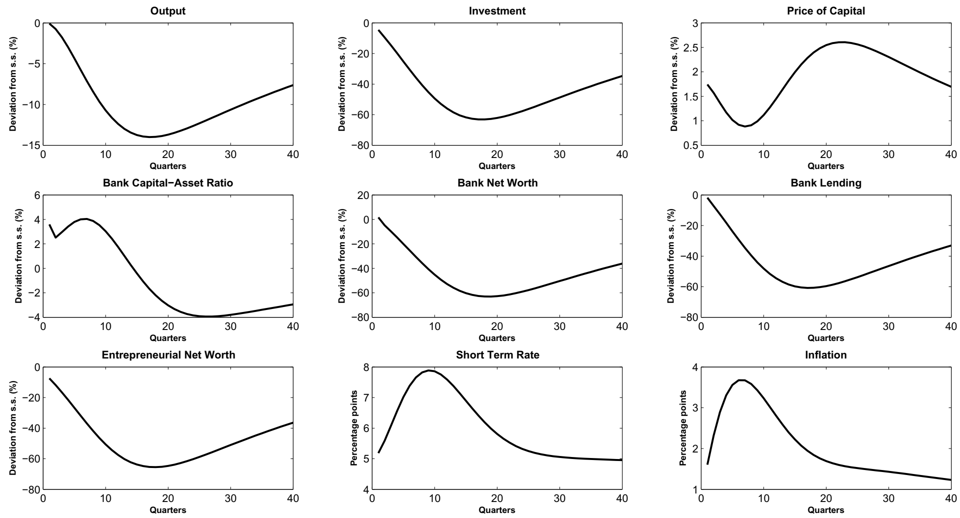


FIGURE 1.2: Impulse response functions of a one standard deviation shock to entrepreneurial capital.

return of entrepreneurial projects would lower the leverage ratio. Even though net worth of banks and entrepreneurs are not affected at impact, lower leverage leads to a decrease in aggregate investments, about 2% at impact. As a result, output and investment fall significantly for several periods. The shock also creates some inflationary pressures, which must be confronted with higher short-term rates. It is particularly interesting to see that even though bank capital to asset ratio continue to increase, total lending continued to decrease. Intuitively, abundance of bank capital does not guarantee smooth credit flow to finance economic activities. The perceived return of economic activity, as is captured by the risk shock, is an important determinant of total lending and consequently to output and investment. The pressure on leverage ratio, and aggregate investment caused by the shock causes earnings of economic agents to decrease which leads to a second-round effects in subsequent periods where we see the net worth of both banks and entrepreneurs decline for several periods. As a result, aggregate investment decreases for several periods and

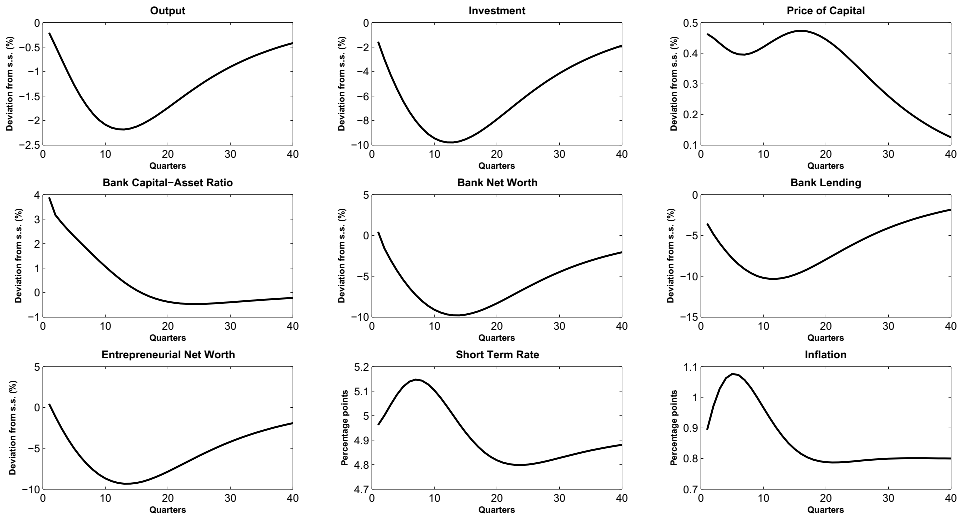


FIGURE 1.3: Impulse response functions of a one standard deviation shock to the return of entrepreneurial projects.

bottoms at 10%, 12 periods after the onset of the shock. Similarly, output also bottoms at a little more than 2%, 12 periods after the initial shock. The disturbances caused by the risk shock creates a severe inflationary pressure similar in magnitude to the recession caused by bank capital shock. The response of monetary authorities by increasing short term rates is also similar, about 5.1% increase in the short-term rates as compared to 5.6%. The magnitude of the three financial shocks on output, investment, net worth of banks, net worth of entrepreneurs, total lending, short term rate, and inflation is demonstrated on Figure 1.4. It is clear from the figure that the magnitude of the effect of the entrepreneurial shock is much higher than those of the two other shocks for all the seven macroeconomic variables. Also note that the magnitude of the effects of bank capital shock and that of the risk shock is very close for all the seven variables. This sort of suggests that shocks to credit demand has more severe consequences than shocks to credit supply. If this is the case, then macroeconomic policies that try to respond to credit supply shocks might have limited effect on stimulating investment and output.

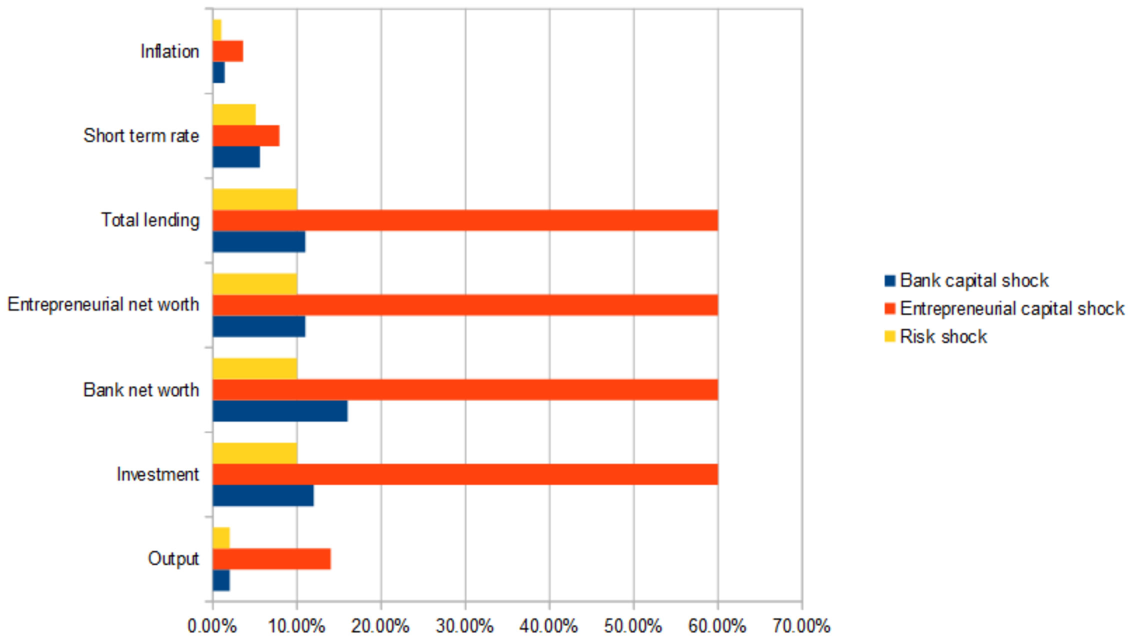


FIGURE 1.4: The magnitude of the effect of financial shocks on key macroeconomic variables.

1.4 Model Estimation

In this section, the model described in section 1.2 is estimated by Bayesian maximum likelihood method. The first objective is to estimate the fourteen parameters that govern the seven shocks in the model; namely, the auto-regressive correlation parameters and the standard deviation of each shock. The second objective is to estimate the contribution of each shock to long-run variations in key macroeconomic variables.

1.4.1 Method

Bayesian methods are widely used in estimating DSGE models to address two well documented problems in macroeconometrics: data limitations and the misspecifications of DSGE models, which is discussed in great details in Fernández-Villaverde

(2010). A DSGE model, like the one described in section 1.2, could be used to construct a likelihood function of a set of time series with length (T), (Y_T^*), and a parameter space (Θ):

$$P(Y_T^*|\theta) \tag{1.59}$$

The parameter vector θ can be estimated by maximum likelihood methods but the statistical properties of those estimates are affected by the short horizon of the used time series. In addition, the feasibility of the maximum likelihood method is in question given the misspecifications of the DSGE model which render the optimal points in the likelihood function to be mis-specified. Bayesian methods provide a remedy to both problems by using generally held beliefs about the parameters (θ) to discipline the likelihood function in (1.59). The beliefs about the parameters are expressed as a prior probability distribution ($p(\theta)$), which s the marginal density of the parameter$/theta$. Note that the likelihood function in (1.59) is a conditional probability distribution and can be expressed as:

$$P(Y_T^*|\theta) = \frac{p(Y_T^*, \theta)}{p(\theta)} \tag{1.60}$$

Also note that the condition distribution of the parameter θ given the data Y_T^* is given by:

$$P(\theta|Y_T^*) = \frac{p(Y_T^*, \theta)}{p(Y_T^*)} \tag{1.61}$$

Combining (1.60) and (1.61), the joint probability distribution function $p(Y_T^*, \theta)$ could be expressed in terms of the two following conditional distributions:

$$p(Y_T^*, \theta) = P(Y_T^*|\theta)p(\theta) = P(\theta|Y_T^*)p(Y_t^*) \tag{1.62}$$

Combining the two terms in the last inequality and change the notation, we can get the following Bayes rule that govern the Bayesian estimation algorithm:

$$P_1(\theta|Y_T^*) = \frac{P(Y_T^*|\theta)p_0(\theta)}{p(Y_t^*)} \tag{1.63}$$

Given the prior distribution of the parameters $p_0(\theta)$ and the likelihood function $P(Y_T^*|\theta)$, the posterior probability distribution of the parameters $P_1(\theta|Y_T^*)$ could be constructed. Note that he expression in the denominator of (1.63) is the marginal density of the sample which is a weighted mean of the sample conditional densities over all the possible values for the parameters. There are few points worth mentioning before describing the estimation exercise. The first is the sensitivity of the results to the choice of the observed variables that are used in the estimation. This stems from the inherent feature of DSGE models in which the variations are derived by a small number of exogenous stochastic processes. As a result, the number of shocks has always been smaller than the number of endogenous variables. When using Bayesian methods, the number of observed variables that are used has to be equal to the number of exogenous shocks. The literature follows two practical approaches: to use few observables or to add measurement errors (see An and Schorfheide (2007) and Fernández-Villaverde (2010) for more discussions). This paper follows the recent literature by limiting the number of observables to the number of exogenous shocks without adding measurement errors (see Smets and Wouters (2007), Jermann and Quadrini (2012), Christiano, Motto, and Rostagno (2014)). The second point is the choice of the detrending method. This is a well-known problem in econometrics in general and is of particular interest to the study of business cycle because business cycle models abstain from explaining the long-run trend that we see in most macroeconomic data. As a result, the observed series have to be detrended in order to match them to the model's variables. In this paper, the log difference method is used following the recent literature. The final point is the sensitivity of the results to the choice of prior beliefs about the parameters' distribution. The starting point in Bayesian estimation is to define prior beliefs about the distribution of the parameters of interest. The priors are then used in the construction of the likelihood function as well as in the subsequent Monte-Carlo simulations resulting in the posterior distribution of the parameters. The obtained posterior distribution in this section is not robust to the choice of the prior distribution. The choice of priors in this paper is governed by what is common in the recent literature and by the widely held beliefs. Although Bayesian estimation is an interesting exercise that will shed some lights on some of what the data suggest about the exogenous shocks, one has to exercise a high degree of caution when examining the results before drawing any conclusion.

Data

There are seven exogenous shocks that drive the fluctuation in all endogenous variables in the model. Consequently, seven macroeconomic series are used to estimate the parameters of interest: growth rates of gross domestic product, hourly compensation in the non-farm business sector, commercial and industrial loans issued by all commercial banks, and leverage ratio of US banks. In addition, I will use consumer price index, federal fund rate, and returns on equity of US banks to match inflation, short term nominal rate, and return on equity in the model. The choice of variables are similar to what was used in the literature,see for example, Christiano, Eichenbaum, and Evans (2005), Christiano, Motto, and Rostagno (2014), and Quadrini (2011).

The data is taken from Federal Reserve Bank of St-Luis (FRED) and it covers the period $1988 - 2010$. All series are seasonally adjusted. Gross Domestic Product, hourly compensation in the non-farm business sector, and commercial and industrial loans issued by all commercial banks are deflated by the GDP implied price deflator and were expressed in per capita terms by dividing them over the working age population aged $15 - 64$. Inflation is expressed as the log difference of the consumer price index (CPI). Finally, the federal fund rate and the return on equity are expressed as gross quarter return.

Prior Distributions of the Parameters

Only a subset of parameters is estimated which includes the AR (1) coefficients and the standard deviations of the seven shocks. The remaining model parameters are fixed at the calibrated values in Table 1.1. Following Jermann and Quadrini (2012) and Smets and Wouters (2007), the prior distributions of the parameters are harmonized as much as possible. The prior distributions of the coefficients of autoregressive processes follow beta distribution with mean = 0.5 and standard deviation of 0.2. Those of the standard deviations of the shocks follow inverse gamma distribution with mean 0.0 and 0.05 degree of freedom. Table 1.2 lists the prior distribution of the shocks' auto-regressive coefficient and standard deviation respectively.

1.4.2 Results

Posterior Distribution of the parameters

Figure 1.5 depicts the prior (in gray) and posterior (in black) distributions of the seven AR(1) shock processes. The dotted green lines are the posterior means. Table 1.2 lists the type type, mean, and SD of the prior distributions as well as the mode, mean, and the 90th percentile of posterior distributions of the parameters of the seven AR (1) shock processes. Technology shock and all the three financial shocks (Bank capital shock, entrepreneurial capital shock, and risk shock) are significantly persistent with AR (1) coefficients' means of 0.99, 0.98, 0.96, and 0.91 respectively.

	Prior			Posterior		
	Parameter	Mean	SD	Mode	Mean	**90%**
ρ_z	Beta	0.5	0.2	0.9999	0.9999	0.9997
ρ_{mp}	Beta	0.5	0.2	0.1205	0.3122	0.2208
ρ_{ξ_p}	Beta	0.5	0.2	0.9766	0.1664	0.0794
ρ_{ξ_w}	Beta	0.5	0.2	0.4962	0.1591	0.0604
ρ_{bk}	Beta	0.5	0.2	0.9092	0.9817	0.9806
ρ_{ek}	Beta	0.5	0.2	0.0490	0.9625	0.9580
ρ_R	Beta	0.5	0.2	0.0340	0.9130	0.8972
σ_z	Invgamma	0.001	0.05	0.0407	0.0447	0.0385
σ_{mp}	Invgamma	0.001	0.05	0.0028	0.0024	0.0021
σ_{ξ_p}	Invgamma	0.001	0.05	1.1818	0.0446	0.0374
σ_{ξ_w}	Invgamma	0.001	0.05	1.309	0.0180	0.0156
σ_{bk}	Invgamma	0.001	0.05	0.0073	3.0972	2.9740
σ_{ek}	Invgamma	0.001	0.05	0.0343	4.5944	4.3242
σ_R	Invgamma	0.001	0.05	0.0142	0.0119	0.0096

TABLE 1.2: Prior and posterior distributions of the shock processes

Monetary policy, price rigidity shock, and wage rigidity shocks are not persistent with coefficients' means of 0.31, 0.16, and 0.15, respectively.

The standard deviation of technology innovation is 0.0407, which is very close to the estimates in the literature. The estimated standard deviations of the innovations of the three financial shock are significant with means of 3.0972, 4.5944, and 0.0119 for the innovations of bank capital shock, entrepreneurial capital shock, and risk shock, respectively. The combination of high persistence estimates along with high estimate of the standard deviation of the innovations contributes to the higher contribution of the technological and financial shocks in the variation of macroeconomic variables.

The Contribution of Shocks to Macroeconomic Variation

In this section, I estimate the contribution of each shock to the variation of key macroeconomic variables; output, hours worked, investment, Inflation, wages, nominal interest rates, return on equity, capital asset ratio, and total lending. This is done

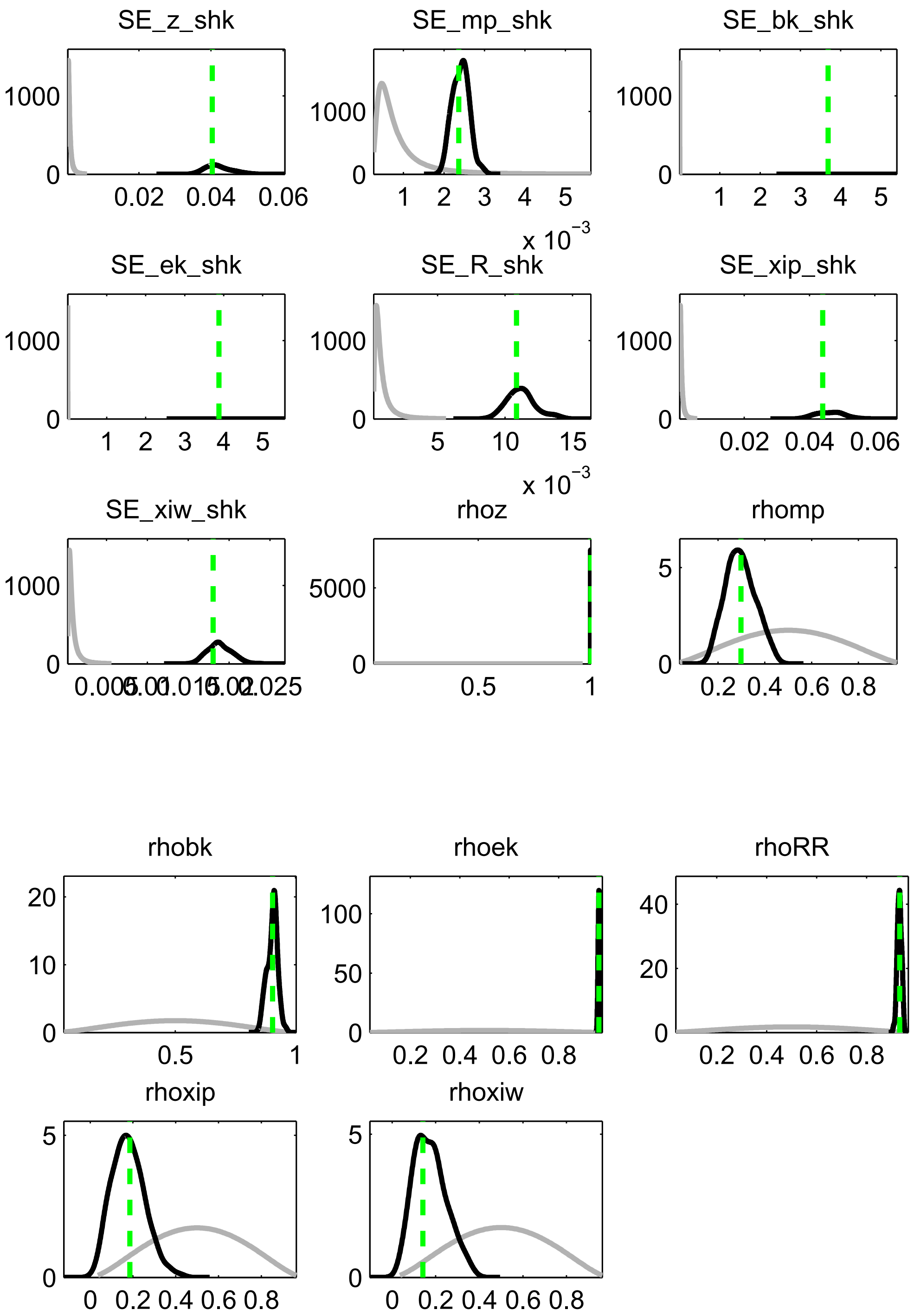


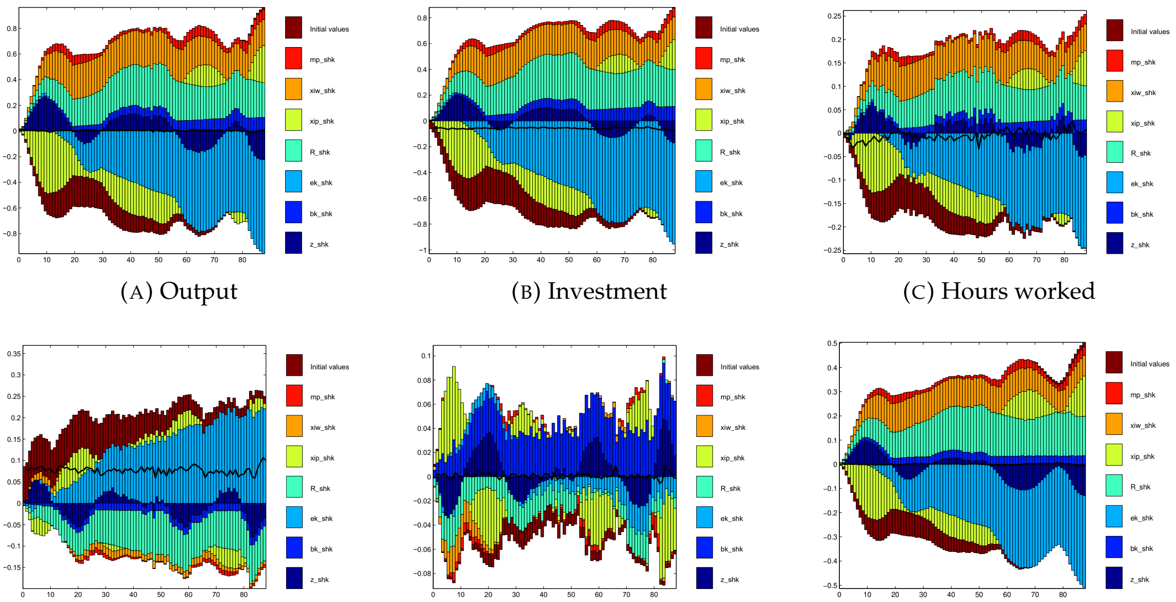
FIGURE 1.5: Priors and posteriors distributions

by variance decomposition procedure which measure the contribution of each exogenous shock to the forecast error variance of the respective real variable. Table 1.3 lists the infinite horizon variance decomposition of the forecast error of output(Y), investment(I), hours worked(H), and banks' total lending (TL).[12] The first observation is that the combined contribution of price mark-up shock, wage mark-up shock, and technology shock to the variation in output counts for about 83%. This is similar to what is reported in Shapiro and Watson (1988) and Smets and Wouters (2007). The same combination is also the leading contributor to the variation in all the remaining macroeconomic variables. The second observation is that the entrepreneurial capital shock is by far the most important financial shock that affects macroeconomic variables. With the exception of the capital-asset ratio, the contribution of the entrepreneurial capital shock in macroeconomic fluctuation is sizable. Entrepreneurial capital shock accounts for approximately 22% of the variation in investment, 15% of the variation in output, and a little more than 18% of the variation in hours of work. The final observation is that the contribution of the monetary policy shock seems to have very little impact on macroeconomic fluctuations. This does not mean that monetary policy has no effect on macroeconomic fluctuations, in fact monetary policy is a potent force in endogenously responding to other macroeconomic and financial shocks. The small effect of monetary policy that is shown in Figure 1.7 counts only for the effect of policy innovations and not for the effect of the monetary policy reaction to other shocks. Figure 1.6 shows the historical variance decomposition of output, investment, hours of work, consumption, capital-asset ratio, and total lending. It is notable how the three financial shocks played larger part during the Great Recession. In particular, Figure 1.7 shows the contribution of real

[12]The first period conditional variance decomposition measure the effect on macroeconomic variable at the time of impact, when the shock hits. The infinite horizon or unconditional variance decomposition measure the long run effect on macroeconomic variables. Financial shocks have higher contribution at one and two period variance decomposition

	Shock to						
Variable	Tech.	BC	EC	Risk	PM	WM	MP
Output	68.71	0.43	15.86	0.60	9.40	4.45	0.55
Investment	61.94	0.54	22.02	1.00	9.39	4.57	0.54
Employment	63.99	0.51	18.67	0.72	10.52	4.96	0.64
CA ratio	65.16	3.82	6.89	2.64	15.16	5.11	1.21
Total lending	62.01	0.54	21.48	1.16	9.64	4.58	0.58

TABLE 1.3: Infinite horizon variance decomposition



(A) Output

(B) Investment

(C) Hours worked

(D) Consumption

(E) Capital-Asset ratio

(F) Total lending

FIGURE 1.6: Shock decomposition

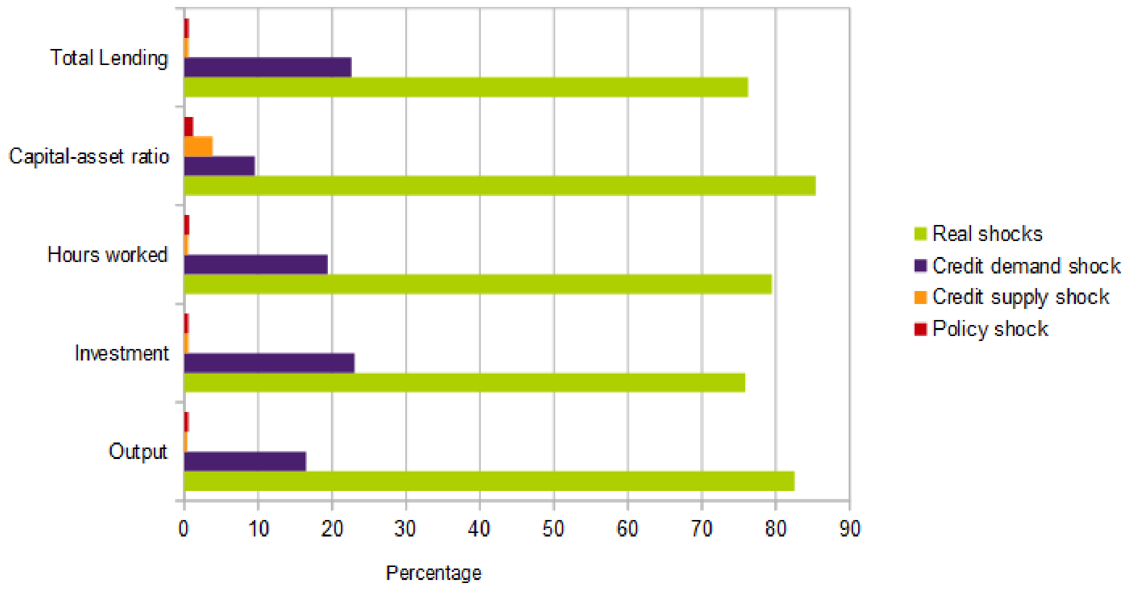


FIGURE 1.7: The magnitude of the contribution of shocks to macroeconomic variations.

shocks, financial shocks, and policy shocks to the variation in output, investment, hours of work, capital-asset ratio, and total lending. The contribution of real shocks in macroeconomic fluctuations is by far the largest and is followed by the contribution of credit demand shocks. The credit supply shock, on the other hand, has a marginal impact compared to that of credit demand shock. In this case, policies that are targeting bank capital might be ineffective in stimulating the economy.

1.5 Conclusion

After the 2007 and 2008 financial crisis and the ensuing recession, the focus in the literature started to shift towards the role that financial shocks play on macroeconomic fluctuations. A consensus started to emerge in the literature about the significance of financial shocks in causing macroeconomic fluctuations and the interest of studying financial market dynamics has become central to understanding the business cycle. The central theme of this paper is to have a comparative analysis of the roles of credit demand shocks versus credit supply shocks in the business cycle. To that end, a DSGE model similar to the one introduced by Meh and Moran (2010) was built and estimated. The model features seven exogenous shocks three of which are financial shocks. The three shocks are called financial shocks because they directly affect components of the financial contract in the model that determines the total credit in the economy. The bank capital shock affects the net worth of banks and therefore, is considered a credit supply shock. On the other hand, the entrepreneurial capital shock and risk shocks are credit demand shocks because they affect the net worth of entrepreneurs and the return on entrepreneurial projects respectively. The other four shocks in the economy includes: technology shock, monetary policy shock, price mark-up shock, and wage mark-up shock.

The simulation exercise shows that the three financial shocks can cause quantitatively significant macroeconomic variations. Entrepreneurial capital shock and risk shock were able to generate variation in output, investment, inflation, and total lending two to four folds greater than the variations generated by the bank capital shock. This points out to the importance of shocks affecting the demand side of credit.

The AR(1) coefficients as well as the standard deviations of all the seven shocks in the model are estimated by Bayesian methods. The estimation procedure used seven time series data: GDP, consumer price index, hourly compensation in the non-farm sectors, federal fund rate, total commercial lending by all banks, leverage ratio of all banks, and return on equity for all banks. The estimated AR (1) coefficients show that all the three financial shocks are quite persistent. On the other hand, the estimated standard deviations of bank capital shock, entrepreneurial capital shock, and risk shock are quantitatively significant. The combination of high standard deviation and large persistence suggests that there is evidence in the data that financial shocks are important driving forces of macroeconomic fluctuations. The empirical results also show that credit demand shocks account for about (16%) of the variations in output and about (22%) of the variation in investment. The credit supply shock, on the other hand, had a marginal effect on the variation in output and in investment.

Three reservations should be made while interpreting the results. The results are very sensitive to the choice of the observed variables that are used in the estimation, the filtering methods used to detrend the observed series, and finally the choice of the prior beliefs that we have about the estimated parameters. The results obtained here are suggestive at best and they are conditional on the choice of observables, the filtering methods, and the prior distributions of the parameters.

The results in this paper support the growing realization in the literature of the importance of financial factors to the study of the business cycle. The paper also puts forward the possibility that credit demand shocks are much more significant than credit supply shocks. However, the used model abstracts from key features of financial cycles. The first is that there is no accumulated debt and entrepreneurs pay the full amount they borrowed in the next period in form of capital goods. The second is that banks and entrepreneurs, or lenders and borrowers, do not manage their balance sheets. In the model, banks and entrepreneurs invest their accumulated earnings in entrepreneurial projects. An active banking sector is of extreme importance from macroeconomic perspective as it allows us to understand why banks choose a particular level of risk and perhaps more importantly is how monetary policy affects the risk-taking behavior of the financial sector. The third issue, which is related to the second issue, is that banks and entrepreneurs cannot issue external equity. Their net worth evolves as a result of accumulated earnings, which leaves them vulnerable to shocks in earnings and to their net worth. This demonstrates that we are still far from fully understanding the links between financial cycles and business cycles. Incorporating more features of the financial cycle into business cycle models should be on the agenda for future research.

Appendices

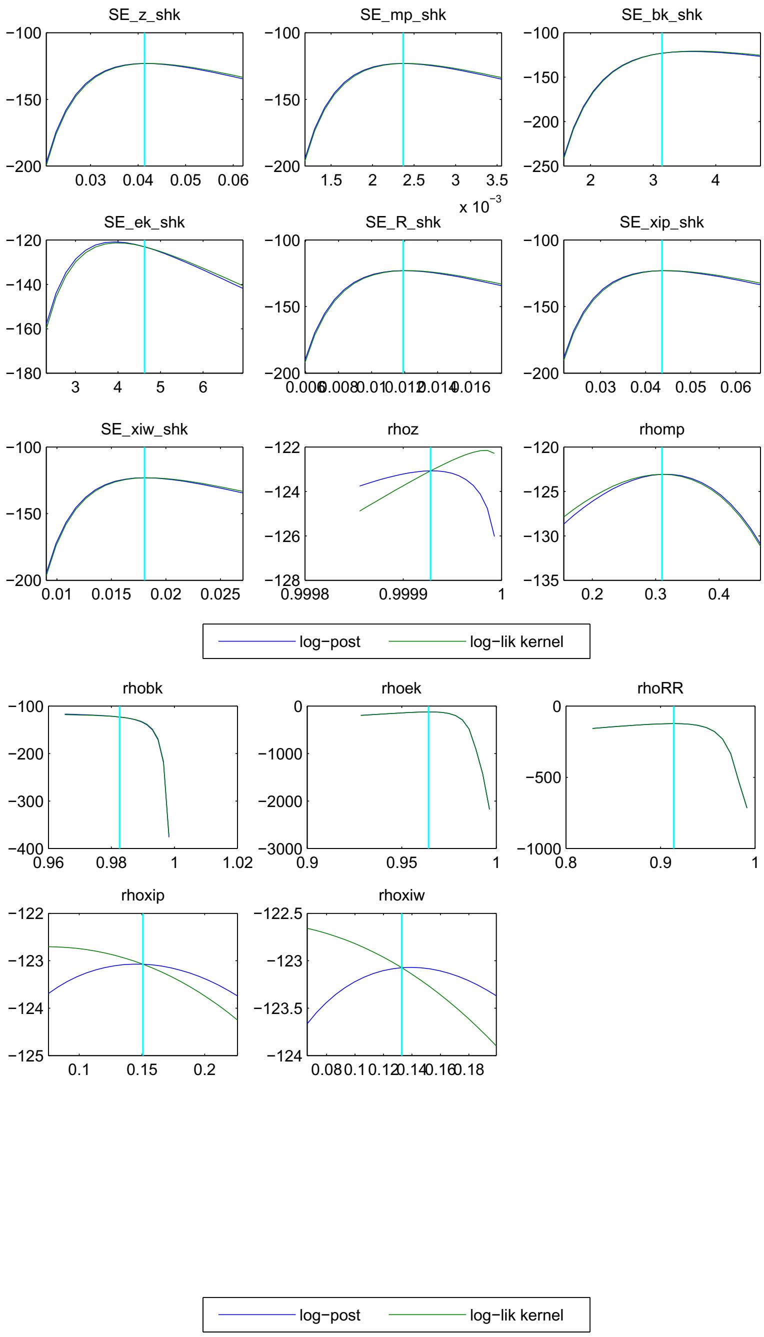
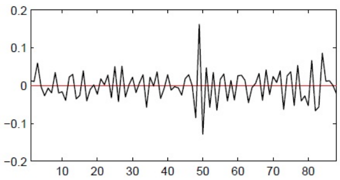
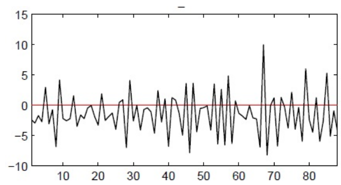


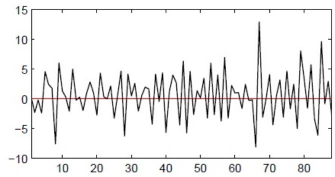
FIGURE 8: Log of the posterior likelihood



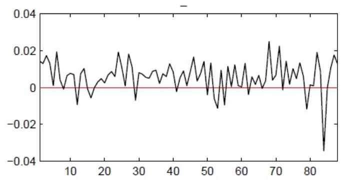
(A) Technology



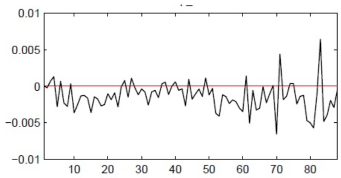
(B) Banks' Capital



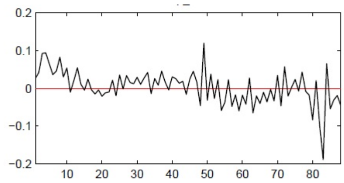
(C) Entrepreneurs' Capital



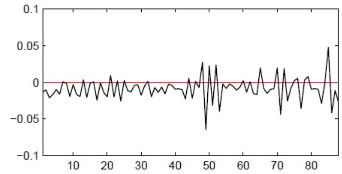
(D) Risk



(E) Monetary Policy



(F) Price Rigidity



(G) Wage Rigidity

FIGURE 9: Historical smoothed shocks

Chapter 2

Household Debt and the Effectiveness of Monetary Policy

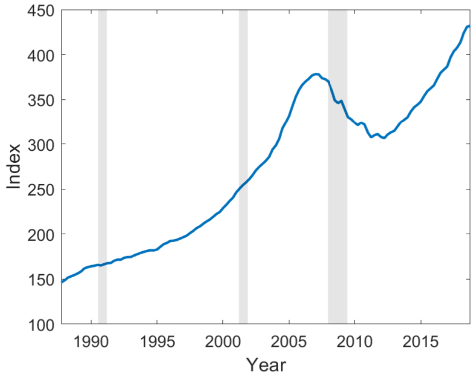
Introduction

Falling house prices, the subsequent large-scale mortgage delinquencies and household deleveraging were at the center of the Great Recession and raised many questions about the macro-financial effects of household debt.[1] The three panels in Figure 2.1 depict the S&P Case-Shiller U.S National Home Price Index, Mortgage debt, and delinquency rate from 1988 to 2019. By December 2007, the official starting date of the Great Recession, S&P/Case-Shiller U.S. National Price Index dropped by over 10 points from a historical record high on February 2007.[2] Similarly, mortgage debt has peaked at 1.4 trillion dollars in the first quarter of 2007 before starting a long period of deleveraging to reach to about one trillion dollars in the first quarter of 2013. The delinquency rate, on the other hand, was 3.66% at the outset of the Great Recession before peaking at 11.53% during the first quarter of 2010.

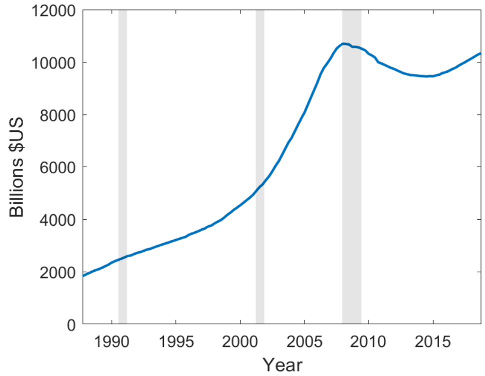
Consumer credit in well-functioning financial markets facilitates economic growth

[1] A mortgage becomes delinquent if the borrower fails to make payments on time. Delinquent mortgages would lead to foreclosure proceedings if the account is not brought to terms in a particular period of time

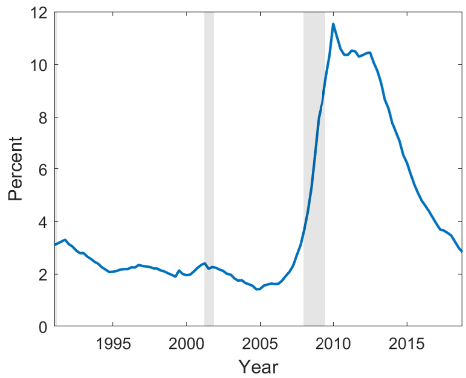
[2] This corresponds to more than 10 percent drop in the weighted average of house prices as compared to the base year.



(A) Home Price Index



(B) Mortgage Debt



(C) Delinquency Rate

FIGURE 2.1: Historical Home Price Index, Mortgage Debt, and Delinquency Rate in the United States

and contribute to consumption smoothing over the life cycle. Rising household debt, however, is a source of economic vulnerability which could trigger economic downturns in case of home price correction, income shock, and/or rising cost of borrowing. This paper aims to answer two fundamental questions: (1) has monetary policy contributed to rising household debt in the periods leading to the Great Recession? And (2) how severe the Great Recession would have been had household debt been lower? In answering these questions, a Factor-Augmented Vector Autoregression (FAVAR) model is estimated using U.S. macroeconomic and financial time-series on output, inflation, commodity price index, federal funds rate, and total household liabilities from 1970-2007 period. Data after 2007 is used to test the ability of the model to replicate the dynamics that we observed during the Great Recession. Tests of stability of the estimated coefficients suggest the existence of a structural break which is interpreted as a change in the transmission mechanism. Therefore, the sample is divided into two periods of low and high household leverage and the model is estimated for the two periods. Shocks to monetary policy, output, and household debt are identified by Cholesky decomposition. The hypothesis of shocks having constant variance across the two periods is rejected and the estimated volatility is determined to be lower in the second period. Comparison of the impulse response functions of output and household debt to a monetary policy shock show a stronger response in the second period. Furthermore, in order to determine whether the stronger response is due to a stronger transmission mechanism or a less responsive monetary policy, the monetary policy reaction functions (or monetary policy rule), the response of policy rate to macroeconomic shocks, in the two periods are estimated. The results suggest that monetary policy was less responsive to macroeconomic shocks in the second period. Therefore, the stronger response of output and household debt in the second period might have been due to a combination of stronger transmission mechanism and a weaker monetary policy reaction. In addition, the paper also presents indications of increased macroeconomic instability due to high household leverage.

To investigate the role of household leverage in the downturn during the Great Recession, a counter-factual experiment is conducted using the estimated FAVAR model with a hypothetical household leverage that is significantly lower than the actual leverage. In the first case, using actual leverage, the model predicts a recession with similar magnitude and dynamics of the Great Recession. When the hypothetical lower leverage is used, the model predicts a moderate recession. This result combined with evidence of macroeconomic instability in the period of high household leverage suggest that high leverage created a fragile economic environment and contributed to the severity of the Great Recession.

The paper contributes to two strands in the literature; monetary transmission mechanism and the role of financial frictions in macroeconomic stability. The paper presents evidence on increasing monetary transmission mechanism through stronger response of household debt to monetary policy shocks. Another contribution of the paper is that rising household debt contributed to macroeconomic instability and to the severity of the Great Recession. The following section presents some stylized facts about the cyclical behavior of home prices and for household debt. The related literature is reviewed in section 2.2. Section 2.3 describes the research methodology. The used data and the results are discussed in section 2.4 followed by a conclusion in section 2.5.

2.1 Stylized Facts on Housing

In order to gain insights into the interactions between the housing market and the macroeconomy, it is important to examine the cyclical behavior of key housing variables and compare them to the cyclical behavior of main macroeconomic variables. Business cycle stylized facts of output, investment, consumption, price level, employment, and total factor productivity are well documented and every macroeconomist know them by heart:

- Investment, consumption and employment are procyclical.
- Investment is at least three times more volatile than output.
- Consumption, labor productivity, and price level are less volatile than output.[3]
- Employment is as volatile as output.[4]
- With the exception of price level, all variables are procyclical.
- All variables show high persistence.

In the following subsections, the cyclical behavior of home prices, residential investment, and household debt are documented.[5]

2.1.1 Home Prices

Figure 2.2 shows the log difference of the seasonally adjusted S&P/Case-Shiller U.S. National Home Price Index and that of U.S. Real Gross Domestic Product. The quarterly observations cover the period from Q4-1987 to Q1-2019. The graph shows that home price is more volatile than output. In the case of the Great Recession, home

[3]This is not the case for many developing economies

[4]Volatility of total hours are much closer to volatility of output while average hours is way less volatile than output.

[5]Data presented in all of the figures in this section is obtained from the St. Louis Fed. FRED

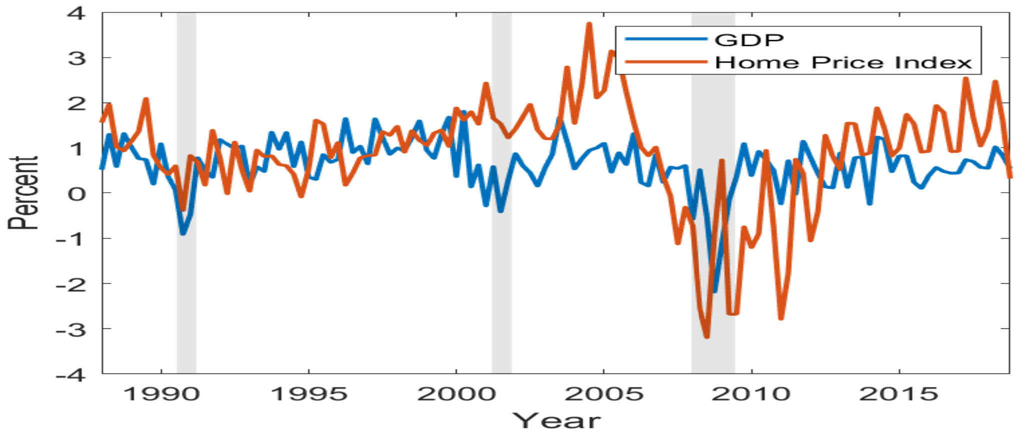


FIGURE 2.2: Quarterly percentage change of home price index and GDP.

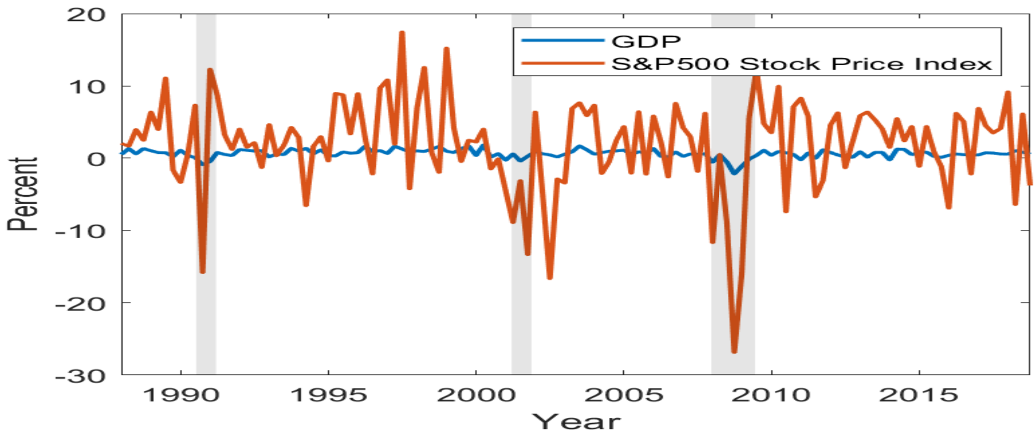


FIGURE 2.3: Quarterly percentage change in s&P 500 and GDP.

prices started to decline well before output. The sharp decline of home price saw the index falling from 184.55 in Q12007 to 177.05 in the first quarter of 2008.

Similarly, Figure 2.3 depicts the log difference of S&P500 Stock Price Index, seasonally adjusted, with that of Gross Domestic Product over the same period. The graph shows that stock prices exhibit similar cyclical properties as home prices suggesting that both of them are more volatile than output, procyclical, and lead the cycle. As Figure 2.4 shows, however, stock price is considerably more volatile.

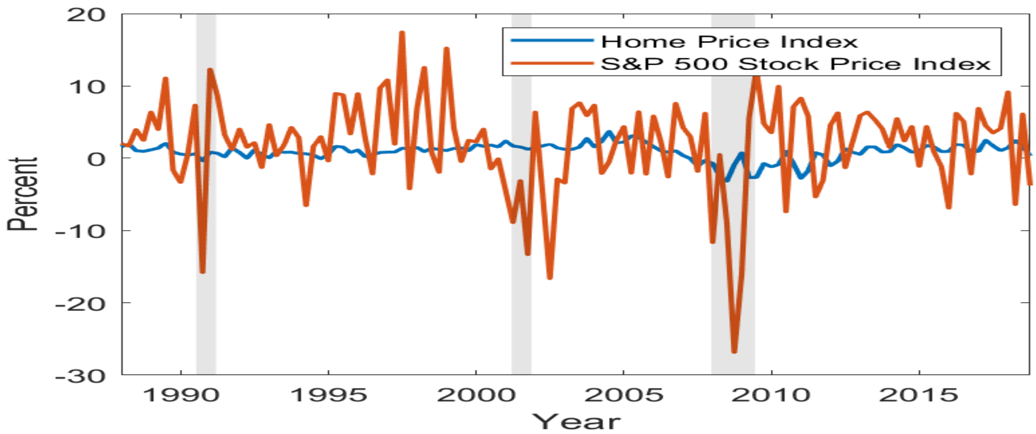


FIGURE 2.4: Quarterly percentage change in S&P 500 and home price index.

2.1.2 Residential Investment

The cyclical component of Private Residential Investment is plotted in Figure 2.5 along with that of Gross Domestic Product. The graph indicates that residential investment is much more volatile than output. Although residential investment lead the cycle during the first and last recessions, it appears to coincide with GDP during the recession in early 2000's. Since aggregate investment is the most volatile component of GDP, it is important to examine the volatility of the two components of aggregate investment: private residential investment and private non-residential investment. Figure 2.6 shows that residential investment is more volatile than non-residential investment and both appear to have some degree of positive correlation.

2.1.3 Mortgage Debt

Mortgages and Consumer Credit are two major components of household debt. Mortgage debt accounts for an overwhelming 74.5% of total household debt. Figure 2.7 depicts the cyclical component of mortgage debt and that of GDP. The graph shows that mortgage debt is more volatile than output. Figure 2.8 shows that the

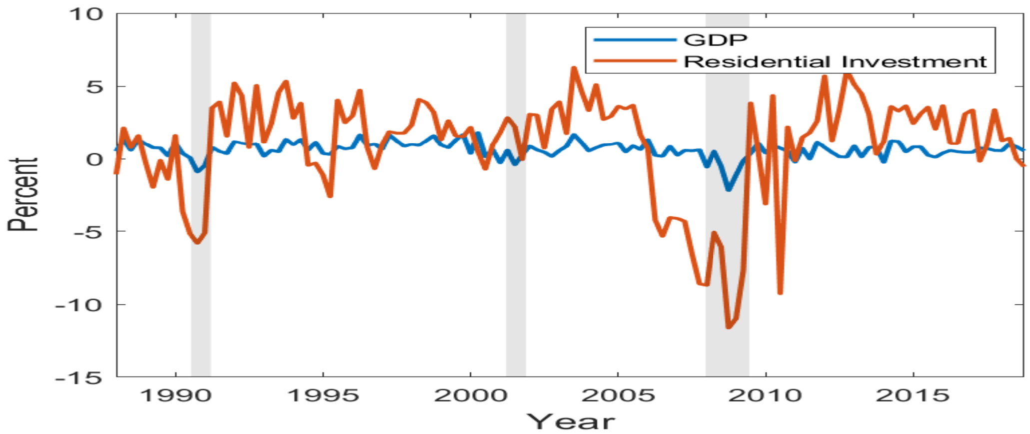


FIGURE 2.5: Quarterly percentage change of residential investment and GDP.

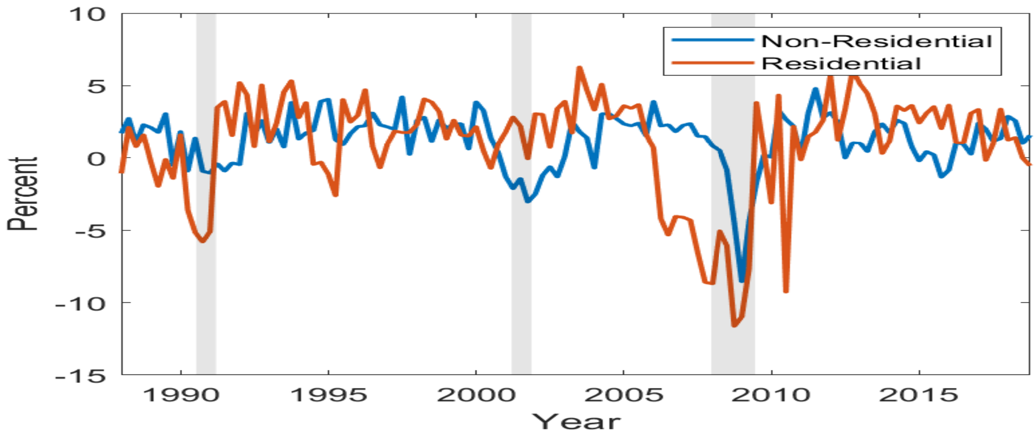


FIGURE 2.6: Quarterly percentage change of private fixed investment and residential investment.

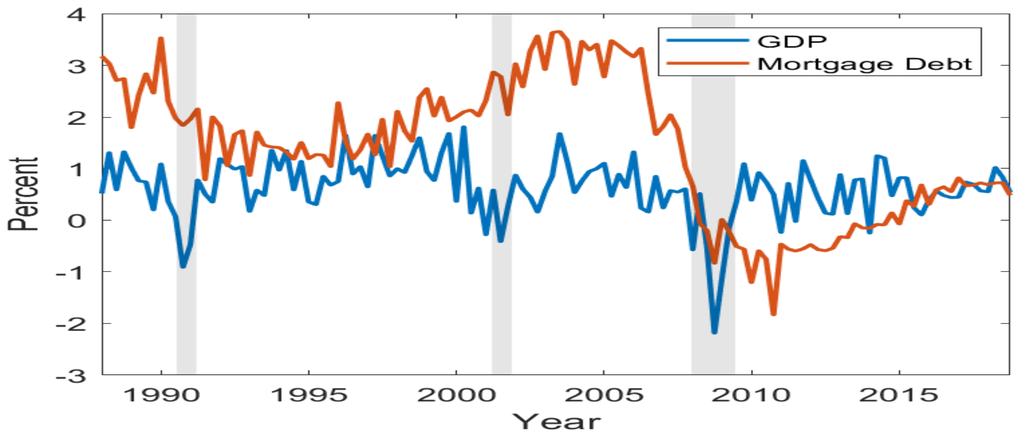


FIGURE 2.7: Quarterly percentage change of mortgage debt and GDP.

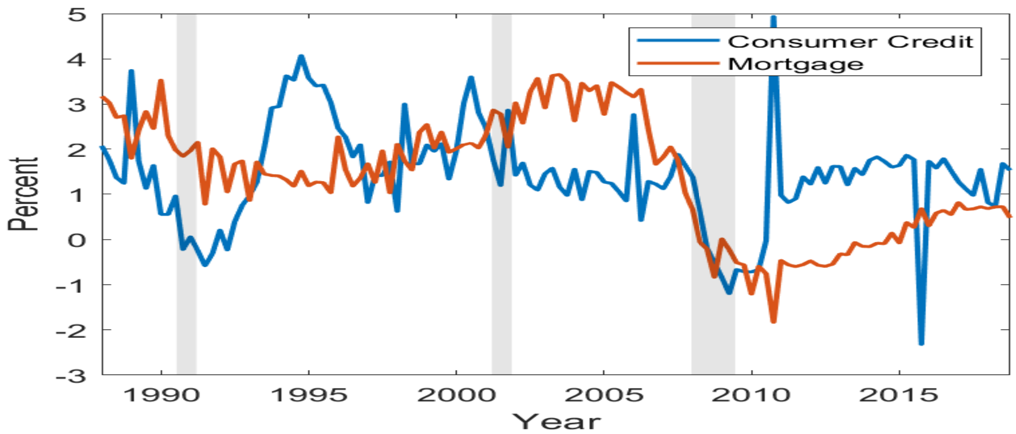


FIGURE 2.8: Quarterly percentage change of consumer credit and mortgage debt.

cyclical component of mortgage debt is more volatile than that of consumer credit. It also shows that the two series have some degree of positive correlation.

2.1.4 Variations and Correlations

Table 2.1 confirms the drawn conclusion from examining the plots in the previous section. The second column shows the relative volatility of the cyclical component of each of the variables to GDP. All variables are more volatile than output but with different magnitudes. The difference in relative volatility between home prices and stock prices is stark. Stock prices are 11.3 times more volatile than output while

Variable	$\frac{\sigma_x}{\sigma_{GDP}}$	$\sigma_{x,GDP}$	ρ_x
Gross Domestic Product	1	1	0.3816
Private Non-Residential Investment	3.3187	0.5868	0.6473
Private Residential Investment	6.2917	0.5535	0.6488
Home Price	2.0321	0.2993	0.7123
Stock Price	11.3125	0.4526	0.1392
Consumer Debt	1.9591	0.3108	0.5880
Mortgage Debt	2.2587	0.2643	0.9133

TABLE 2.1: Relative volatility, correlation, and autocorrelation of seven macroeconomic series.

home prices have twice the volatility of output. Similarly, residential investment is 6.29 times more volatile than output while non-residential investment is approximately three times more volatile than output. On the other hand, both components of household debt have similar relative volatilities. Consumer debt is about two times more volatile than output and mortgage debt is 2.25 times the volatility of output.

The third column shows the coefficient of correlation of each variable with output. Positive coefficients of correlation indicate that all series are procyclical. Private non-residential investment has a similar correlation with output as private residential investment, 0.586 and 0.553 respectively. Consumer debt has a slightly higher correlation of output than mortgage debt, 0.311 and 0.264, respectively. In contrast, the level of correlation between stock prices and output is about 50% higher than the correlation between home prices and output. The last column shows the autocorrelation coefficient of each variable.[6] With the exception of stock prices, all series are persistent and significantly more persistent than output. Residential and non-residential investment have autocorrelation coefficient of about 0.64. Mortgage debt is much more persistent than consumer debt, 0.913 and 0.588 respectively. Home

[6]The reported autocorrelation coefficients are computed with the first lag. Figure 2.9 depicts the entire autocorrelation functions.

prices are persistent with coefficient of autocorrelation of 0.712 while stock prices have very low persistence of about 0.14. These different patterns are further demonstrated in the full autocorrelation functions depicted in Figure 2.9. Autocorrelation functions of Output, residential investment, non-residential investment, and home prices die out after 4-10 lags while that of mortgage debt dies out after 16 lags.

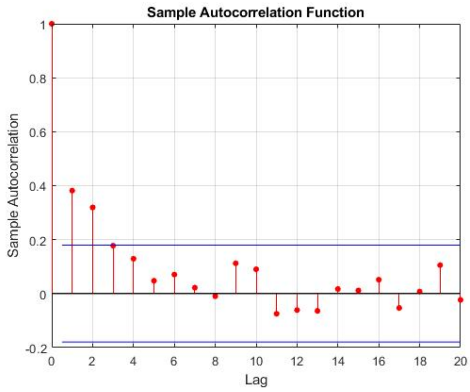
2.2 Household Debt and the Business Cycle: Literature Review

The literature of monetary transmission mechanism and the role of financial frictions in macroeconomic stability is vast. Therefore, this section is not intended to be a comprehensive review of the literature. The section starts by reviewing the literature on the role of housing in the transmission of macroeconomic shocks and in macroeconomic stability before reviewing the literature on monetary policy and rising household debt.

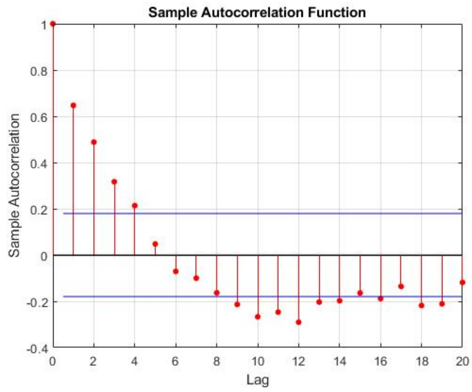
2.2.1 Transmission Mechanism of Macroeconomic Shocks

In their groundbreaking work, Kydland and Prescott (1982) used the rigorous new classical growth model to study the business cycle.[7] In doing so, they revolutionized the research methodology and paved the way to a rich strand of research that is still active today.[8] In their Real Business Cycle (RBC) model, there was no financial sector, no borrowing, and all variables were real. An equally important contribution of their paper is the conclusion that the business cycle is a real phenomenon that could be explained by shocks to real variables. Their model featured only one shock to total factor productivity or technological shock and was able to remarkably replicate most of the stylized facts of the business cycle. One key feature of the model is the response of investment to technological shocks. A positive/negative

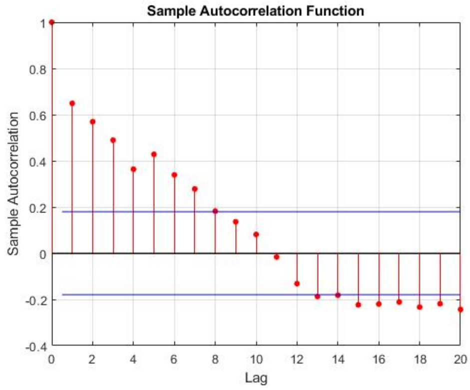
[7] See Hansen (1985) for a different version of the model.
[8] See King and Rebelo (1999) for a detailed review.



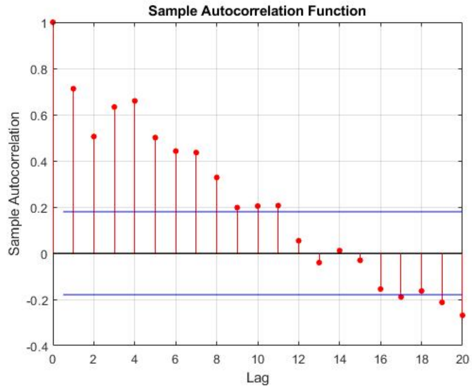
(A) GDP



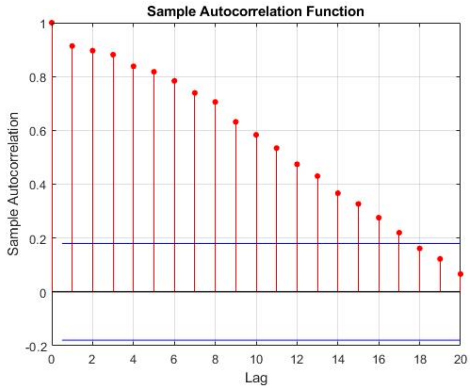
(B) Non-Residential Inv.



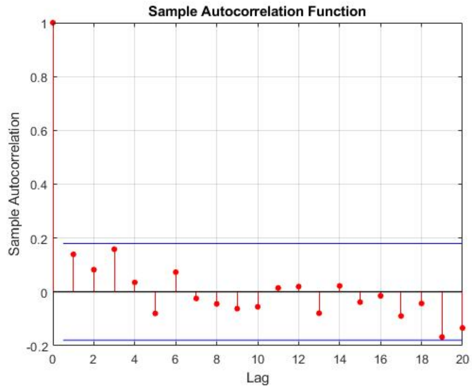
(C) Residential Inv.



(D) Home Price



(E) Mortgage Debt



(F) Stock Price

FIGURE 2.9: Auto-correlation functions

technological shock would raise/oppress the return on capital and consequently increase/decrease investment.[9] The response of consumption to technological shocks in the model is due to the wealth effect generated by changes in employment, wages, capital stock, and the price of capital.

Although the housing market is not explicitly modeled in the early RBC theory, we could use the early RBC model as a framework to explain the role of the housing market in the transmission mechanism of technological shock. In the national accounts, residential investment is part of aggregate investment, therefore, residential investment and housing stock are part of aggregate investment and aggregate capital in the RBC theory. In this framework, changes in total factor productivity affects the return on housing, residential investments, and housing stock. We should also expect that changes in equilibrium home price to have a wealth effect on aggregate consumption. In particular, a positive technological shock would increase the marginal productivity of housing which leads to an increase in residential investment and stocks. In equilibrium, we would expect to observe higher home prices which in turn would have a positive wealth effect leading consumers to consume more.[10]

The RBC model has some limitations when confronted with data. Firstly, the magnitude of the technological shock that is needed to replicate the business cycle's stylized facts is larger than what is supported by empirical research on total factor productivity.[11][12][13] The second limitation is widely known as the equity premium puzzle and was first explained by Mehra and Prescott (1985). It simply states that

[9] A second propagation channel in the model links technological shocks to hours of work and employment through returns on labor.

[10] This wealth effect is the same as the wealth effect that would work through higher wages as a result of a positive productivity shock

[11] See King and Rebelo (1999) for more details

[12] Another related limitation is that the model requires levels of technological retrogression that are hard to justify.

[13] RBC models with time-to-build have addressed this measurement issue and succeed to match the volatility and the persistence of investment that we see in the data. See Prescott (2016) for more detail

the return on equities that is implied by RBC model is too small compared to the observed equity premium.[14] Thirdly, the model only features one real macroeconomic shock. By not considering other potentially important macroeconomic shocks, early RBC model seems to overstate the role of productivity shock in macroeconomic fluctuations. Subsequent research extended the basic RBC model to include a number of other shocks and features into the model. The resulting class of models became to be known as Dynamic Stochastic General Equilibrium (DSGE) models. The evolution of DSGE models involved many types of exogenous fundamental shocks. For example, shocks to oil prices, preferences, degrees of nominal rigidities, and adjustment costs have been featured in numerous DSGE models and their respective macroeconomic effect has been studied.[15][16][17]

Housing, on the other hand, has three unique characteristics when compared to stock equities which constitute conceptual challenge to the early RBC model. Contrary to stock equities, housing has a consumption value, is largely financed by debt, and is widely used as collateral. These unique characteristics make housing investment decisions fundamentally different than investment decisions of stock equities. Therefore, from a modeling perspective, using a fully developed DSGE model featuring a financial sector is needed to study the transmission mechanism of macroeconomic and financial shocks.

2.2.2 The Role of Financial Frictions

Financial markets have been in existence, in one form or another, since the recorded human history to facilitate the transfer of money between borrowers and lenders.

[14] According to Mehra and Prescott (2003), RBC models generate equity premium of about 1 percentage point while observed average yearly equity premium is about 6.9 percentage points.

[15] See Ramey (2016) for a literature review on macroeconomic shocks

[16] The inclusion of financial sector, financial frictions, and financial shocks are important developments in DSGE models will be discussed in section (2.2.2).

[17] Monetary policy shocks have always been the usual suspect in causing business cycle fluctuations, further discussion of monetary policy in section (2.2.3).

Households might choose to borrow to invest in a home or in an entrepreneurial project. Household debt is also used to cover sudden unexpected expenses or to finance the purchase of durable consumption goods and big-ticket items. Financial products such as mortgages, lines of credit, credit cards, and personal loans are widely used to finance household debt. Firms, on the other hand, might borrow to cover short term fluctuations in their cash flows, to finance daily operations or the creation of new projects and products. Corporate bonds, business loans, and lines of credit are popular financial products used by firms. Governments at all levels constitute the third major borrower in the credit markets. Public debt is used to finance investment in infrastructure, education, health, and defense.[18] On the supply side of the credit markets, we have wealthy individuals and institutional investors lending money in order to increase their wealth overtime.[19]

Despite the motivation and the objectives of individuals and institutions in participating in borrowing and lending, private and public debt is central to economic growth and macroeconomic stability. The idea that debt is an engine of economic growth should not be surprising since a significant amount of debt is used to finance investments in growth fundamentals such as entrepreneurial projects, infrastructure, and human capital. Levine (1998) and Beck and Levine (2004) found that the level of financial development and the respective higher levels of private debt lead to higher economic growth.[20]

In the life-cycle models with frictionless financial sector, household would borrow to smooth their consumption over the life-cycle. This result is known in the literature as the permanent income hypothesis which states that in anticipation of

[18] Even though I might refer to debt held by private firms and governments, the focus of this paper is on household debt.

[19] Precautionary savings and retirements savings is a separate strand of economic research. See Fernández-Villaverde and Krueger (2007) and Fernandez-Villaverde and Krueger (2011) for a literature review

[20] Recent studies by Arcand, Berkes, and Panizza (2015)and Sahay et al. (2015) painted a less optimistic picture about the long run economic effect of household debt. They show that investment on non-productive resources and higher probability of financial crisis associated with higher leverage could hinder the positive effect of debt on economic growth

future increase in income and in the presence of a well-functioning and frictionless financial sector, economic agents would borrow to smooth consumption.[21] The important result of the permanent income hypothesis is that household debt plays a very important role in macroeconomic stability in terms of consumption smoothing.

Allowing economic agents in DSGE models to borrow from a frictionless financial sector has important macroeconomic implications. In the context of business debt, as new entrepreneurial projects arise that require funding beyond the resources available to firms, the existence of a frictionless financial sector gives firms access to capital in order to finance these projects. In Equilibrium, the existence of frictionless financial sector would result in higher levels of investment, capital, consumption, output, and higher asset prices. In the context of household debt, on the other hand, frictionless financial sector will enable households to finance residential investments in housing and other durable goods. The equilibrium effect would be similar to that of business debt, in particular, higher levels of residential investment, housing structures, consumption, output, and higher home prices.

The lure of debt stems from the notion of frictionless financial markets where there is no risk of default (willingly or not), no information asymmetry between borrowers and lenders, and no adverse selection problem facing lenders. In such a utopian world, funds would be available to meet immediate needs and to finance costly investments. In reality, however, financial markets are plagued by frictions that limit the smooth flow of funds between borrowers and lenders, potentially disrupting the efficient allocation of resources.[22] Starting from late 1990s, the question of the macroeconomic effect of financial frictions started to take prominence in the literature.

There are two ways to model financial frictions in DSGE models. The first is

[21] The permanent income hypothesis dates back to the work of Friedman (1957) and Hall (1978)

[22] In addition to default and information asymmetry, financial markets exhibit numerous risks such as market risk, credit risk, liquidity risk, and operational risk.

what Bernanke, Gertler, and Gilchrist (1999) termed as agency cost which is simply the modeling of the problem of information asymmetry between borrowers and lenders. In this setup, lenders have to undertake costly monitoring of borrowers to guarantee the payback of loans.[23] The second way to model financial frictions is to assume that lenders require collateral from borrowers to secure any loan. In this setup, the capacity to borrow is limited by the value of the collateral and more importantly, credit markets are vulnerable to fluctuations in the value of the collateral.[24]

Macroeconomic effect of rising debt in the presence of financial frictions is a two-way road and is a concern for business debt as well as household debt. On the one hand, rising debt levels might exacerbate the macroeconomic effect of real shocks by intensifying the effect of the financial accelerator.[25] In DSGE models with financial frictions in the form of collateral constraints, for example, adverse real macroeconomic shock would lower the value of the collateral and consequently put pressure in the ability of firms to borrow, which in turn would put further pressure on asset prices. On the other hand, excessive leverage could also, independently, threaten financial and macroeconomic stability by serving as a source of financial shocks.[26][27]

The heterogeneity of households has recently taken much attention in the literature where economists have begun to study the extent to which debt distribution affects macroeconomic aggregates. The idea simply is that debt distribution determines the extent to which differences in the marginal propensity to consume between constrained and non-constrained households affect aggregate demand in case

[23] Some examples includes Bernanke, Gertler, and Gilchrist (1999), Blanchard, Dell'Ariccia, and Mauro (2010), and Christensen and Dib (2008)

[24] Some examples includes Brunnermeier and Sannikov (2014), Gerali et al. (2008), Gilchrist, Ortiz, and Zakrajsek (2009), Iacoviello and Minetti (2008), and Kiyotaki and Moore (1997a)

[25] For more detailed information regarding the vicious cycle of the financial accelerator, see Bernanke, Gertler, and Gilchrist (1999).

[26] Some examples of financial shocks that have been studied in the literature include: asset prices shock, credit worthiness shock, risk appetite shock, return on investments shock, and liquidity shock.

[27] Numerous papers have studied the macroeconomic effect of financial shocks in the wake of the Great Recession. See the first chapter of this thesis for a review.

of a macroeconomic shock. Consider for example a heterogeneous agent model with two types of households, those that are highly indebted and those that are not. Each household type faces a borrowing constraint, the first type has reached its borrowing limit and the second has not. Consider a financial shock which causes the value of the collateral to depreciate. This shock might lead the highly indebted agents to default or to start a deleveraging process whereby they would reduce their spending on consumption and residential investment. If this reduction in spending is not offset by an increase in spending by less indebted agents, we would face a decrease in aggregate demand which in itself would put further pressure on asset prices and the value of the collateral. This is an example of how highly indebted households might trigger a cycle of default and deleverage that could lead to a lower aggregate demand.[28]

The sensitivity of the response of home price and household debt to real and financial shocks becomes more layered in the context of housing being financed by mortgages and at the same time being used as a collateral. In general, the entire transmission of real and financial shocks would be dependent on the characteristics of mortgage contracts such as the types mortgage rate, the term of interest, or amortization.[29]

2.2.3 Debt and Monetary Policy

An obvious limitation of the RBC model is that it does not model the role of money and therefore is not suited for studying the business cycle effect of money. Sidrauski

[28]Korinek and Simsek (2016) discussed the negative externalities of household debt in a sense that households do not take into account the risk to aggregate demand when they make their borrowing decisions.

[29]Mortgage rate could be fixed or variable. The term of the mortgage refers to the time period after which the mortgage rate would be renegotiated. Typically, the mortgage term is between one and five years. Amortization of a mortgage refers to repayment frequencies and duration. Usually mortgages have a duration of twenty to thirty years with biweekly or monthly payments. Lastly, a mortgage can be open or close pertaining to whether the debtor is allowed to repurchase the debt earlier than specified in the amortization agreement. Usually, open mortgages allow for repayment options at a given cost.

(1967) and Clower (1967) introduced two ways to incorporate money in neoclassical models either by introducing money in the utility function or by having goods that can be purchased only by cash. Equipped with a neoclassical model with money, we can easily model monetary policy in terms of growth of money supply and evaluate the effect of monetary policy on real macroeconomic variables.[30] The surprising result was that in the context of this model, in absence of any specific restrictions on utility and production functions, money is neutral and monetary policy has no real economic effect.[31] For example, an aggressive growth of money supply will just lead to inflation with no effect on real variables. If the model prediction is true, monetary policy would have no role to play in macroeconomic stability.

The triumph of the proponents of neutrality of money proved to be short-lived as Christiano, Eichenbaum, and Evans (2001) incorporated nominal rigidities of Taylor (1980) and Calvo (1983) into DSGE models. With prices and wages being slow to adjust, aggressive money growth would affect real economic variables.[32][33] For example, when nominal interest rate is decreased as a result of an accommodating monetary policy, modeled as a Taylor rule, nominal rigidities in the model would lead to a decrease in real interest rate. This would increase the return on capital, ultimately increasing investment and output. This is the classical interest rate channel of monetary transmission mechanism through which monetary policy shocks transmit to the real economy.

In models with frictionless financial sector, the traditional interest rate channel would have a greater magnitude since a change in the real interest rate would not

[30]Another way of modeling monetary policy is by Taylor role which set nominal interest rate by targeting inflation and/or output. However, there should be lending in the model for Taylor role to be relevant, Consult section 2.2.2 for a review of this class of models.

[31]Neutrality or non-neutrality of money is a decade-long question. see King and Rebelo (1999) for detailed discussion

[32]Menu cost, incomplete information, long term contracts, and geographical immobility in the labor market were among the reasons cited as to why prices and wages are rigid and slow to adjust, see Calvo (1983) for detailed discussion

[33]Modeling price and wage rigidities involves introducing imperfect competition in intermediary goods and labor markets which facilitates a mechanism for setting prices and wages.

only alter investment incentives but would alter the cost of borrowing as well. An accommodating monetary policy in this framework would ultimately lower the real interest rate and the cost of borrowing which in turn induce more investment and spending. Consequently, we should expect a rise in newly issued household debt during periods of easy monetary policy and a decline during periods of restrictive monetary policy.

Frictions in the financial sector constitute another channel for the monetary policy namely the balance sheet channel. According to this channel, a decrease in the nominal interest rate would lead to an increase in asset prices, which inflate the collateral value of credit-constrained consumers. Consequently, economic agents are able to borrow more.

In the context of household debt and the use of housing as a collateral, an accommodating monetary policy would stimulate output through interest rate channel and the balance-sheet channel. In the first channel, lowering the nominal interest rate would encourage borrowing, investment in housing, and consumption by lowering the cost of borrowing and increasing the return on housing. In the balance-sheet channel, on the other hand, negative monetary policy shock would ultimately fuel home prices which would increase the value of collaterals and make it easy for household to borrow.[34] Recent studies have further examined the effect of different features of mortgage contracts as well as the distribution of assets and debt on the significance of interest rate and the balance-sheet channels of monetary transmission mechanism.[35]

Household debt matters to policy makers because it constitutes a double-edged tool for monetary policy. On the one hand, economic stimulus depends in part on

[34] This is not the only channels of monetary transmission mechanism. For a complete review on the monetary transmission mechanism see (ramey2016macroeconomic)

[35] There is a large literature on the effect of high level of business debt on the effectiveness of monetary policy. See Kiyotaki and Moore (1997a), Bernanke, Gertler, and Gilchrist (1999), and Brunnermeier and Sannikov (2014) for more details.

households being able to borrow, while on the other hand, too much borrowing constitutes a threat to financial stability. Given that the broad objectives of monetary policy are to stimulate economic activities during downturns and to promote macro-financial stability, the level of household debt should be a concern to monetary authority because it poses a threat to financial stability and, at the same time, it might curtail the ability of monetary policy to stimulate aggregate demand during economic downturns.

2.3 Methodology

2.3.1 Factor-Augmented Vector Autoregressive Model

Dynamic Factor Models

Reliable macroeconomic series have a short horizon, typically forty to fifty years at the most, and the vast majority are observed at monthly or quarterly frequencies. This might lead to having datasets with the number of series exceeding the number of observations. Dynamic Factor Models (DFM) emerged in the seventies with the work of Geweke (1977) and Sargent, Sims, et al. (1977) to deal with this peculiarity of macroeconomic time-series data. Take any dataset with a large number of series (N), the underlying unobserved factors behind the variation of all the series is $n << N$. By modeling this intuitive relationship between the observed series and the latent factors, DFM can be used to estimate the factors and generate forecasts for large number of macroeconomic series.[36] The remarkable ability of DFM to extract a few latent factors from a large number of observed series matched a central

[36] The central idea that a small number of latent factors generate most if not all of the variation in macroeconomic series has been supported empirically. See Giannone, Reichlin, and Sala (2004) and Stock and Watson (2011) for more details.

and intuitive problem in macroeconomics, where it is widely believed that the variation in all macroeconomic series is caused by few exogenous shocks. The following discussion of the methodology is based on Stock and Watson (2011).

Consider the following Vector Auto-Regression model:

$$X_t = \Gamma(L)X_{t-1} + e_t \tag{2.1}$$

where X_t and e_t are vectors of size $(N \times 1)$, L is the lag operator, and $\Gamma(.)$ is the $(N \times N)$ matrix of coefficients. The econometric challenge posed by the peculiar nature of macroeconomic data is well demonstrated in this model; the number of unknown coefficients to be estimated and, the elements of $\Gamma(.)$, would exceed the number of observations as N gets larger. Furthermore, the problem is even more pronounced when the number of lags increases. As a result, macroeconomists have been forced to omit the information captured by numerous observed macroeconomic variables.

Dynamic factor models present a solution to the curse of dimensionality suffered by VAR models. Instead of modeling X_t in the previous example as an autoregressive vector, DFM models the evolution in X_t according to the following two equations:

$$X_t = \Gamma(L)f_t + e_t \tag{2.2}$$

$$f_t = \Psi(L)f_{t-1} + u_t \tag{2.3}$$

where f_t is a $(n \times 1)$vector of factors (n is much smaller than N). $\Psi(.)$ is of size $(n \times n)$ and called the dynamic factor loading which determines the evolution of factors. $\Gamma_i(L)$ is of size $(N \times n)$ and called the dynamic factor loading for the i_{th} series X_{it} and $\Gamma_i(L)f_t$ is called the common component for the i_{th} series.

The disturbances e_t are uncorrelated with the factor innovations at all leads and lags. In particular, $(e_t u_{t-j}) = 0, \forall i$. The errors are also assumed to be uncorrelated at all leads and lags, $e({}_{it}u_{js}) = 0 \quad \forall s$ and $\quad \forall i \neq j$.

Factor Estimation

To use the DFM in (2.2) for forecasting purposes, one needs to estimate the factors f_t, the factor loading matrix $\Psi(L)$, and the common component matrix $\Gamma(L)$. For the purpose of this paper, however, only the factors need to be estimated since the goal is not forecasting but to use the factors in a FAVAR model.

The factors can be consistently estimated using non-parametric methods which can handle higher dimension series.[37] Principal component estimation is an example of non-parametric methods that is shown to give consistent estimates of the factors. Moreover, if N is large enough, the estimated factors would be so precise that they may be treated like data in other regression, which is exactly the objective of this paper.

Let $\Lambda = (\lambda_0, \lambda_1, ..., \lambda_p)$ be a stacked matrix of the lags coefficients where λ_i is an $N \times q$ matrix of the i'th lag coefficients and let $F_t = (f_t', f_{t-1}', ..., f_{t-p}')$ be a $n \times (p+1)$ matrix where f_t' is a $n \times 1$ vector of factors at time t. With appropriate selection matrices $\Theta(L)$ and G, the DFM in (2.2) can be written as:

$$X_t = \Lambda F_t + e_t \tag{2.4}$$

$$\Theta(L) F_t = G u_t \tag{2.5}$$

[37]Other parametric and semi-parametric methods can be used to estimate the factors. See Stock and Watson(2014) for detailed discussion of these methods.

Formally the factors estimator $\hat{F}_t$ as the solution to the following least squares minimization problem:

$$\min_{F_t \forall t, \Lambda} V(F, \Lambda) = \frac{1}{NT} \sum_{t=1}^{T} (X_t - \Lambda F_t)'(X_t - \Lambda F_t) \quad \text{subject to} \tag{2.6}$$

$$N^{-1}\Lambda'\Lambda = I_n. \tag{2.7}$$

The condition $N^{-1}\Lambda'\Lambda = I_n$ is necessary for the consistency of $\hat{F}$.[38]

Let $\hat{\Sigma}_x$ be the sample variance matrix of X_t, such as $\hat{\Sigma}_x = T^{-1} \sum_{t=1}^{T} X_t X_t'$ and let $\hat{\Lambda}$ be the matrix of eigenvectors associated with ordered n largest eigenvalues of $\hat{\Sigma}_x$. The solution to (2.6) is $\hat{F}_t = N^{-1}\hat{\Lambda}' X_t$ which is the scaled first q principal components of X_t.

FAVAR Model

Bernanke, Boivin, and Eliasz (2005) proposed FAVAR as a solution to the problem of dimensionality and invertibility of SVAR.[39] The intuitive idea behind FAVAR is to augment the low-dimension VAR with the factors estimated from a higher dimension dataset according to the previous section. Consider $Z_t = [Y_t \quad X_t]$ where Y_t is a vector of s macroeconomic series of interest and X_t is a higher dimension dataset of size N. Including Z_t in a VAR model is unfeasible due to the dimensionality problem. At the same time, excluding X_t and running VAR with only Y_t might lead to the invertibility problem in addition to leaving out potential valuable information that is included in X_t.

[38] For a detailed discussion about the consistency of the conditional least squares estimator obtained from (2.4), see Stock and Watson (2011).

[39] Invertibility occurs when the innovations of low dimension structural VAR is not invertible which leads to the failure of identifying the structural shocks.

Formally, the FAVAR can be expressed as:

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Psi(L) \begin{bmatrix} \hat{F}_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \tag{2.8}$$

Bernanke, Boivin, and Eliasz (2005) proposed a two stage procedure to address the shortcomings of low-dimension VAR in a feasible way. In the first stage, the higher dimension dataset X_t would be used to estimate n factors by the principle component estimator $\hat{F}_t$. The second stage is to use the estimated factor along with Y_t in the FAVAR model in (2.8).

2.3.2 Identification

FAVAR model in (2.8), similar to any other VAR model, can be estimated and used for forecasting. $(e_t^{'} e_t)$ is diagonal by definition since the errors are assumed to be uncorrelated. In reality, however, there is a contemporaneous structural relationship between macroeconomic variables. Allowing for this contemporaneous effect, the model in (2.8) becomes:

$$A \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Psi(L) \begin{bmatrix} \hat{F}_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \tag{2.9}$$

where A is a square matrix of size $(n+s) \times (n+s)$ whose elements capture the contemporaneous relationships between the series in $[\hat{F}_t \quad Y_t]'$.

Multiplying both sides of (2.9) by A^{-1} yield:

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Gamma(L) \begin{bmatrix} \hat{F}_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t \tag{2.10}$$

where $\Gamma(L) = A^{-1}\Psi(L)$ and $u_t = A^{-1}e_t$. The problem of identification stems from the fact that without further structural assumptions, it is impossible to identify the structural shocks e_t from the residuals in (2.10).[40]

One popular method to identify structural shocks uses Cholesky decomposition of the covariance matrix of the estimated residuals. Given the definition of the residuals u_t in (2.10), the covariance matrix of the residuals $\Sigma_u = u_t^{'} u_t$ can be decomposed according to the following expression:

$$\Sigma_u = u_t^{'} u_t = Q' I Q, \tag{2.11}$$

where I is an identity matrix of size (n+s) and Q is a triangular matrix of size $(n+s) \times (n+s)$ with the diagonal elements of ones. Using the fact that $u_t^{'} u_t = (A^{-1})^{'} I A^{-1}$ and the Cholesky decomposition in (2.11), one can identify the structural shocks by setting $A^{-1} = Q$. Note that this identification method is sensitive to the ordering of variables in the model. To demonstrate this point in the context of this paper, recall that the objective is to identify monetary policy shocks defined as the unexpected changes in the Federal Funds rate. To identify these shocks by Cholesky decomposition, the order of the policy variable in the FAVAR model in (2.10) should correspond to whether the matrix Q in (2.11) is an upper or lower triangular.

Consider the case where Q is an upper triangular matrix. Therefore, the policy variable should be the last variable in the vector Y_t in the FAVAR in (2.10). Recall that the elements of the i'th row in u_t in (2.10) are the residuals corresponding to the i'th variable in the model. By ordering the policy variable last in the model, the corresponding residuals would be the last row in u_t. Formally, this means that the residuals of the policy variable are in fact the monetary policy structural shocks.

[40] For further discussion on contemporaneous effect and the identification problem in VAR, consult Bernanke, Boivin, and Eliasz (2005) and Ramey (2016)

Intuitively, this means that other shocks do not affect the policy variable contemporaneously.

Although the purpose of this paper is to identify monetary policy shocks, Cholesky decomposition can be used to identify all the remaining shocks. The order of the remaining variables also matters since the contemporaneous effect of the shocks on the endogenous variables is sequential. For example, the second variable to the last will be contemporaneously affected by two shocks; monetary policy shock and its own shock. Given that monetary shock is identified and by using the second to the last row in Q, one can identify the vector of the second shock. The process of identifying the remaining shocks would follow in a similar sequential fashion. This sequential identification process intuitively means that each endogenous variable would be contemporaneously affected by its own shock and by shocks of all the variables that are ordered after it in the system and not by shocks to the variables that precede it.

Although Cholesky decomposition is the most commonly used identification method, other identification methods are gaining popularity in the literature. For example, some studies use theoretical structural restrictions such as time restrictions and sign restrictions to identify what became to be known as Structural VAR, or SVAR. High frequency and external instrument methods are examples of less often used but highly promising identification methods.[41]

2.3.3 Impulse Response Functions

Once the model in (2.10) is estimated and the monetary policy shocks are identified, the effect of unexpected changes in the policy variable on all the endogenous variables in the model are estimated using impulse response functions.

[41] For detailed review of identification methods, see Ramey (2016).

Recall that the moving average representation of (2.10) is given by:

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = D(L)e_t \tag{2.12}$$

where e_t is a vector of structural shocks and $D(L)$ is a lag polynomial in the estimated coefficient matrix $\hat{\Gamma}$ and in the identification matrix Q.[42] The estimated impulse response of the variable i h periods after the realization of monetary policy shocks e^{mp} can be formally expressed as:

$$\frac{dY^i_{t+h}}{de^{mp}_t} = D_h(L), \tag{2.13}$$

where e^{mp}_t is the shock in the policy variable at time t and $h \in [1, 2, 3, ..., H]$ is an index denoting subsequent periods over a given horizon H.

Estimating impulse responses by (2.13) is widely used in the literature and is shown by Stock and Watson (2011) to be optimal if the underlying model captures the data generating process well. In the case of model misspecification, however, the iterative method in (2.13) would not give precise estimates and the forecasting error would be compounded in longer horizon. Jordà (2005) and Chang and Sakata (2007) introduced two alternative methods using local projection and log autoregression to estimate impulse responses.[43]

2.3.4 Policy Reaction Function

Changes in impulse response functions of macroeconomic variables to monetary policy shocks could be a result of changes in the transmission mechanism or in the

[42] In fact, to generate impulse response functions to a monetary policy shock we only need the last column of the identification matrix Q

[43] For more details on these methods, consult Ramey (2016)

reaction of monetary policy to macroeconomic conditions. In order to accurately interpret the obtained impulse response functions, the monetary policy reaction function must be estimated. In doing so, the methodology in Boivin and Giannoni (2002) is followed.

The policy reaction function is modeled as:

$$R_t = \phi^0 + \phi^\pi \hat{\pi}_{t+h_\pi|t} + \phi^y \hat{Y}_{t+h_y|t} + \sum_{i=1}^{P} \rho_i R_{t-i} + \epsilon_i. \tag{2.14}$$

According to (2.14), the monetary policy rate R_t is mainly determined by the expected output $\hat{Y}_{t+h_y|t}$, expected inflation $\hat{\pi}_{t+h_\pi|t}$, and the lags of the policy rate R_{t-i}. Expectation of output and inflation are projections of Y_{t+h_y} and π_{t+h_π} on the information available at time t over the horizons h_y and h_π respectively. The inclusion of the lags of the policy rate aims to capture the persistency of the policy rate that we see in the data.[44] The policy reaction function in (2.14) is estimated by the Generalized Method of Moments.[45] Following Boivin and Giannoni (2002), the optimal forecasting horizon is determined by the J-Hansen over identification test, which measures the distance between the over-identified model in (2.14) and its unrestricted counterpart. Intuitively, a higher p-value of the J-Hansen test of a particular model implies stronger empirical support for the underlying forecasting horizons.

2.4 Data and Results

2.4.1 Data

The data is obtained from a large macroeconomic database, FRED-QD, that is publicly available from the Federal Reserve Bank of St Louis's Economic Data (FRED).

[44] Taylor (1993) and Clarida, Gali, and Gertler (2000) have estimated similar policy rules

[45] See Boivin and Giannoni (2002) for a discussion on the inefficiency of the least square estimation in this case

The database contains 135 macroeconomic series divided into the following eight groups:

- Output and income
- Labour market.
- Housing.
- Consumption, orders, and inventories.
- Money and credit.
- Interest and exchange rates.
- Prices.
- Stock market.

All series were properly transformed to remove trends and seasonality

2.4.2 Estimating the Factors

The first step in specifying the FAVAR model is to determine which variables to include in the vectors X_t and Y_t in (2.8) and (2.2) respectively. Appendix A list the 113 series that are included in the vector X_t to estimate the factors in (2.2). The principal component method is used to estimate the principle factors. Figure 2.10 depicts a scree plot where eigenvalues of the covariance matrix of the vector X_t are plotted in descending order. Figure 2.11 shows that the eight leading factors explain 94.15% of the variation in X_t with the first factor contributing an overwhelming 63.01%.

Vector Y_t includes five series: Real Gross Domestic Product (GDP), Consumer Price Index for All Urban Consumers (CPIAUCSL), Commodities Producer Price

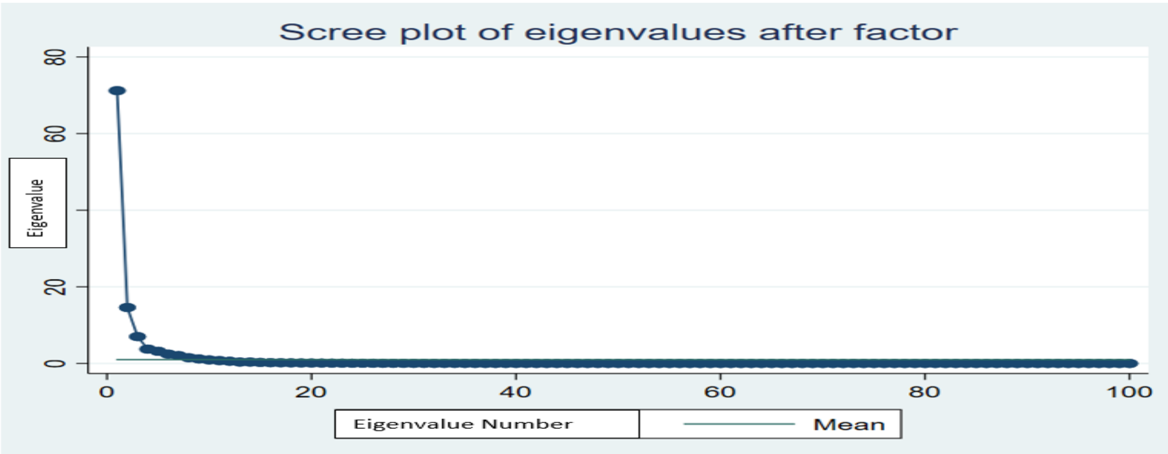


FIGURE 2.10: Scree plot of eigenvalues

```
Factor analysis/correlation                    Number of obs    =        190
    Method: principal-component factors        Retained factors =          8
    Rotation: (unrotated)                      Number of params =        876
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	71.20299	56.50929	0.6301	0.6301
Factor2	14.69371	7.65541	0.1300	0.7601
Factor3	7.03830	3.28866	0.0623	0.8224
Factor4	3.74964	0.16521	0.0332	0.8556
Factor5	3.58443	1.11293	0.0317	0.8873
Factor6	2.47151	0.33053	0.0219	0.9092
Factor7	2.14098	0.63547	0.0189	0.9282
Factor8	1.50551	0.30660	0.0133	0.9415
Factor9	1.19890	0.25528	0.0106	0.9521
Factor10	0.94363	0.16134	0.0084	0.9604
Factor11	0.78229	0.20450	0.0069	0.9674
Factor12	0.57779	0.15810	0.0051	0.9725
Factor13	0.41969	0.04753	0.0037	0.9762

FIGURE 2.11: Factor analysis by principal component method.

Index (PPICMM), Effective Federal Funds Rate (FEDFUNDS), and Real Total Liabilities of Household and Nonprofit Organizations (HHDEBT). Recall that $\hat{F}_t$ in (2.8) should be the variation in the factors that is orthogonal to Y_t. Therefore, $\hat{F}_t$ would be the residuals from regressing the principles eight factors on Y_t.

2.4.3 Results

Identified Vector Autoregressive Model

Model Estimation

There are twelve variables that are included in the model, two of which are exogenous. The ten endogenous variables enter the model in the following order: Real Gross Domestic Product (GDP), Consumer Price Index for All Urban Consumers (CPIAUCSL), Commodities Producer Price Index (PPICMM), the estimated factors(fpc1, fpc3, fpc4, fpc5, fpc6), Real Total Liabilities of Household and Nonprofit Organizations (HHDEBT) , and Effective Federal Funds Rate (FEDFUNDS) .[46] Note that fpc2 is excluded because it doesn't seem to be significant by Granger causality Wald test. The two exogenous variables are the log and the first difference of the ratio of household liability to personal income (LOGDEBTR and DEFDEBTR) respectively. Granger Causality Wald test supports the exogeneity of the two variables and their inclusion enhances the out of sample prediction of the model specially in predicting the great recession. Figure 2.12 shows the estimation result using the sample period 1973Q1 to 2007Q3. In terms of the three variables of interest (GDP, HHDEBT, and FEDFUNDS), the model explains much of the variation in these variables as indicated by R-squared.[47] Figure 2.13 shows the eigenvalues

[46]The order of the variables is in line with the assumption in the literature that Federal Funds Rate does not affect real variables within the period. See Bernanke and Blinder (1992) for details.

[47]Note the high p-value for PPICM which implies the irrelevance of the variable. However, the inclusion of a measure of commodity prices would enhance the response of inflation in the model as discussed by Bernanke and Blinder (1992). Also note that the exclusion of PPICM would not affect the main results of the paper.

Vector autoregression

Sample: 1973q1 - 2007q3		Number of obs	=	139
Log likelihood =	-1686.718	AIC	=	31.89522
FPE =	50.50285	HQIC	=	36.44213
Det(Sigma_ml) =	.0164168	SBIC	=	43.08422

Equation	Parms	RMSE	R-sq	F	P > F
GDP	53	.574777	0.6807	3.525266	0.0000
CPIAUCSL	53	.371731	0.6520	3.099103	0.0000
PPICMM	53	6.16581	0.3274	.804962	0.7999
fpc1	53	1.87874	0.6533	3.116691	0.0000
fpc3	53	1.23284	0.5636	2.135967	0.0009
fpc4	53	1.04169	0.7821	5.935693	0.0000
fpc5	53	1.54899	0.5796	2.280337	0.0003
fpc6	53	1.31731	0.5302	1.866625	0.0051
HHDEBT	53	.643126	0.7867	6.101292	0.0000
FEDFUNDS	53	.643563	0.7784	5.809314	0.0000

FIGURE 2.12: FAVAR model estimation result.

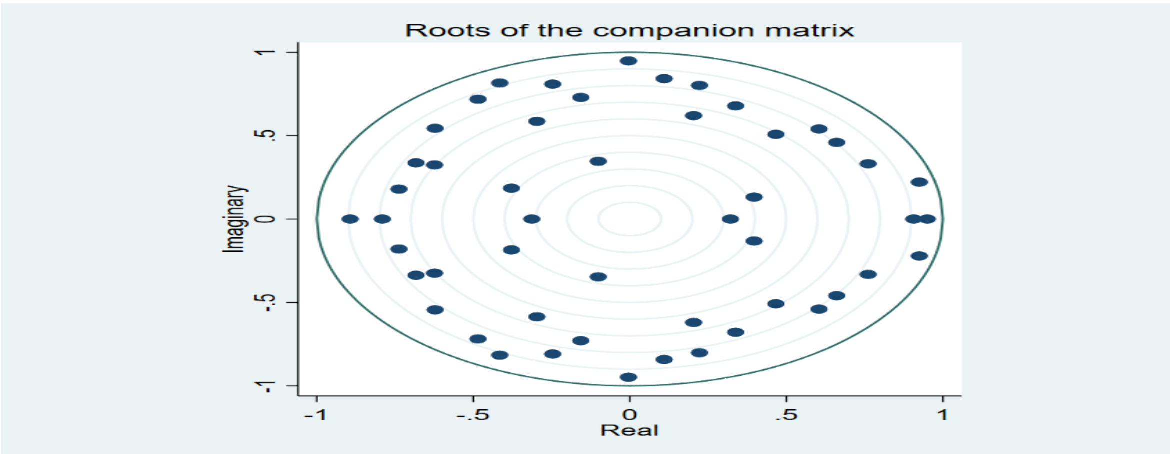


FIGURE 2.13: Estimated FAVAR companion matrix

of the companion matrix of the estimated FAVAR model. All the roots lie inside the unit circle demonstrating the stability of the model. To verify the performance of the model, Figure 2.14 compares forecasts generated by the model to the actual data. The red line in the left graph is the one-step ahead forecast of GDP over the period (1973-2010). The model forecast tracks the direction of actual GDP very well in general, especially during the five recessions that are included in the sample period (1973-2007). The model is also able to forecast the magnitude and the timing of the recessions of the early 1990's and 2000's but is underestimating the magnitude

FIGURE 2.14: 1-step a head and dynamic forecast using the estimated FAVAR.

of the 1970's and 1980's recessions. Furthermore, the model forecasted the recovery period in all in-sample recessionary episodes rather well with the exception of the recession of early 2000's, which the model forecasted to be shorter-lived than it actually was.

The one-step ahead forecast also shows that the model is doing well in out-of-sample prediction. The sample period is up to 2007Q3, which excludes the episode of the Great Recession. The model is able to fairly predict the pattern of the decline in GDP that was observed during the Great Recession and the pattern of recovery that followed, although the magnitude and the timing are different from what were observed. The graph to the right of Figure 2.14 shows the out-of-sample dynamic forecast of the model for the period (2007-2008). Expectedly, the dynamic forecast doesn't show the accuracy of its one-step ahead counterpart. However, the dynamic forecast predicted a recession to occur between 2008 and 2009 that has similar magnitude and longevity to that of the Great Recession.[48]

[48]In the last subsection, I utilize the model's ability to generate recessionary episodes of similar characteristics to the Great Recession to run counter-factual experiments about what would the state of the economy be had we had lower level of household debt from 2007 onward.

	Regressors								
Dep.	HHDEBT	GDP	FEDF	CPI	PPC	fpc1	fpc3	fpc4	fpc5
HHDEBT	0.071	0.0014	0.0128	0.036	0.0186	0.0008	0.0003	0.0482	0.0007
GDP	0.5634	0.8500	0.1529	0.0005	0.0864	0.2079	0.0011	0.0009	0.2389
FEDF	0.0632	0.0889	0.0000	0.0000	0.0000	0.8168	0.0004	0.7050	0.1018
CPI	0.9812	0.3051	0.1950	0.0141	0.2800	0.6167	0.0601	0.5699	0.1086
PPC	0.9345	0.9337	0.9966	0.6008	0.6372	0.9812	0.3219	0.9991	1.0000
fpc1	0.0000	0.3526	0.0336	0.3317	0.0009	0.4059	0.3078	0.0077	0.0435
fpc3	0.2110	0.0535	0.5752	0.1147	0.0130	0.7819	0.6853	0.3692	0.0910
fpc4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
fpc5	0.2099	0.0022	0.0022	0.0043	0.0110	0.0002	0.0001	0.6143	0.2309

TABLE 2.2: p-values of Wald test of coefficient stability.

The Effect of Monetary Policy

One of the objectives of this paper is to investigate whether the effect of monetary policy on household debt and on output has changed during periods of high levels of household debt. In the context of the model in this paper, there are two possible sources of change in the effect of monetary policy. The first is that the propagation of shocks to the policy rate has changed over time; the second is that the magnitude of the shocks has changed overtime.

A test of the instability of the VAR estimated coefficients over the entire sample is conducted to check the stability of the propagation mechanism. For each equation of the system, the stability of all the coefficients of the lags of one of the regressors are jointly tested using a Wald test. Table 2.2 presents the p-values of all the tests. Out of 81 tests, the null hypothesis of a stable coefficient was rejected in 37 cases at 5% confidence. This could be interpreted as evidence of changes in the propagation mechanism.[49] The results of the Wald tests are mixed with respect to the timing and the causes of the structural break. One potential cause could be the massive growth of household debt after 1992. In what follows, the full sample is divided into two

[49] I follow Boivin and Giannoni (2002) in interpreting the results.

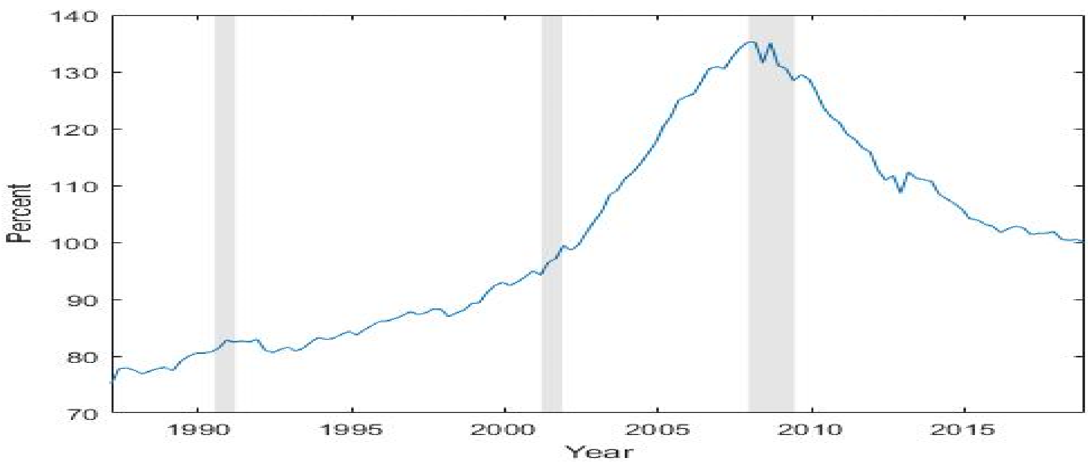


FIGURE 2.15: Household Leverage Ratio: Household Debt Relative to Personal Income

subsamples: the first is from 1971 to 1992 and the second is between 1992 and 2007. Wald tests were performed to test the stability of the coefficients in the two subsamples, which supports the choice of the year 1992 as the year of the structural break. As Figure 2.15 shows, household debt in the first period was less than 82% of personal income and was greater than 82% during the second period reaching to a massive level of 130% in the build-up to the Great Recession.[50] The first three entries in the last row of Table 2.3 show the p-values of testing the null hypothesis of a constant variance of the error term in the federal funds equation in the model, during the full sample and during each of the two subsamples. There is statistically significant evidence that the errors are heteroskedastic during the full sample as well as during the first sample. The p-value of 0.8268 shows evidence of homoscedastic errors during the second period. Furthermore, the hypothesis of equal standard deviation of the unexpected shocks to federal funds rate in the two subsamples is tested. The hypothesis is rejected at 5% level of confidence. The statistical evidence of changes in the magnitude of monetary policy shocks prior to and after 1992 is reflected in the point estimates obtained in the two periods. As shown in Table 2.4,

[50]The choice of the 82% threshold is totally arbitrary and is based on conventional financial wisdom.

	p-value			
	H_o : $Constant Variance$			H_o : $\sigma_1 = \sigma_2$
Exogenous Shock	Full Sample	Period 1	Period 2	Period 1:Period 2
Output Shock	0.3828	0.2928	0.5107	0.0938
H.H. Debt Shock	0.9409	0.3320	0.9568	0.4890
M.P. Shock	0.000	0.0000	0.8268	0.0113

TABLE 2.3: p-values of testing the hypothesis of homoscedastic errors during a given period and the hypothesis of equivalent standard deviation in two periods.

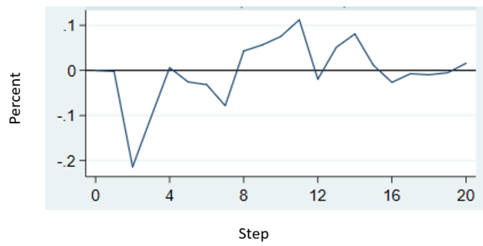
	Standard Deviation		Ratio
Exogenous Shock	Period 1	Period 2	$\frac{\sigma_1}{\sigma_2}$
Monetary Policy Shock	0.52778	0.110108	4.79
Output Shock	0.625202	0.468404	1.33
H.H. Debt Shock	0.525816	0.437423	1.202

TABLE 2.4: Standard deviation of exogenous shocks to monetary policy, output, and household debt

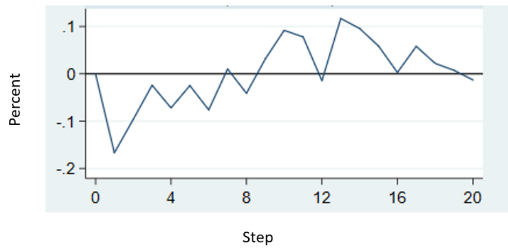
the standard deviation of exogenous shocks to monetary policy is estimated to be 0.52 in the first period and 0.11 in the second. These point estimates as well as the aforementioned statistical evidence are in line with numerous studies in the literature which support the conclusion that the magnitude of macroeconomic shocks has been decreasing over time.[51]

The two graphs in the left half of Figure 2.16, Figures(A) and (B), show the response of output to a one standard deviation shock to the federal funds rate during the two sub samples. The response of output on impact during the periods of low household debt is more than twice as much as that during the periods of high level of household debt. A positive shock to the policy rate (an increase in the federal Funds rate) decreased output in the two sub-samples, however, the decrease in output is more pronounced during periods of high debt. This could be seen by the more persistence impulse response in (C) than in (A). Intuitively, a higher household debt

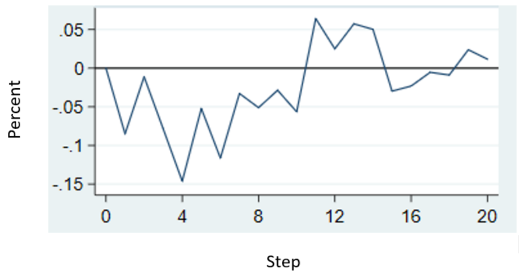
[51] Table 2.4 also shows similar trend in the standard deviation of exogenous shocks in output and in household debt.



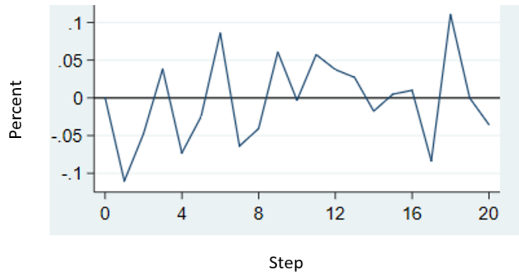
(A) GDP IRF, Low Debt Period



(B) Household Debt IRF, Low Debt Period



(C) GDP IRF, High Debt Period



(D) Household Debt IRF, High Debt Period

FIGURE 2.16: Impulse response functions of output and household debt to one standard deviation shock in the policy rate during both periods

corresponds to a higher debt service share of income in case of a tighter monetary policy, which would lead to a larger decrease in aggregate spending and in output. The two graphs in the right half of Figure 2.16, Figures (B) and (D), depict the response of household debt to a one standard deviation shock in the policy rate during the two subsamples. A positive shock to the policy rate (an increase in the federal Funds rate) decreases household debt in the two subsamples,however, the response is slightly weaker during the period of high household debt. Forecast error variance decomposition is another useful measure of the effect of monetary policy shocks on the variation of output and household debt, especially when the impulse response functions show intermittent persistence. As shown in Figure 2.17, monetary policy shocks have contributed to 4% of the variation in output and to 4% of that of household debt during the first period. While the contribution of monetary policy shocks to the variation of output in the second period stayed at 4%, its contribution to the variation of household debt dropped to 2%. Taking into account that the magnitude of monetary policy shock in the first period is 4.79 times higher than that in the second period, it could be concluded that the response of output and household debt to monetary policy shock is stronger during the second period. The response of output is particularly interesting since it shows a reversal of the reported findings in the literature that the response of output to monetary policy shock has been weaker after 1984. Boivin and Giannoni (2002) argued that the change in the response of macroeconomic variables to monetary policy shocks may be due to a change in the propagation mechanism or by a change in the policy reaction function of the monetary authorities. Therefore, the stronger response of output and household debt that is shown in Figure 2.16 could be a result of a stronger transmission mechanism (household credit channel in particular) or a less active policy reaction function. Although a thorough structural investigation into the policy reaction function similar to the work of Boivin and Giannoni (2002) is needed, the estimation of the policy reaction function in (2.14) in the two periods could give some useful insights. The estimated coefficients of the policy reaction function, as well as, their the statistical significance are very sensitive to the chosen horizon. The choice of the forecasting horizon is done following Boivin and Giannoni (2002), where the chosen horizon corresponds to the smallest J-statistic of the over-identification restrictions test proposed by Hansen (1982). A combination of $(h_y = 1, h_\pi = 3)$ and $(h_y = 1, h_\pi = 5)$ yields the largest p-value of the J-Hansen over-identification tests in the two periods respectively.[52]

As shown in Table 2.5, the coefficients of inflation and output are positive and statistically significant in the first period while only the coefficient of inflation estimated to be positive and statistically significant in the second period. Furthermore, the estimated policy rule shows a significant decrease in the coefficients of output

[52]Note that the probability of type two error of J-Hansen test increases with the number of endogenous variables. Given that I have ten endogenous variables, the test yields a p-value larger than 0.1 with all horizons

	Period 1: $h_y = 1, h_\pi = 3$		Period 2:$h_y = 2, h_\pi = 2$	
	Estimate	$P > \|z\|$	Estimate	$P > \|z\|$
Output	0.161	0.000	-0.013	0.584
Inflation	1.687	0.000	0.135	0.007
J-Hansen-test	p-value=0.8239		p-value=0.9611	
L.R. Effect of Output	0.2988		-0.0411	
L,R. Effect of inflation	3.1288		0.4275	

TABLE 2.5: Estimation results of the monetary policy reaction function.

and inflation across the two periods. The long-run effect of inflation on the policy rate has decreased from 3.12 in the first period to only 0.42 in the second period. On the other hand, the long-run effect of output has become statistically insignificant in the second period. This suggests that monetary policy reaction was weaker in the second period.

Rising Household Debt and Macro-Financial Instability

The question of financial stability and the role of financial shocks in macroeconomic fluctuations started to take more prominence in the literature after the Great Recession. This section focuses on the investigation of whether high levels of household debt pose a threat to financial-macro stability. The estimated standard deviation of the three fundamental shocks in the model is lower in the period of high household leverage. As shown in Table 2.5, the standard deviation of output shocks has decreased by about 42% in the second period. Similarly, the standard deviation of shocks to output and household debt has also decreased in the second period by 25% and 16% respectively. This might indicate that during the second period, which was characterized by high household leverage, financial and macroeconomic variables were more stable.

The reported error forecast variance decomposition in Figure 2.17 shows the sharp increase in the contribution of household debt shocks to the variation in output and

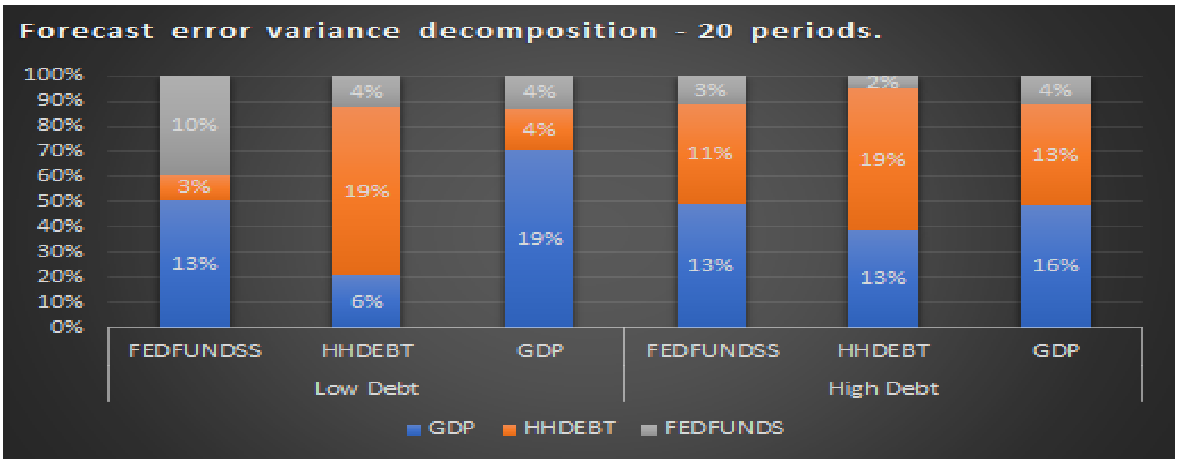


FIGURE 2.17: Forecast error variance decomposition of output, household debt, and the policy rate during the two periods.

in the policy rate during the period of high household leverage. Specifically, 11% of the variation in federal funds rate in the second period is contributed to household debt shocks compared to only 3% in the first period. Similarly, the contribution of household debt shock to the variation in output during the second period was 13% compared to just 4% in the first period.

The change in the contribution of output shocks to the variation of federal funds rate and output across the two periods shows dynamics opposite to that of household debt shocks. While the contribution of output shocks to the variation in the federal funds rate has stayed at 13% in the two periods, the contribution of output shocks to the variation in output has decreased from 19% to 13%. This warrants further investigation into the contribution of higher level of household debt to financial instability where shocks originating in the financial sector would have significant effect on the real economy.

Counterfactual Experiment with Lower Household Leverage

In section 2.4.3, it is shown that the model generates out-of-sample forecast of growth in output that resembles the fluctuations in output during the Great Recession. This

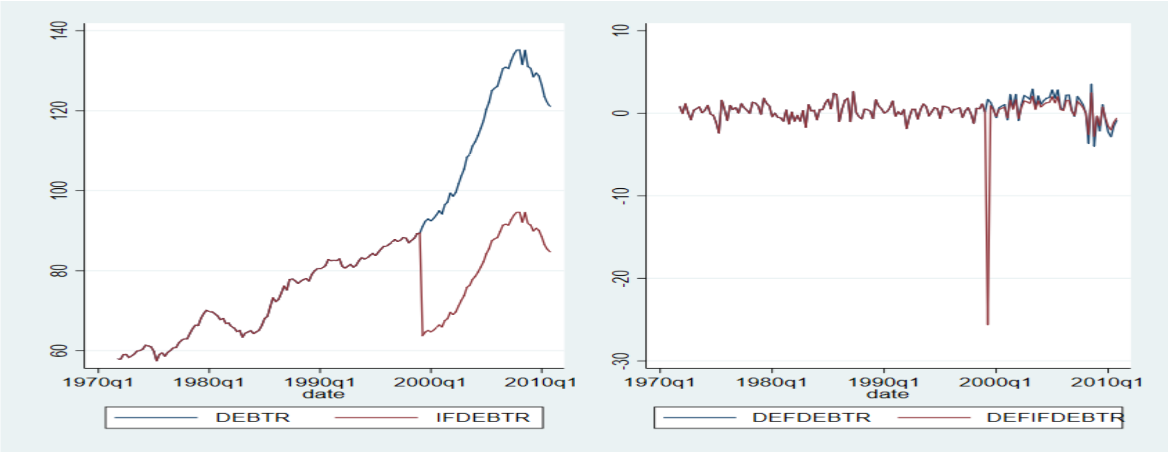


FIGURE 2.18: Hypothesized vs. actual household leverage (IFDEBTR Vs. DEBTR)(left) and the difference in log of the hypothesized vs. actual household leverage (LOGIFDEBTR Vs. LOGDEBTR)(right).

feature of the model could be used to evaluate hypothetical and counterfactual scenarios. In particular, would the magnitude of the economic downturn experienced during the Great Recession have been lower had the household leverage been significantly lower throughout the period between 2007-2010? To answer this question, a hypothesized leverage ratio that is 25% less than the actual ratio starting from 1999 is generated. Hypothesized and observed ratios are depicted in Figure 2.18. In this hypothetical scenario, household leverage in the years leading to the Great Recession is between 60% and 95%, which could be considered moderate to high leverage.

Recall that the square and the first difference in household debt ratio are exogenous variables in the model. Figure 2.19, shows the dynamic forecast of the model using the square and the first difference in the hypothesized leverage ratio as well as the dynamic prediction of the model using the actual leverage ratio. Under a lower household leverage scenario, the severity of the predicted recession would be about 50% less. This result is consistent with the conjecture that lowering household leverage could lower the magnitude and possibly the occurrence of a recession. Given that household leverage in this paper is defined and constructed as the

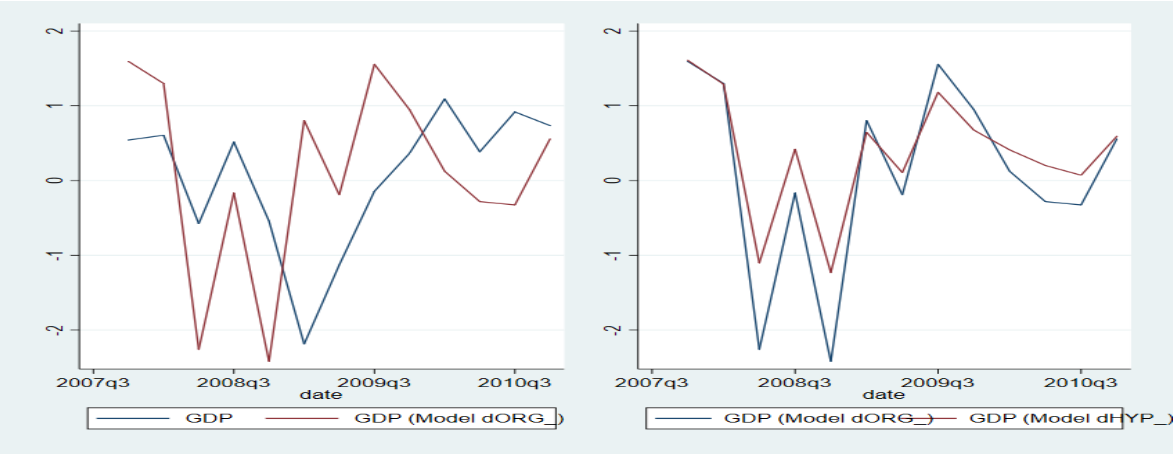


FIGURE 2.19: Out-of-sample prediction vs. actual output(left) and out-of-sample prediction vs. out-of-sample prediction with hypothesized household leverage.

ratio of household debt to personal income, decreasing leverage would entail either curtailing household debt or ensuring that income grows at a faster rate than household debt. Monetary policy, as shown in previous section, is a potent force in affecting household debt and personal income. Macroprudential policies designed to limit market access to mortgages, either in conjunction with monetary policy or not, could also be effective in lowering household leverage.

2.5 Conclusion

The paper has two central questions: (1) has monetary policy contributed to rising household debt in the periods leading to the Great Recession? and (2) how severe the Great Recession would have been had household debt been lower. To answer these questions, the paper first investigated whether the monetary transmission mechanism changed during periods of high levels of household debt and whether rising household debt contributes to financial and macroeconomic instability. Next, a counter-factual experiment was conducted to answer the hypothetical question of whether the Great Recession would have occurred had household leverage been significantly lower?

A FAVAR model is estimated using 116 macroeconomic series from FRED-QD macroeconomic database. The full sample covers the period from 1971 to 2007 which was then divided into two subsamples; pre-1992 period and post-1992. The sample breakpoint is the third quarter of 1992 when household debt reached to unprecedented level of 80% of personal income and continued to increase afterwards. By construction, the first period has relatively low level of household leverage as compared to the second period. The Great Recession period (2008-2009) was intentionally omitted in order to use it as a benchmark for out-of-sample prediction.

The model was first estimated using the full 1971-2007 sample in order to test its stability and forecasting power. It was demonstrated that the model's performance is enhanced by including difference in log and the square of household leverage as exogenous variables. In particular, the model's ability to generate out-of-sample forecast was sharply increased with the inclusion of household leverage ratio as an exogenous variable. Remarkably, the model predicted the timing, the magnitude and the dynamics of the Great Recession very well.

The full sample was also used to evaluate the structural stability of the model's coefficients as well as whether the shocks are homoscedastic. The result of the Wald tests suggests the existence of a structural breakdown which I have interpreted as evidence of a changing transmission mechanism. I also found evidence that the variance of monetary policy shocks is not constant over the full sample period.

The model was next estimated using the two subsamples in order to further investigate the change in the monetary transmission mechanism in the two periods. The estimation results from the two periods show a number of differences. First, the standard deviation of the identified monetary policy shocks is five times larger during the first period. Secondly, the resulting impulse response functions and error variance decomposition of output and household debt to a one standard deviation monetary policy shock is stronger in the period of high household leverage.

The stronger reaction of output and household debt to the monetary policy shock during the second period may be due to a stronger transmission mechanism or a weaker reaction of the monetary policy. To parse out the two effects, monetary policy reaction functions during both periods were estimated by generalized method of moments. Since the estimated reaction function is known to be sensitive to the forecasting horizon, I used J-Hansen over identification test to select the optimal horizon. The results suggest that response of the monetary policy to output and inflation has been weaker during the second period. This further suggests that the stronger response of output and household debt to monetary policy shock could have been a result of a combination of a stronger transmission mechanism and a weaker monetary policy reaction.

The last contribution of the paper and perhaps the most important is the finding that if household leverage had been 25% lower, the severity of the Great Recession would have been 50% lower. In carrying out this hypothetical scenario, a hypothetical household leverage was constructed to be 25% less than the actual observed leverage from 1999 onwards. The model's out-of-sample prediction was next compared, using the hypothesized leverage as exogenous variable, to the model's -out-of-sample prediction using actual leverage.

Chapter 3

Housing Risk Premia and Monetary Policy Surprises

Introduction

The limited ability of the monetary authority to stimulate the economy by lowering the overnight rate during the Great Recession revived the need for deeper understanding of the link between monetary policy rate on the one hand, and financial and economic variables on the other. The effect of changes in the overnight rate on equity returns had received considerable attention in the literature before the events of the Great Recession. Bernanke and Kuttner (2005) studied the impact of monetary policy changes on equity returns and found that 25 basis-point cut in the federal funds rate leads to a one percent increase in stock market index.[1] Furthermore, they found that the effect on expected excess returns account for the largest part of the response of stock prices.

In contrast to previous recessions, stock market crash was not the main protagonist of the Great Recession. In fact, declining home prices and the subsequent financial distress in the housing market were at the center of the 2008 financial crisis and

[1] The terms equity returns, stock equity returns, and stock market returns are used interchangeably throughout the paper

the ensued economic downturn. Unlike its effect on stock equity returns, the effect of changes in overnight rate on home equity returns (measured by the percentage change in home price index) has not received enough attention in the business cycle literature and the link between monetary policy rate and home equity returns is understudied at best.

The study of the relation between monetary policy and home prices is important for three reasons, the fist is the effectiveness of monetary policy since changes in asset prices is one of the channels of monetary transmission mechanism, the wealth effect channel. The dynamics of the channel is that changes in the policy rate would affect interest rate, which would lead to changes in asset prices (including real estate assets), consequently, consumer would change their consumption behaviour in response to the changes of the value of their asset holdings. Secondly, it is important for financial market participants since they make their investment decisions based on monetary policy actions and on their understanding of the response of asset prices to those policy actions. The third reason perhaps the more relevant in the context of the Great Recession, is that the housing market could be seen by itself as a source of macroeconomic shocks. Hence, a better understanding of the link between the housing market and the policy rate could enhance the design of monetary policy.

This paper investigates whether monetary policy surprises affect home equity excess returns, measured as the percentage change in home price index minus the three-month treasury bill rate, and the channel through which the effect transmits. In particular, the paper assesses whether the effect transmits through expected future interest rates, expected future dividends, or expected future excess returns.

Following the methodology employed by Bernanke and Kuttner (2005), home equity excess returns is decomposed into three components: discounted sum of expected future interest rates, expected future dividends, and expected future net excess returns. The three decomposed components next feeds into a VAR model featuring Federal Funds Rate and main macroeconomic indicators to study impulse response of home returns to monetary policy surprises.

The following section presents stylized facts about home price in the United States. Section 3.2 reviews the related literature and section 3.3 describes the applied methodology. Data and results are discussed in section 3.4 and section 3.5.

3.1 Stylized Facts on Housing

This section presents descriptive statistics on three themes: 1) comparison between home equity returns, measured as percentage change in home price index, and stock equity returns, measured as percentage change in stock price index, 2) home equity returns at the national and state levels, and 3) efficiency, or inefficiency, of the housing market.

3.1.1 Home Prices and Stock Prices

Figure 3.1 shows the quarterly percentage change of GDP and S&P Case-Shiller home price index. Home equity returns seems to be procyclical, leading the cycle, and as volatile as output. Table 3.1 shows that home equity returns are twice as volatile as output and almost twice as persistent. A correlation of 0.29 between output and home equity returns show some degree of procyclicality. Figures 3.2 and 3.3 depict the quarterly percentage changes of S&P 500 price index with S&P Case-Shiller home price index and that of GDP respectively. It is clear that stock equity return is dramatically more volatile than home equity returns and output. In particular, stock equity return is 11.31 times more volatile than output. Similar to home equity returns, stock equity returns are procyclical with 0.45 correlation with output. On the other hand, stock equity return is much less persistent than home

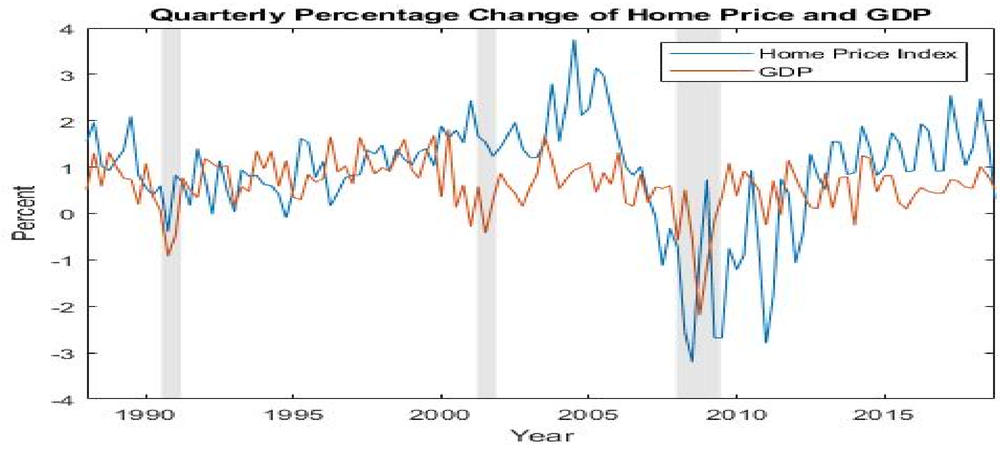


FIGURE 3.1: Quarterly percentage change of home price index and GDP.

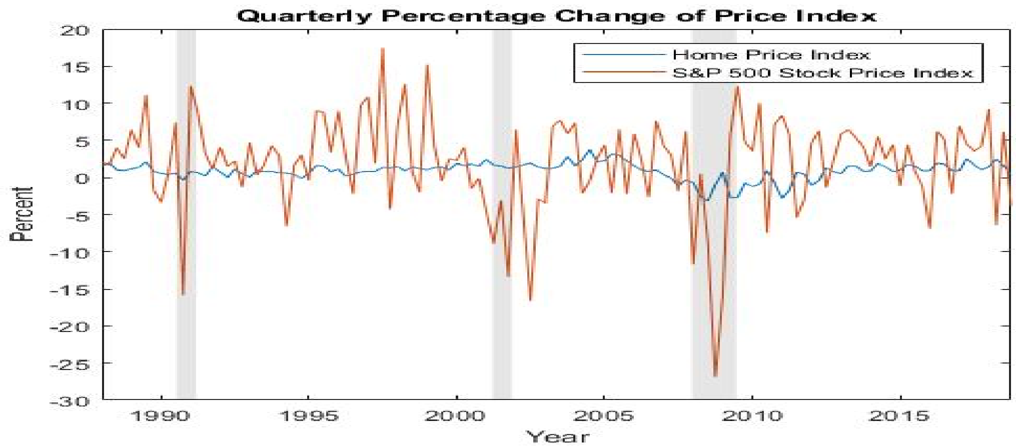


FIGURE 3.2: Quarterly percentage change of home price index and stock price index.

equity, with the coefficient of correlation for stock equity returns equals to 0.13 while that of home equity returns is 0.71.

3.1.2 Risk and Return in Home Price

Rational and risk-averse investors take riskiness of assets into consideration in valuating assets and in making investment decisions. Housing investment decisions should not be any different and the question to ask is weather home prices show a

FIGURE 3.3: Quarterly percentage change of stock price index and GDP.

Variable	$\frac{\sigma_x}{\sigma_{GDP}}$	$\sigma_{x,GDP}$	ρ_x
GDP growth	1	1	0.3816
Home equity return	2.0321	0.2993	0.7123
Stock equity return	11.3125	0.4526	0.1392

TABLE 3.1: Relative volatility, correlation, and autocorrelation of seven macroeconomic series.

trade-off between returns and the risk that is well documented for stock equities.[2] Figure 3.4 is a scatter plot of average return and volatility of home price indices of fifty-one states. The figure clearly shows the variation of average returns and volatility across states. In addition, the plotted regression line shows positive correlation between average returns and volatility, which suggests that investors do expect higher returns for riskier homes. Figure 3.5 shows the volatility of home price returns at the state level relative to the volatility of the home price returns at the national level. Alaska and Nevada have the highest relative volatility (volatility of the home price returns at the state level relative to the returns at the national level) with 2.60 and 2.58, respectively. Relative volatility of home price returns in Iowa is the lowest among all states and it is about half of the national volatility. Note that the quarterly average returns and volatility of home price at the national level are

[2]Note that housing investment decision has also a consumption value that is hard to measure. This aspect of housing investment is not considered in this paper.

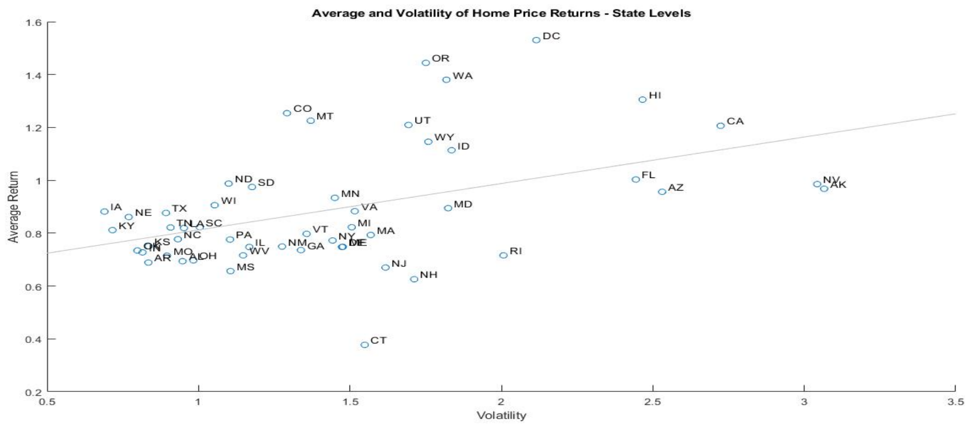


FIGURE 3.4: Average return and volatility of home price - state level

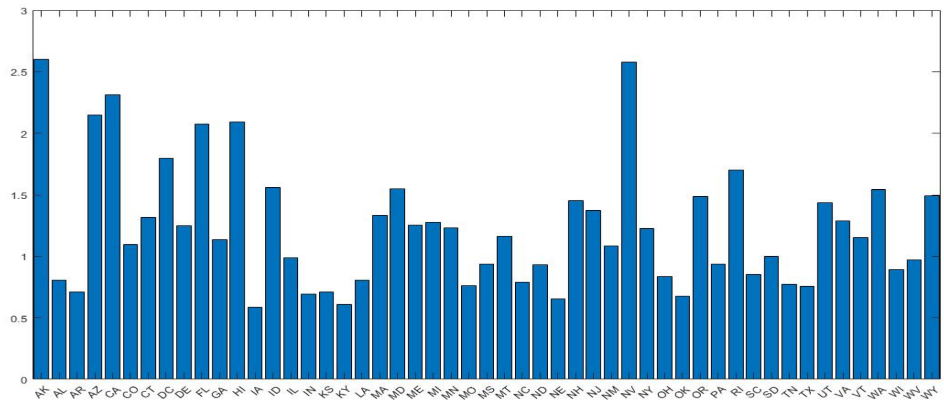


FIGURE 3.5: Relative volatility of home price returns at the state level to the volatility of home price returns at the national level

0.88 and 1.17, respectively. Figure 3.7 demonstrates that in the majority of cases, states with higher home price volatility, than the national level, have higher average returns and vice versa. This further supports the existence of risk premium in the housing sector.

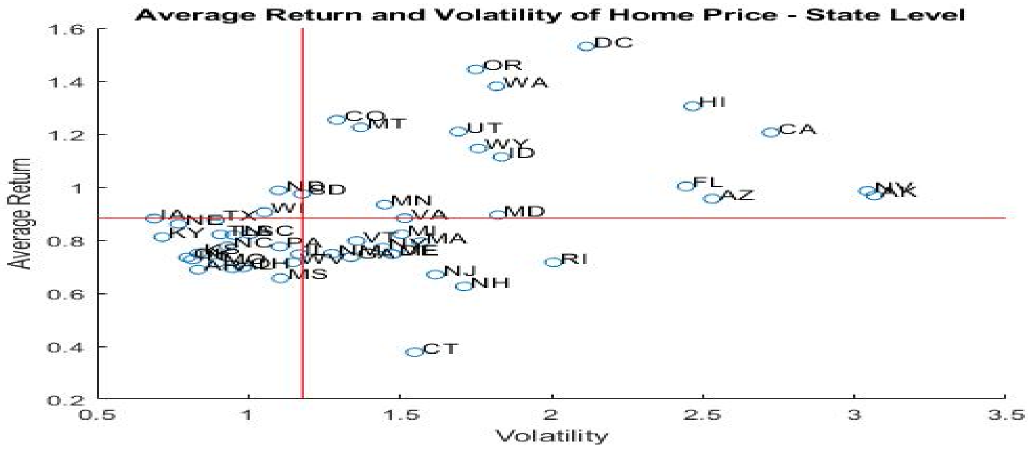


FIGURE 3.6: Average Return and Volatility of Home Price - State Level

3.2 Home Prices, Business Cycle, and Monetary Policy - Literature Review

3.2.1 Home Prices and the Business Cycle

Home prices could affect macroeconomic variables in three ways: by affecting consumption through the wealth-effect channel, by adjusting portfolio choices of investors, and by altering collateral values for borrowers. The wealth-effect channel is well demonstrated in classical RBC models, where a negative shock to home prices decreases the wealth of homeowners which in turn causes households to decrease their consumption. In DSGE models with financial frictions, where housing could be used as collateral, a decrease in home prices lowers the value of the collateral, which in turn forces credit-constrained consumers to decrease consumption. Investors make their portfolio choices based on the relative risk-adjusted returns and volatility of various assets. As is the case with any other investment asset, changes in home prices would alter portfolio choices of investors. A drop in home prices pushes investors towards assets with relatively higher returns. Muellbauer and Murphy (1990) is among the earliest papers to argue that the increase in house prices in the United Kingdom in the 1980s generated a wealth effect on aggregate consumption. Attanasio and Weber (1994) used micro data and argued that higher aggregate consumption was driven by expectation of higher future income rather than by wealth effect. Furthermore, they found that wealth effect is more pronounced in older households claiming that younger households would mainly respond to income shocks. Attanasio, Leicester, and Wakefield (2011) show that change in house prices could also have a significant wealth effect on younger household since housing is used as a collateral for more borrowing. Gorea and Midrigan (2017) show that long-term mortgages that are costly to refinance leads to substantially less wealth effect.

Berger et al. (2017) explained that faced with higher home prices, homeowners would adjust their asset portfolios either by selling their homes or borrow against their home equities. In this context, transaction costs in the housing market plays a role in the size of the wealth effect. They show that higher transaction cost is associated with lower wealth effect.

Numerous empirical papers in the literature attempted to measure the wealth effect of home prices by measuring the consumption elasticity. Additional examples include, Case, Quigley, and Shiller (2005), Carroll, Otsuka, and Slacalek (2011), Attanasio et al. (2009), and Campbell and Cocco (2007). Using reduced form regressions, they estimated a positive elasticity between home prices and aggregate consumption which ranges from 0.02 to 1.2.

Using IV regression to address a potential identification problem in reduced form models, Mian, Rao, and Sufi (2013) estimated consumption elasticities to be between 0.34 and 0.38. Using another micro-level data, Kaplan, Mitman, and Violante (2016) obtained similar estimates.

3.2.2 Asset Prices, Risk Premia, and Monetary Policy

In the past three decades, a strand in the literature studied the effect of monetary policy surprises on stock equity return. Simple regressions of equity return on surprise changes in the federal fund rate show a significant negative relationship which indicates that stock markets react to monetary policy surprises. Bernanke and Kuttner (2005) emphasized that the negative relationship between stock equity returns and the policy rate does not mean that markets only react to monetary policy surprises. They emphasized that financial markets are, in fact, forward looking and market participants react to expectations about future policy changes and expectations about economic changes.

Thorbecke (1997) used an identified vector autoregression model to document that stock prices respond to monetary policy shocks. Jensen, Mercer, and Johnson (1996) and Jensen and Mercer (2002) studied the response of stock market to changes in the discount rate.

Using data on Eurodollar futures to identify interest rate shocks, Rigobon and Sack (2004) estimated a significant response of the stock market to interest rate surprises. Using a similar identification method by using futures data to identify monetary policy surprises, Bernanke and Kuttner (2005) found a significant stock market response to changes in policy rate. Sousa (2010) empirically investigated the relationship between monetary policy and asset markets and found that there is a negative relationship between contractionary monetary policy and stock market performance.

Given that market responds to policy changes, a more subtle and challenging task would be to explain the channels through which monetary policy surprises affect asset returns. Although a fully developed theory has yet to be built, Bernanke and Kuttner (2005) suggested that there are potentially three channels for monetary policy to affect asset returns. In the case of an accommodating monetary policy, lowering the nominal interest rate would either decrease future expected interest rates, increase expected future dividends, and/or decrease expected excess return. In all cases asset prices would increase.

Bernanke and Kuttner (2005) used the response of high frequency financial variables around key monetary policy announcements rate to identify monetary policy surprises. They found that the monetary policy rate affects stock prices mainly through future expected excess returns.

Patelis (1997), Goto and Valkanov (2002), and Boyd, Hu, and Jagannathan (2005). Recent studies such as Campbell et al. (2012), Gertler and Karadi (2015), Paul (2020), Nakamura and Steinsson (2018), and Corsetti, Duarte, and Mann (2018) also used high frequency identification to assess the impact of monetary on economic variables and on asset prices. Paul (2020), in particular, used current short-term rate surprises as a proxy for structural monetary policy shocks and found that the reaction of stock and house prices to monetary policy shocks was low before 2007-2009 financial crisis.

Other studies investigated the effect of monetary policy on asset prices through its influence on future expectation. Galí and Gertler (2007), Bjørnland and Jacobsen (2010), Bjørnland and Leitemo (2009), Kurov (2010), and Castelnuovo and Nistico (2010) show that stock prices are forward looking and that monetary policy affect stock prices by influencing investors' expectations.

Another strand in the literature studied the effect on the stock market of the interaction between monetary policy and fiscal policy. Chatziantoniou, Duffy, and Filis (2013), Jansen et al. (2008), and Lawal et al. (2018) found that the interaction between monetary and fiscal policy exert significant pressure on the stock market. Similarly, Nwaogwugwu (2018) found that money supply and government spending have significant effects, in the short-run and the long-run, on the stock markets.

Even though housing markets have similar dynamics to the stock markets and potentially have significant economic and policy implications, the effect of monetary policy surprises on home equity returns and the mechanism through which the effect is disseminated is under investigated.

3.3 Methodology

3.3.1 The Effect of Monetary Policy Surprises on Housing Returns

The first step in the analysis is to determine the effect of monetary policy surprises on home equity excess returns. To do so, the following basic vector autoregression (VAR) model is built:

$$Y_t = \Gamma(L)Y_{t-1} + e_t \tag{3.1}$$

where Y_t, Y_{t-1} and e_t are vectors of size $(N \times 1)$, L is the lag operator, and $\Gamma(.)$ is the $(N \times N)$ matrix of coefficients. In addition to home equity excess returns and the federal funds rate, vector Y_t includes the major determinants of housing returns.[3] The model is estimated by least squares. The effect of monetary surprises on home equity excess returns is then be estimated by impulse response functions.

3.3.2 Forecasting VAR

After documenting the response of home equity excess returns to monetary policy surprises, the focus is turned to the question of the mechanism through which the effect is disseminated. The three possible channels are expected future interest rates, expected future dividends, and expected future excess returns.

[3] Model specification is discussed in section (3.4.2)

Since the three channels consist of future expectations, a forecasting VAR model is built to model future expectations of home excess returns, interest rates, and dividends following Campbell and Ammer (1993) and Bernanke and Kuttner (2005).

Let y_{t+1} be the excess return on home equity defined as differences in log of home price minus the risk-free rate. Following the approach of Campbell and Ammer (1993) , home excess equity returns are expressed as:

$$e^{y}_{t+1} = e^{\tilde{d}}_{t+1} - e^{\tilde{r}}_{t+1} - e^{\tilde{y}}_{t+1} \tag{3.2}$$

where e^{y}_{t+1} is the revision in expectation between period t and $t+1$.The remaining terms in (3.2) represent the discounted sum such that:

$$e^{\tilde{d}}_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j d_{t+j} \tag{3.3}$$

$$e^{\tilde{r}}_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+j} \tag{3.4}$$

$$e^{\tilde{y}}_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j y_{t+j} \tag{3.5}$$

where ρ is a discount factor, d_{t+j} is dividends/rent, r_{t+j} is interest rate, y_{t+j} is home equity excess return.

The following forecasting VAR is built to model changes in future expectations and to estimate the terms in (3.2) to (3.5).

$$z_{t+1} = Az_t + \epsilon_{t+1}, \tag{3.6}$$

where z is a vector containing excess home equity returns, the real interest rates, and some additional variables that help in forecasting these two variables. Using the estimated forecasting VAR, the identities in (3.5) are given by:

$$e^{y}_{t+1} = s_y \epsilon_{t+1} \tag{3.7}$$

$$e^{\tilde{y}}_{t+1} = s_y \rho A (1 - \rho A)^{-1} \epsilon_{t+1} \tag{3.8}$$

$$e^{\tilde{r}}_{t+1} = s_r (1 - \rho A)^{-1} \epsilon_{t+1} \tag{3.9}$$

$$e^{\tilde{d}}_{t+1} = e^{y}_{t+1} + e^{\tilde{y}}_{t+1} - e^{\tilde{r}}_{t+1} \tag{3.10}$$

where s_y and s_r are appropriate selection matrices.

3.3.3 Variance Decomposition of Home Equity Returns

Given the decomposition of current home equity excess returns in equation (3.2), the variance decomposition of current housing excess return could be expressed as:

$$\begin{aligned} Var(e^{y}_{t+1}) = \quad & Var(e^{d}_{t+1}) + Var(e^{r}_{t+1}) + Var(e^{y}_{t+1}) - 2Cov(e^{d}_{t+1}, e^{r}_{t+1}) \\ & -2Cov(e^{d}_{t+1}, e^{y}_{t+1}) + 2Cov(e^{r}_{t+1}, e^{y}_{t+1}) \end{aligned}$$

3.3.4 The Effects of Federal Fund Surprises

To investigate the channels through which federal fund surprises affect home equity excess returns, the following VAR model is estimated:

$$X_t = \Gamma(L) X_{t-1} + v_t \tag{3.11}$$

where X_t includes the constructed decomposed components of home excess returns $e^{\tilde{y}}$, $e^{\tilde{r}}$, and $e^{\tilde{d}}$, in addition to the federal funds rate and other important determinants of home equity returns. Monetary policy surprises are identified by a Cholesky decomposition in which the structure of the system depends on the ranking of the variables. In particular, a shock to a variable in the system is assumed to instantaneously affect that particular variable as well as all the following variables. The preceding variables will only respond with a lag. By placing the federal funds rate last, it is assumed that all the variables in the system responds to the monetary policy surprises with a lag. Once monetary policy surprises are identified, impulse responses of the components of excess home equity returns to policy surprises will be estimated and compared to the impulse response of home equity excess return that is obtained in section 4.1.

3.4 Data and Results

3.4.1 Data

The data used in estimating the three VAR models comes from the St-Louis Federal Reserve Economic Data (FRED) from the Federal Reserve Bank of St-Louis on: Real Disposable Personal Income (RDISPINCOME), Industrial Production Index (INDP), S&P/Case-Shiller National Home Price Index (HPINDEX), Consumer Price Index for All Urban Consumers (CPIAUCSL), Commodities Producer Price Index (CPICMM), Effective Federal Funds Rate (FEDFUNDS), 1-Month Treasury Bill, and 30-Year Fixed Rate Mortgage Average in the United States. All the series are seasonally adjusted and properly transformed to address non-stationarity.

3.4.2 The effect of Monetary Policy Surprises on Home Price Excess Returns

The VAR model in this section is built to estimate the effect of monetary policy surprises on the excess home equity returns in the US. The vector Y_t includes home price excess returns, industrial production, disposable personal income, 30-year mortgage rate, and the federal funds rate. Home equity excess returns are constructed using the monthly S&P/Case-Shiller index and the 1-month treasury bill

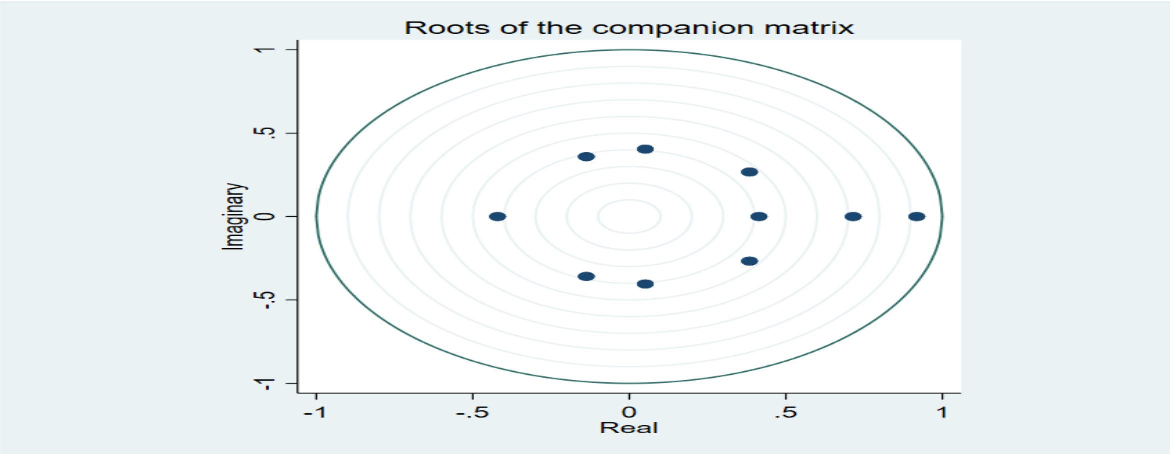


FIGURE 3.7: Roots of the companion matrix of the VAR model

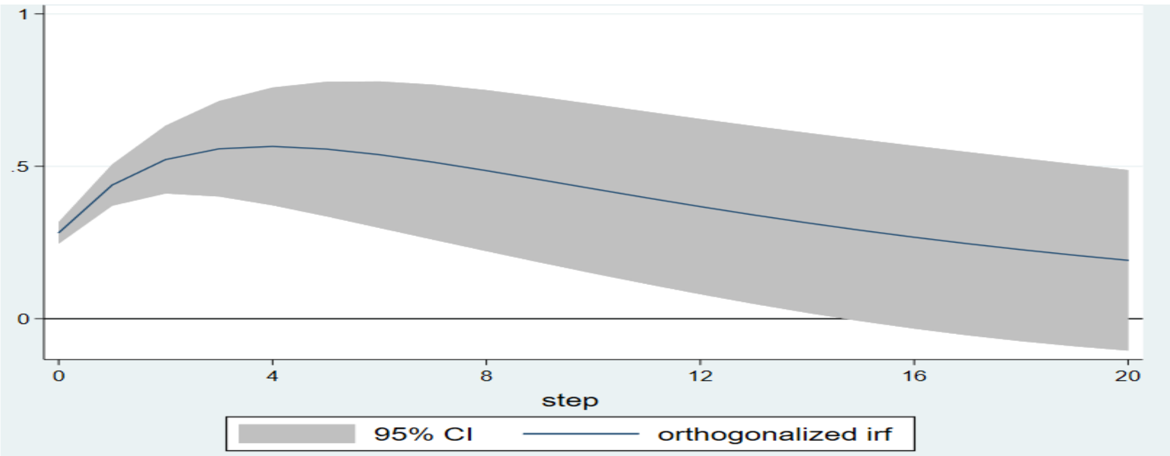


FIGURE 3.8: Impulse response function of a shock to Federal funds rate in the VAR model

rates. In particular, excess returns are constructed as monthly growth rates of home prices minus one-month treasury rate.

Figure 3.7 shows that all roots of the companion matrix for the estimated VAR lie within the unit circle, which indicates that the system is stable (stationary). Monetary policy surprises are estimated to initially be about 27 basis points as it is shown in Figure 3.8. A negative monetary policy surprise of 27 basis points initially has no immediate impact on excess returns at impact but leads to an increase in excess returns in subsequent periods. The increase in home price excess returns peaks at 1.3% in the second quarter following the initial policy surprise. The results could be in-

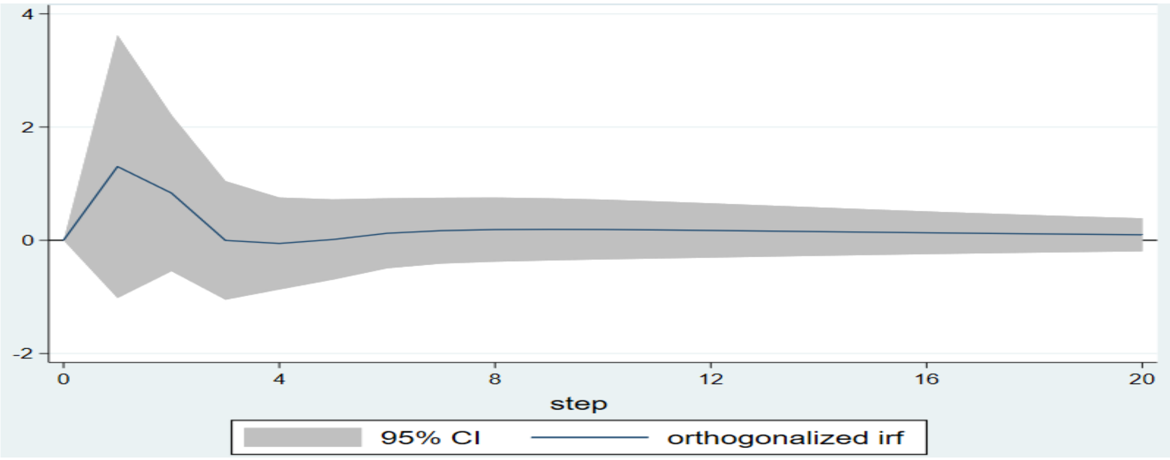


FIGURE 3.9: Impulse response of home excess returns to a a shock to the Fed funds rate

terpreted as evidence for the effectiveness of the wealth effect channel of monetary transmission mechanism since it provides evidence of a strong response of home prices to policy rate surprises. In particular, the decrease in policy rate triggers asset revaluation process leading to home price appreciations, which increase the wealth of homeowners. Ultimately, homeowners would increase their consumption and investment either by increasing spending or by borrowing against their home equity.

Forecasting VAR

Having demonstrated that monetary policy surprises affect housing excess returns, the questions now is: what are the channels through which this effect takes place? The first task in answering this question, following Bernanke and Kuttner (2005), is to decompose current excess returns into three components: discounted sum of expected future excess returns, discounted some of future interest rates, and discounted sum of future dividends.

A forecasting VAR model is built using growth in housing excess returns and the one-month treasury bill minus growth in consumer price index. Figure 3.10 depicts the current housing excess returns and the resulting decomposed series. Table 3.2

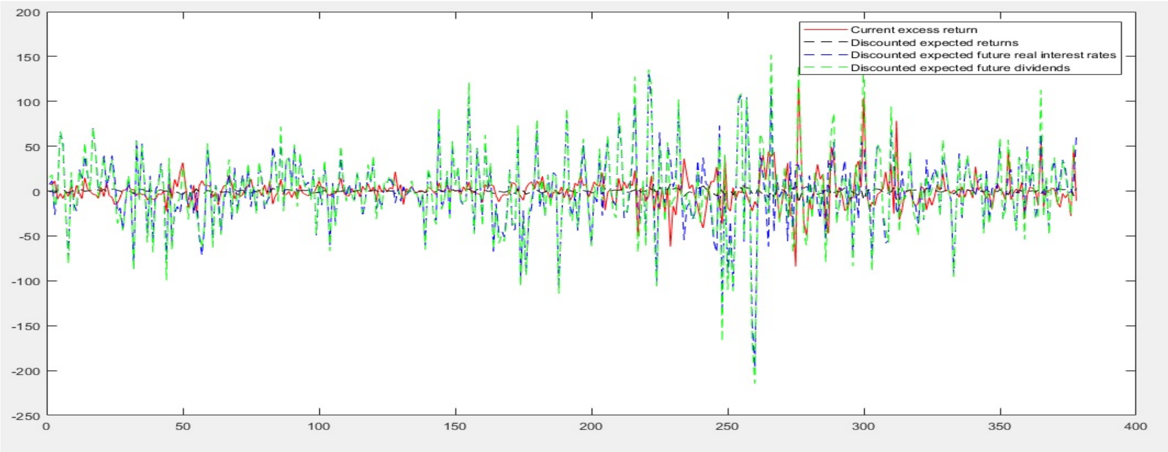


FIGURE 3.10: Current home excess returns and its three decomposed components

	Total	Share
Current Excess Returns(y)	321.564	100
Discounted Sum of Future Excess Returns (ey)	5.5137	1.71
Discounted Sum of Future Real Interest Rates (er)	1634.4	508.265
Discounted Sum of Future Dividends (ed)	2119	658.96
-2Cov(ed,er)	-3494.2	-1086.03
-2Cov(ed,ey)	-41.2	-12.8186
2Cov(er,ey)	98.17	30.53

TABLE 3.2: Variance decomposition of housing excess returns.

lists the variance of housing current excess returns as well as the variances of and the covariances between discounted sum of future excess returns, future interest rates, and future dividends. The contribution of the discounted sum of future excess returns is about 1.7% of the variation in the current housing excess returns. Most of the variation seems to be explained by future dividends and future real interest rates, which have a combined contribution of an overwhelming 80%. The results are not surprising since it supports the conventional wisdom that housing is a safe investment, which is shown to be the case given that variations in future excess returns seems to have contributed so little to the variation in current housing excess returns.

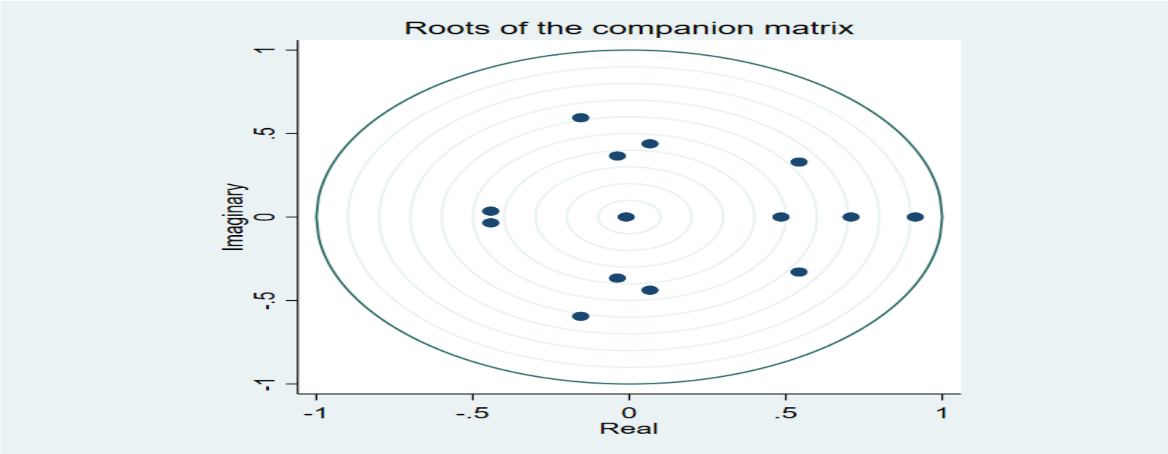


FIGURE 3.11: Roots of the companion matrix of the forecasting VAR model

Model Estimation and Identification of Monetary Policy Surprises

The three decomposed elements of current housing excess returns that were constructed by the forecasting VAR model in the previous section are used along with growth rates of industrial production, growth rates of disposable personal income, 30-year mortgage rate, and the federal funds rate in a VAR model to estimate the propagation mechanism of monetary policy surprises in affecting housing excess returns.

Similar to the methodology used in section (3.4.2), monetary policy surprises are identified using Cholesky decomposition assuming that the federal funds rate instantaneously responds to shocks to all the variables in the system while all other variables respond to monetary policy surprises with a lag. Stability of the VAR model is demonstrated by Figure 3.11 where the roots of the companion matrix are shown to lie inside the unit circle.

Monetary policy surprise is estimated to be of about 27 basis points as is shown in Figure 3.12. Recall that the magnitude of the monetary policy surprise that was used in section 3.4.2 was also 27 basis points, which makes the comparison of the two impulse responses easier. Figures 3.13 and 3.14 show the impulse response

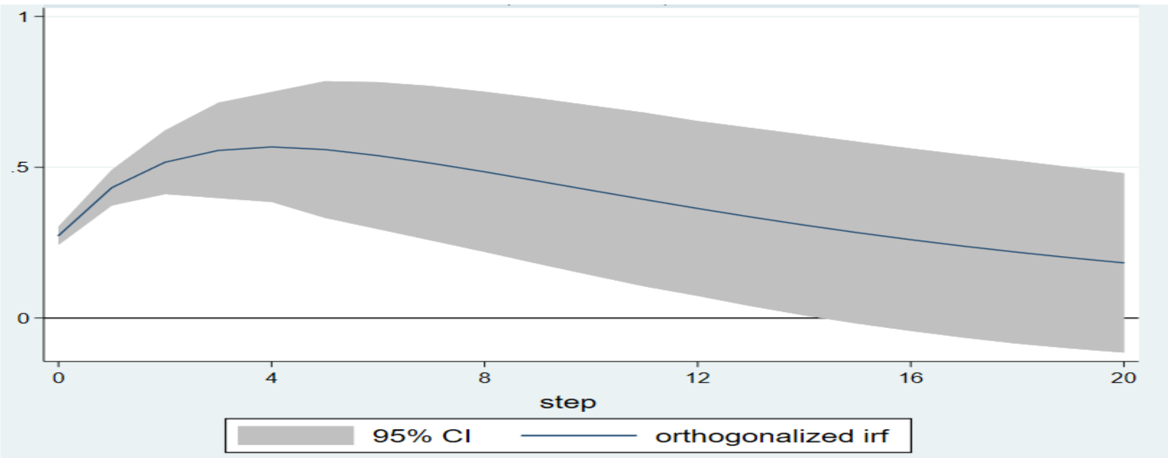


FIGURE 3.12: Impulse response function of a shock to Federal funds rate

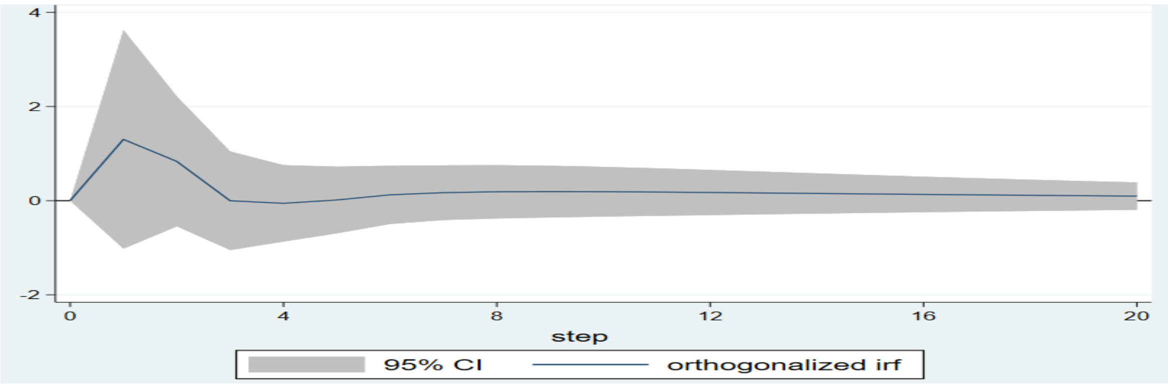


FIGURE 3.13: Impulse response of current housing excess returns

function of current housing excess returns and expected future housing excess returns, respectively. A 27-basis point decrease in the policy rate would lead to 1.3% increase in current housing excess return. The same shock leads to a 2.5% increase in the discounted sum of expected future excess returns, which is interpreted as the size of the risk premium channel. In the contrary, a decrease of 27 basis point in the federal funds rate leads to, as shown in Figures 3.15 and 3.16 , about 11% increase in both the discounted sum of expected future real interest rates and the discounted sum of expected future dividends. This is a very interesting result since it suggests that monetary policy surprises affect housing returns through interest rate and dividend channels more than through risk premium channel. This result is different

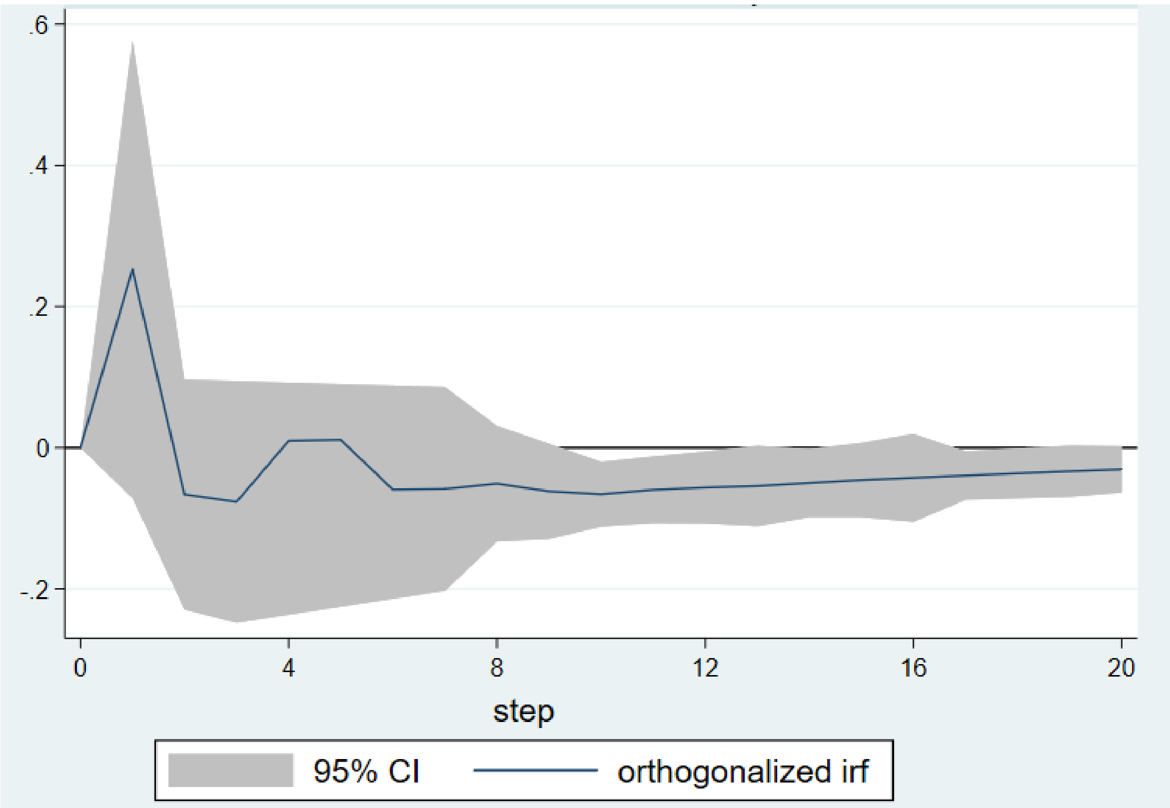


FIGURE 3.14: Impulse response of discounted sum of expected housing excess returns

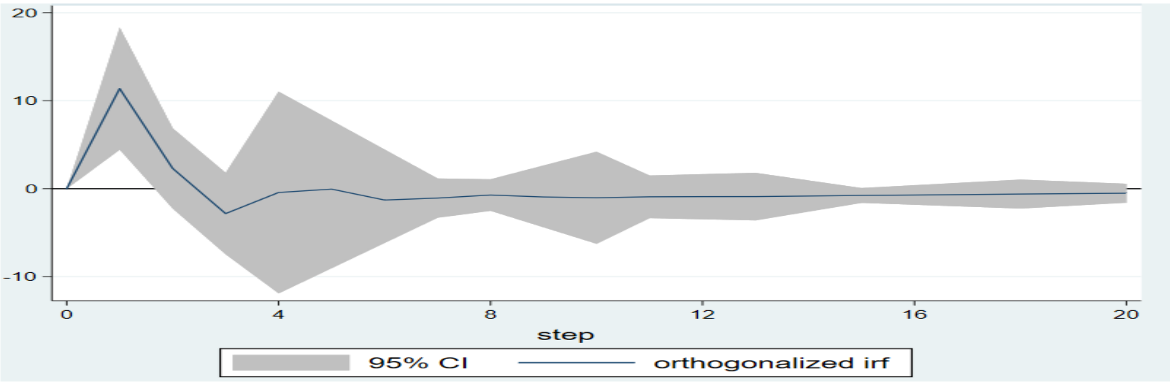


FIGURE 3.15: Impulse response of discounted sum of expected future interest rates

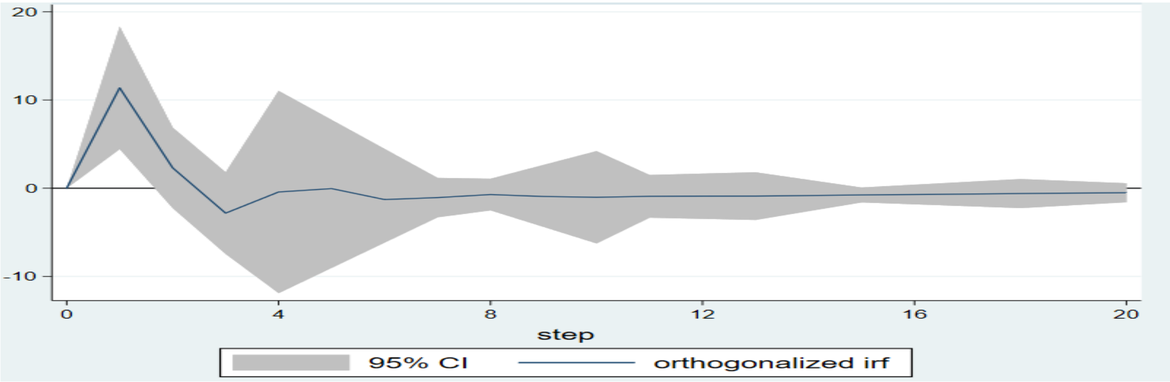


FIGURE 3.16: Impulse response of discounted sum of expected future dividends

than what Bernanke and Kuttner (2005) found for the effect of monetary surprises on stock equity returns, where they showed that the risk premium and dividend channels played an overwhelming role. The results suggests that monetary policy has marginal effect on how investors perceive the riskiness of housing investment. Rather, the strength of monetary policy stems from affecting expectation of future interest rate and future dividends.

3.5 Conclusion

Numerous papers in the literature have been dedicated to the study of the interaction between stock prices and monetary policy. A notable example is the work of Bernanke and Kuttner (2005) which studied the effect of monetary policy surprises on stock equity return and concluded that monetary policy surprises increase equity excess returns. Furthermore, they also attempted to explain the mechanism through which monetary policy surprises propagate to stock equity returns. They found that the effect of monetary policy surprises on equity excess returns mainly goes through its effect on expected future excess returns.

This paper has studied the effect of monetary policy surprises on housing excess returns and to identify the channels through which this effect propagates. Using the same methodology as in Bernanke and Kuttner (2005), I found that a 27 basis point increase in federal funds rate would lead to a 2% increase in housing excess returns.

Using a forecasting VAR model, current housing excess returns were decomposed into three components: discounted sum of expected future excess returns, discounted sum of expected future real interest rates, and discounted sum of expected future dividends. Variance decomposition shows that variation in expected future returns explains just about 1.7% of the variation in housing current excess returns.

The three components series are then used in a VAR model to estimate the effect of monetary policy surprises on the three components. A 27 basis points decrease in the federal funds rate is shown to lead to a modest increase of 2.5% in housing expected future excess returns in comparison to the 11% increase in both the expected future real interest rate and the expected future dividends. This suggests that monetary policy has a marginal effect on how investors perceive the riskiness of real estate investment.

Contrary to how monetary policy surprises affect equity excess returns, the results indicate that monetary policy surprises seem to affect current housing excess returns through its effect on expected future interest rate and expected future dividends more than through expected future excess return.

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