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Financial Frictions in Data: Evidence and Impact

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Abstract

This paper investigates financial frictions in US postwar data to understand the interaction between the real business cycle and the credit market. A Bayesian estimation technique is used to estimate a large Vector Autoregression and New Keynesian models demonstrating how financial shocks can have a large and sluggish impact on the economy. I identify the default risk and the maturity mismatch channels of monetary policy transmission; I further employ a generalized-IRF to establish countercyclicality of risk spreads; and I show that the maturity mismatch shocks produce a stronger impact than the default risk shocks.

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Contents

List of Tables

List of Figures

I.   Introduction

This paper is an empirical study of the interaction between the real business cycle and financial markets. Risk premiums are the central links between credit markets and the real economy. Movements in risk premiums and their economic implications are key to understanding the health of corporates and countries alike. However, what are the transmission mechanisms of shocks between the real economy and the credit markets? Importantly, how does economic policy, in particular, monetary policy, affect the cost of funding and net worth? These are the key questions that this paper aims to address. To do so, I estimate the impulse response functions (IRF) implied by two classes of modelsempirical Vector Auto Regression (VAR) and structural Dynamic Stochastic General Equilibrium (DSGE) models. In this way, I can trace out the effect of policy, as well as that of real and financial innovations, on the economy.

The first contribution of this paper is to scrutinize large-scale New Keynesian models with financial frictions (see, Furlanetto, Gelain, and Taheri Sanjani (2014)), as they provide the groundwork for understanding the transmission mechanisms of credit channels. I estimate two New Keynesian DSGE models, with and without financial frictions. I then estimate a medium-scale VAR model using the same observables as the ones that I used to estimate the DSGE models with financial frictions. I compare the impulse responses to a monetary policy shock across the DSGE models with those of the true data-generating process. This experiment provides strong support for the model with financial frictions relative to the frictionless model.

The second contribution of this paper is to investigate credit channels of monetary policy transmission. The credit spread and net worth are the channels highlighted by the financial accelerator theoretical framework. I find that while the response of net worth is in line with the prediction of financial accelerator theory, credit spread presents something of a puzzle. To solve the spread puzzle, I highlight two important intrinsic properties of credit spread, namely the "default risk" and the maturity term structure, or "liquidity risk." In response to a monetary policy shock, the credit spread (BAA-FFR) and maturity mismatch spread (AAA-FFR) fall to negative values upon the impact of shock, while the default risk spread (BAA-AAA) rises upon impact.[1]

To check the robustness of the results with respect to the information inclusion, I consider two different size-reduced form models. I find that in the small-scale VAR system, even when I decompose different risk channels of credit spread, the premium anomaly is still present. This provides a good motivation for considering a large system. This paper is not the first one pointing out the shortcomings of a small information set. Giannone and Reichlin (2006) provides a comprehensive analysis of information inclusion in addressing the non-fundamentalness problem. Bernanke, Boivin, and Eliasz (2005) shows that considering a large dataset, consisting

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[1]In this paper, I use the terms liquidity risk spread and maturity mismatch spread interchangeablythey both refer to "AAA-FFR".

of the information that policy makers care about, within the factor-augmented VAR (FAVAR) framework, is indeed important in order to properly identify the monetary transmission mechanism. The way this paper differentiates itself is to show the presence of such limitations for the credit channel of monetary policy transmission.

The third contribution of the paper is to investigate the cyclical properties of the credit spread and its components. The business cycle shock in this paper is closely linked to the notion of cyclical shock in Giannone, Lenza, and Reichlin (2012). This issue is particularly interesting as the DSGE literature does not seem to provide a definitive conclusion regarding the cyclicality of the credit spread (see De Garve (2008), Gelain (2010), Dib and Christensen (2005), Faia and Monacelli (2007), and Meeks (2006)). My generalized impulse response analysis shows that credit spread and both of its risk components are countercyclical.

The fourth and final contribution of the paper is to study the transmission of the disruption originating in the credit market into the real economy. An exogenous increase in the default risk or liquidity risk of borrowers would harm their financial position. This, in turn, deteriorates their capacity to repay loans and hence increases their cost of funding. The impulse response analysis further shows that the impact of a liquidity risk shock is more severe than that of a default risk shock. A policy implication would be the critical importance of having in place measures that prevent the emergence of liquidity shortages.

This work bridges two recent strands of literature, namely, financial frictions (see Taheri Sanjani (2014), Christiano, Motto, and Rostagno (2014), and Gertler and Kiyotaki (2010)) and large Bayesian VAR models (see De Mol, Giannone, and Reichlin (2008) and Banbura, Giannone, and Reichlin (2010)). Giannone, Lenza, and Reichlin (2012) studies the response of money and credit variables to the monetary policy shocks and cyclical shocks in the euro area. Den Haan, Sumner, and Yamashiro (2007) provides a similar analysis on the US data, using a different technical approach. A recent relevant work is Ahmadi (2009), which uses factor-augmented VAR to study the effect of monetary policy shocks and credit spread shocks during episodes of high and low volatilities in common components of credit spread. The spread data in Ahmadi (2009) comprises corporate bond yields. Yates, Pinter, and Theodoridis (2013) studies the effect of risk-news shocks, and the business cycle. They use VIX as a measure of perceived risk in the market. Boivin, Giannoni and Stevanovic (2013) examines the dynamic effects of credit shocks in US data within a structural factor model framework. Their variance decomposition results emphasize the important effect of credit shocks on several real activity measures, price indicators, leading indicators, and the credit spread.

This paper is organized as follows. Section 2 describes the database and the model. Section 3 describes the impulse response analysis by looking at the monetary policy shock, the cyclical shock, and the spread shock. Section 4 concludes.

II.   Data and Model

In what follows, I describe the data set that I used, model specification, and the shocks identification.

A.   Data

The data set includes 34 US quarterly variables. The sample ranges from 1971Q1 to 2009Q1. The data include the following 6 blocks: macroeconomic variables, short-term interest rates, Treasury-bill rates with different maturities, corporate bond yields, financial variables, and net worth variables. I obtained data from the Federal Reserve Economic Data - FRED - St. Louis Fed. Appendix 7 describes the data labels and the transformation applied to each series in detail. The data feed the models in annualized log-levels, except those variables which are defined in terms of annualized rates, such as interest rates, corporate bond yields, and Tbill rates, among others, which are taken in levels. I work with three different VAR models, including increasingly larger sets of variables. Comparing the results across small and large models provides a robustness check with respect to information inclusion:

1. A small-scale modelthe prototypical monetary VAR model augmented by spread and equity variableswith six variables, namely, GDP, GDP Price Index, Federal Funds Rate, AAA yield, BAA yield, and net worth.

2. A medium-scale model, which includes nine variables. This data set is used to estimate my DSGE models; hence I call it the JPTBGG data set. It contains seven macroeconomic variables, specifically, output, consumption, investment, hours, wage, inflation, and interest rate, along with two financial variables, namely, spread and net worth. This data set is per capita, as it is used to estimate the DSGE models. Furlanetto, Gelain, and Taheri Sanjani (2013) contains the full description of this data set. The main purpose of this exercise is to cross-check the monetary policy propagation in VAR and DSGE models.

3. A large-scale model, with 34 variables, using a data set that nests the first specification and also includes a number of important additional labor market, financial, and monetary variables.

Table 2, in Appendix 7, provides definitions of variables and the transformation applied to them.

Spread. Credit risk spread, BAA-FFR, is widely used in DSGE estimation literature as an observable for external finance premium (EFP). The VAR response of this proxy to a monetary

policy shock is contrary to the prediction of DSGE models. The reason behind this puzzle is that BAA-FFR contains two types of risks, namely, default risk and maturity mismatch risk. I decomposed these two channels and use AAA-FFR as the proxy for the maturity mismatch channel and BAA-AAA as the proxy for the default risk channel. Both BAA and AAA contain bonds with long maturities.[2] In the next section, the impulse response analysis will shed light on the choice of this decomposition. Figure 1 shows the corporate bond yields (BAA and AAA), the credit spread (BAA-FFR), the maturity mismatch spread (AAA-FFR), and the default risk spread (BAA-AAA).

Table 1: Correlation Between Spreads and GDP Growth

Variable	BAA-FFR	AAA-FFR	BAA-AAA
Correlation	-0.0238	0.0557	-0.3416

Figure 1: Spreads

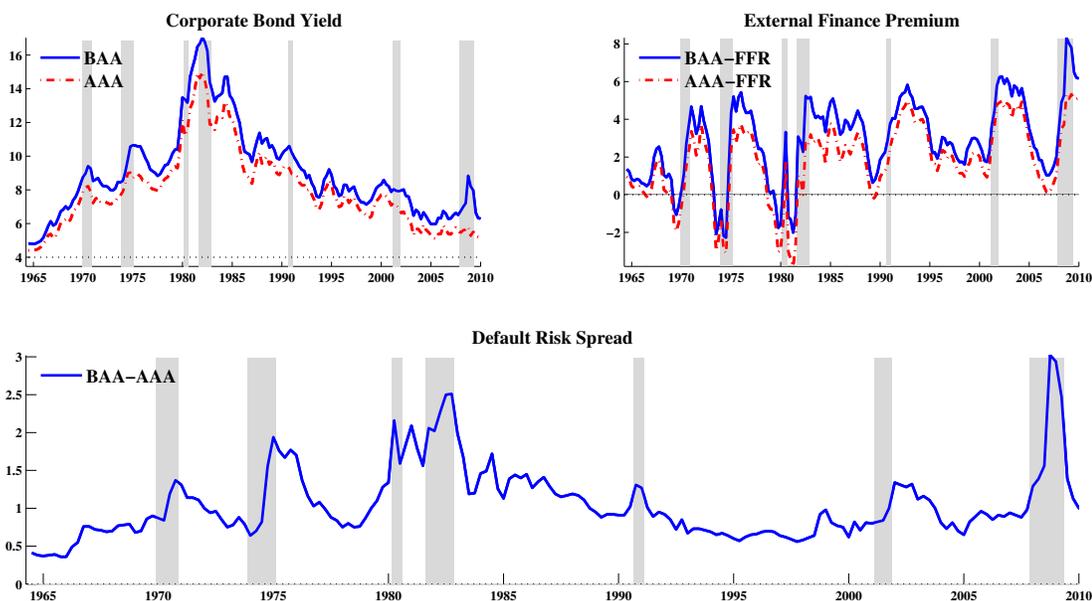The contemporaneous correlations of EPF and its components with log-GDP growth rate are reported in Table 1. While EFP and default risk spread are negatively correlated with log GDP growth, the correlation with maturity mismatch spread is small but positive. Considering

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[2]Moody's tries to include bonds with remaining maturities as close to 30 years as possible, according to the St. Louis Fed.

the contemporaneous correlation is not enough for understanding the cyclical properties of a variable, one should instead consider the generalized IRF exercise. In the next section, I will show that all three spreads are countercyclical. Moreover, in response to a monetary policy shock, the correlation between GDP and the default risk spread is negative, while this correlation is positive relative to the maturity mismatch spread.

Net worth. The net worth block is quite rich. The database includes six different definitions of net worth. Figure 16 in Appendix 8 exhibits these six series. I use the symbols NW1 to NW6 to show these six variables. The full description of these variables is in the data appendix. The choice of equity variables is theoretically in line with the spirit of entrepreneurs' net worth in the financial accelerator mechanism; hence, I focus on the equity value of nonfinancial corporates, financial business, and household balance sheets. A recent work by Christiano, Motto, and Rostagno (2013) uses the Wilshire 5000 index as a measure of net worth that is used to estimate its DSGE. Table 3 in the Appendix presents the correlation between the Wilshire index and my six notions of net worth for the same time span (1971Q1 to 2012Q4). As is seen in the table, these net worth series are highly correlated with the Wilshire 5000 index. [3]

B. Model

With y_t being the vector of endogenous variables with n entries, assume the economy evolves as:

$$
\begin{aligned}
y_t &= c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t \\
e_t &\sim N(0_n, \Sigma),
\end{aligned}
\tag{1}
$$

where e_t is an $n \times 1$ vector of exogenous shocks and Σ is the covariance matrix of shocks. Σ and $c, A_1, ..., A_p$ contain the model's unknown parameters. I estimate a VAR model with thirteen lags ($p = 13$). For a large system of 34 variables with 13 lags, the model is richly parameterized. This dense parameterization gives rise to the issue of over-fitting and unstable inference. To address this problem, I use the Bayesian shrinkage technique proposed by De Mol, Giannone, and Reichlin (2008) and Banbura, Giannone, and Reichlin (2008). Under the shrinkage technique, the model's coefficients shrink toward a parsimonious naive benchmark, hence reducing estimation uncertainty.[4] This core idea lies behind the use of the Minnesota

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[3]The Wilshire 5000 index is a market-capitalization weighted index which measures the market value of all stocks traded in the United States.

[4] By setting the degree of shrinkage in relation to the cross-sectional dimension, as suggested by Bannura, Gianine, and Reichlin (2008), the performance of the VAR model improves. Essentially we set the shrinkage parameter so as to avoid over-fitting. Shrinkage is a device for reducing estimation uncertainty via the imposition of priors. Uncertainty is reduced at the cost of introducing a bias. This is the typical bias-variance trade off. Interestingly, it has been shown that when data are characterized by substantial comovement, as is the case for

prior proposed by Litterman (1980) and Doan, Litterman, and Sims (1983). The degree of the priors' informativeness can be optimized in a hierarchical way. Following the novel approach proposed by Giannone, Lenza, and Primiceri (2012), I select the degree of informativeness of the two prior distributions in order to maximize the marginal likelihood.

Next, I use the estimated model to identify three structural shocks and assess their transmission mechanisms. More specifically, I compute the IRF to a monetary policy shock, generalized IRF, and the spreads shocks. The analysis of the monetary policy shock has been widely used in the literature because, among other issues, it allows one to discriminate between competing theoretical models. In this paper, a monetary policy shock is defined as a one percent exogenous deviation in the Federal Funds Rate and it is characterized by a recursive identification scheme (see Christiano, Eichenbaum, and Evans (1999)).

Generalized IRF (GIRF)[5] is the IRF to a shock on real GDP which is ordered first. It is a linear combination of shocks that have historically moved GDP. This can be interpreted as a business cycle shock and is closely linked to the notion of cyclical shock in Giannone, Lenza, and Reichlin (2012). Investigating GIRF allows for the uncovering of the relationship between the business cycle and the external finance premium along with its components. I compare the responses of spreads to this shock with those to a non-anticipated change in the policy short rate. The comparison is informative, since, over the typical cycle, a monetary policy shock induces a positive correlation between the cycle and the maturity mismatch spread and a negative correlation between the cycle and the default risk spread. The GIRF further shows that spread series are countercyclical.

A spread shock is an exogenous increase in the spread. It is identified by assuming that the variables of real economic activities, prices, and short- and long-rates, which are contained in blocks 1, 2, and 3, do not react contemporaneously to the shock. At the same time, financial variables and the net worth can change upon the impact of the shock. Intuitively, this is because variables related to real economic activity are slow moving and financial variables are quicker in reacting to changes in the economy. External finance premiums and/or spreads, which link the real side of the economy to the financial side, should be located between general macroeconomic data blocks (1, 2, 3) and the financial blocks (5, 6). A novel approach is proposed in this paper, in order to compute impulse responses of the economy to a shock originating in the

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macroeconomic time series, the bias tends to be negligible (Del Mol, Giannone, and Reichlin (2008) provides a theoretical proof). For empirical evidence on the reliability of Bayesian VAR models for large systems, see Banbura, Giannone, and Reichlin (2008) and Giannone, Lenza, and Primiceri (2009). In particular, Giannone, Lenza, and Primiceri (2009) estimates the Bayesian and classical VAR models using the simulated data from DSGE and computes impulse response functions to a monetary policy shock. The authors find that the IRFs obtained using the Bayesian VAR (BVAR) models do not have substantial bias but are much more accurate than estimates obtained using maximum likelihood.

[5]The generalized impulse response function to h=variable j corresponds to a recursively identified shock in which variable j is ordered first. Proposition 3.1 on page 20 of Pesaran, Shin, and Yongcheol (1998) provides a theoretical proof.

credit market. This approach allows for the identification of the spread shocks, using the level variables. In this way, one can use the same system, with the same order of variables that was initially used to identify the MP shock and the GIRF, in order to produce the responses to spread shocks, using only a Cholesky decomposition.[6] This approach allows for estimating the model using the corporate bond yields directly, instead of using spreads time series. The main advantage of this approach is to make the choice of the prior on risk factors straight forward; one can set a random walk prior on the bond yields, though setting an appropriate prior on spread series is not trivial. Hence, it would be easier to identify the spread shocks within a transformed model. The identification works as follows.[7]

Assume there are two dynamic systems of variables, which can be converted into the other through a linear transformation, H:

$$Y_t^1 = B_1^1 Y_{t-1} + e_t^1, var(e_t^1) = \Sigma_t^1$$
$$Y_t^2 = B_1^2 Y_{t-1} + e_t^2, var(e_t^2) = \Sigma_t^2,$$

where: $Y^1 = HY^2$, $A^1 = HA^2$, $\Sigma_t^1 = H\Sigma_t^2 H'$.

For example, if $Y^1 = \begin{bmatrix} GDP \\ GDEF \\ FFR \\ BAA - FFR \\ NW \end{bmatrix}$,$Y^2 = \begin{bmatrix} GDP \\ GDEF \\ FFR \\ BAA \\ NW \end{bmatrix}$, then the H-Transformation would be:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

Matrices of coefficients are obtained by estimating model (2), A^2 and Σ^2. Then I use the H-transformation in computing the impulse responses of model (1), which contains a linear transformation.

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[6]Following Banbura, Giannone, and Reichlin (2008), Boivin, Giannoni, and Stevanovic (2013), and Stock and Watson (2005, 2005b) I divide my variables into two categories: fast moving and slow movingthe former mainly contains financial variables and the later contains real variables. Due to monetary policy inertia, the interest rate does not react contemporaneously to developments in the financial market, which are fast moving. Also, the seminal work of Bernanke, Gertler, and Gilchrist (1998) uses a VAR to benchmark their DSGE model. They use Cholesky decomposition as their main identification scheme; essentially to identify the policy shock, they order the funds rate after the price and output variables, based on the view that monetary policy can respond contemporaneously to these variables but can affect them only with a lag. They order the spread variable after the fund rate based on the assumption that innovations in these variables do not contain any marginal information that is useful for setting current monetary policy.

[7]To check the roboustness of Cholesky identification of spread shocks please see page 135.

III.   Impulse Response Analysis

The VAR model is an effective tool for studying the complex dynamic interrelation in data. By estimating the impulse response functions using VAR, I can trace out the effect of policy as well as real and financial innovations on the economy. A comprehensive IRF analysis has been performed to investigate three issues: model validation, shock transmission, and cyclicality. The main goal of this work is twofold: first, to uncover the degree in which empirical results match theoretical prediction and, second, to understand the reactions and properties of the credit spread. In what follows, I first describe how the analysis of the effects of monetary policy innovations can be used as a model selection tool. This approach has been used extensively in the literature (see Giannone, Lenza, and Primiceri (2012), Christiano, Eichenbaum, and Evans (1999), among others). The first contribution of this paper is to scrutinize large-scale New Keynesian models which feature different rigidities and frictions, by directly using data as the benchmark. More specifically, I evaluate the effect of the financial accelerator mechanism in enhancing the performance of Smets and Wouters (2007)-style monetary NK models. The first subsection provides a detailed discussion of the model validation exercise.

Next, I study monetary policy shock propagation into external finance premium and net worth channels. These are the two channels which are highlighted by the financial accelerator theoretical framework. Finally, I study the robustness of the results with respect to information inclusion. Understanding the response and properties of credit spread are particularly interesting, as this variable measures the linkage between financial factors and real activities. Hence, most of the discussion in this section centers on the spread and its components. In subsection 3, I discuss the implications of an exogenous increase in the external finance premium. The evidence presented in this paper draws attention to the importance of distinguishing between different risk channels of credit spread. The credit spread (BAA-FFR) drops to a negative value upon the impact of a monetary policy shock. This is contrary to the prediction of the financial accelerator mechanism. I call this anomaly the spread puzzle.

To solve the spread puzzle, I highlight two important intrinsic properties of this series, namely, the maturity term and the default risk. The BAA and AAA bond yields, by construction, are long-maturity variables; this is because Moody's includes bonds with remaining maturities as close to 30 years as possible. By assuming that AAA is the rate paid in the no-default scenario, one can think about BAA-AAA as a proxy that captures the default risk. Similarly, the AAA-FFR spread can capture the maturity mismatch risk. [8] This decomposition allows for studying the effects of these two risk channels independently. The impulse response evidence, presented in the following subsection, shows that, while both series have similar cyclical properties, they respond differently to a monetary policy shock. Moreover, the economy has a similar trajectory under an exogenous increase in either of these spreads; this is while the magnitude of responses to a maturity mismatch spread shock is bigger than that of a default

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[8]In this paper, I use the terms liquidity risk spread and maturity mismatch spread interchangeablythey both refer to "AAA-FFR".

risk spread shock. Appendix 6 summarizes the findings.

A. Model Validation

I consider two competing estimated models. 1) Justiniano, Primiceri, and Tambalotti (2013)'s monetary DSGE model is my baseline model. Hereafter I call this the JPT model. 2) The JPT model amended by the financial accelerator mechanism of Bernanke, Gertler, and Gilchrist (1999) is then considered. I call this model JPTBGG. For details on the implementation, see Furlanetto, Gelain and Taheri Sanjani (2013). I use seven conventional macroeconomic variables and two financial variables to estimate the JPTBGG model. The macroeconomic observables are similar to the ones in Justiniano, Primiceri, and Tambalotti (2013). The financial observables contain the credit spread, which is proxied by BAA-FFR[9] and per capita net worth. Figure 2 compares the response of seven macroeconomic observables to the monetary policy shock across the JPT and JPTBGG models. The responses of two financial variables in the JPTBGG model, spread and net worth, are also included in the panel. As is clear from this figure, the magnitudes of the responses generated from the DSGE model with financial frictions are greater than those from the DSGE model without financial frictions. This result is intuitive, as the accelerator block works as a feedback loop and thus amplifies the response of the economy to the shocks.

Figure 3 reports the median, as well as the 16th and 84th percentiles of the posterior distribution of the impulse responses to a monetary policy shock. By comparing Figures 2 and 3, one can observe that a VAR analysis favors the model with financial frictions, as the sizes of responses are closer to each other. In response to a rise in the nominal interest rate, real activity decreases, but the response of prices in the VAR model exhibits the so-called price puzzle. In what follows, I show that this counterintuitive positive response of price to a monetary contraction will disappear in a VAR with large information sets (Bernanke, Boivin, and Eliasz (2005) and Banbura, Giannone, and Reichlin (2008)). Notice that the DSGE response does not exhibit the price puzzle. The response of spread and net worth in DSGE-IRFs can be explained by the financial accelerator mechanism. Following a contractionary monetary policy shock, asset prices drop, which also means that the asset side of entrepreneurs' balance sheets drops; this would affect the supply of funds in a negative way. Therefore, the external finance premium rises. Net worth, or equity, in the BGG block is defined as: asset minus liabilities. A drop in the asset side of a balance sheet would result in a drop in equity. The spread puzzle holds in the JPTBGG-VAR responses. The evidence from a large VAR model, presented in the next section, shows that information inclusion helps address this anomaly.

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[9]Note that the main results of the paper regarding the dynamic movements of IRFs do not change, as they primarily show the dynamic response of the equilibrium equations. The general behaviors of IRFs directly result from the mathematical formulation of our model, not the estimation detail (see Gilchrist, Ortiz, and Zakrajsek (2009) and Christiano, Eichenbaum, and Evans (2013).
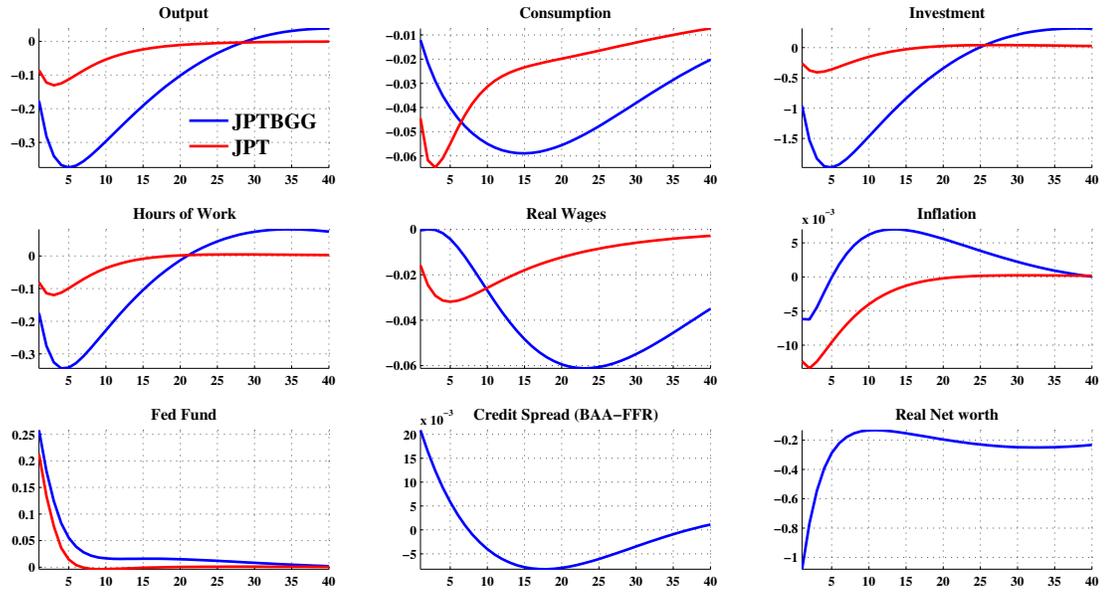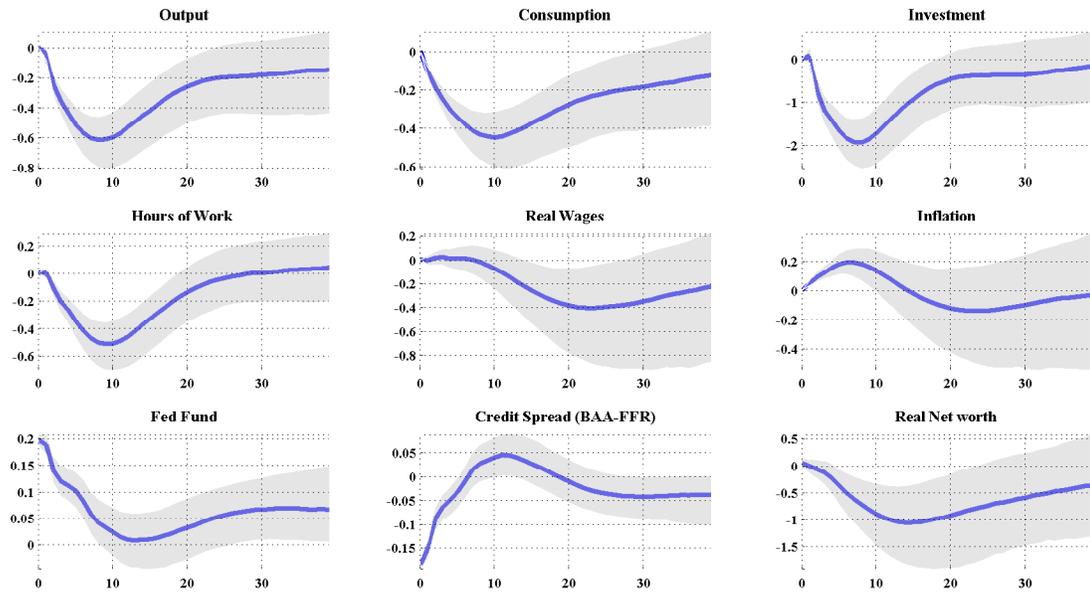
Figure 2: IRF -DSGE JPT versus JPTBGG

Figure 3: IRF -VAR using the JPTBGG data-set

Next, I estimate the impulse responses to monetary policy shocks, using a medium-scale BVAR model with the same nine variables used to estimate the JPTBGG model. Then, I identify a monetary policy shock, using the standard recursive identification scheme, assuming that prices and real activity do not react to the monetary policy shock contemporaneously. The only variables that can react contemporaneously to monetary policy shocks are the financial variables (spread and net worth), while the policy rate does not react contemporaneously to financial variables (see Christiano, Eichenbaum, and Evans (1999)).

B.   Monetary Policy Transmission

Next, I investigate monetary policy transmission within a small and large system. Cross-comparing the results between two systems provides a check for robustness. Moreover, it has been shown in Giannone and Reichlin (2006) that including auxiliary variables would address the non-fundamentalness problem. The analysis of this exercise shows that the spread puzzle holds in a small-scale VAR model but not within a large-scale VAR. This provides further a motivation for studying spread shocks within a large system. For more discussion on the importance of information inclusion, see Giannone and Reichlin (2006).[10]
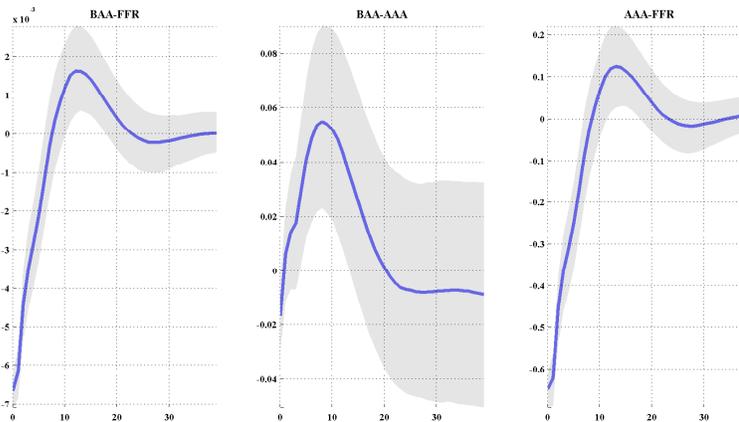

Figure 5: Spread responses to monetary policy shock in small-scale VAR

Small-scale VAR model. My small data set is the prototypical monetary VAR, augmented by risk and equity variables. The data set contains six variables: GDP, GDP price

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[10]According to Giannone and Reichlin (2006), even for those cases in which the desired model is a small-size system, one should extend the data set by including the auxiliary variables, in order to check for the possibility of non-fundamentalness. The additional auxiliary variables should fulfill the following criteria: (i) they should have forecasting power (Granger-cause) for the variables of the original small-size system; they should also have strong commonality with the original information set and small idiosyncratic dynamics; and finally, (iii) they should be weakly cross-sectionally correlated with them. Within the augmented system, the original desired shocks will be recoverable only if they are pervasive.
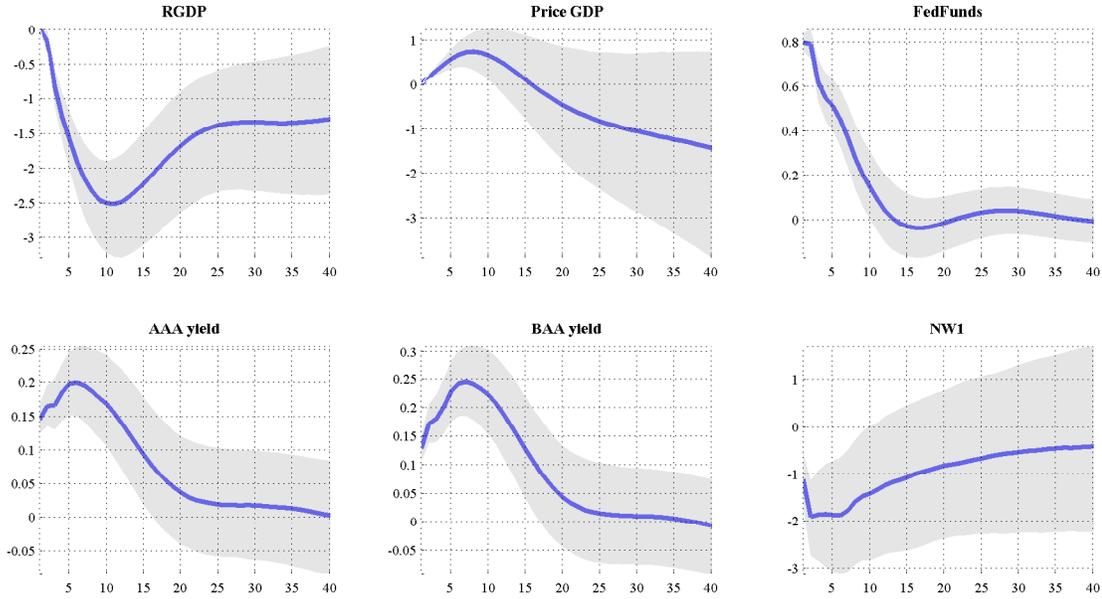
Figure 4: Monetary policy shock in a small-scale VAR

index, Federal Funds Rate, AAA yield, BAA yield, and net worth. I estimate this model first and then use the H-transformation to produce impulse response functions to one percent exogenous deviation in the Federal Funds Rate. Figures 4 and 5 report the median as well as the 16th and 84th percentiles of the posterior distribution of the impulse responses to a monetary policy shock in a small-scale VAR model. Figure 5 focuses on the responses of credit spread and its components.[11] Within the accelerator context, the credit spread is defined as the rates paid on rental capital minus the risk-free rate. As seen in the figure, in response to a contractionary monetary policy shock, output goes down and yields go up; credit spread (BAA-FFR) and its components, default risk spread, and maturity mismatch spread, drop below zero upon impact and gradually go up. These responses are contrary to the prediction of the financial accelerator mechanism. The drop in maturity mismatch spread is bigger in size than the default risk spread. Equity or net worth drops upon the impact of shock, which is in line with the financial frictions mechanism. When the short-term rate goes up, asset prices go down and the asset value of balance sheets drop; on the other hand, the risk-free rate paid on liabilities goes up, hence equity declines.

Large-scale VAR model. Figures 6 and 7 report the median as well as the 16th and 84th percentiles of the posterior distribution of the impulse responses to a monetary policy shock within the large-scale VAR model. A contractionary monetary policy in the large VAR model generates a turn down. GDP, consumption, investment, and employment, among other variables related to real economic activities, substantially contract. Prices decrease with a lag.

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[11]I construct the IRF to credit spread, BAA-FFR, by subtracting the IRF of the BAA yield from the short-term interest rate (FFR).

Monetary aggregates, M1 and M2, also decrease, indicating liquidity effects. Stock prices go down upon impact and stay low. Moreover, the long rates jump up upon impact, though less in degree than the short-term rate (for more on the sticky response of interest rates at longer maturity, see Peersman and Smets (2001)). The exchange rate and the corporate bond yields appreciate. Note that the price puzzle is not present anymore, thanks to the information inclusion. Equity variables depreciate as is predicted by theory.
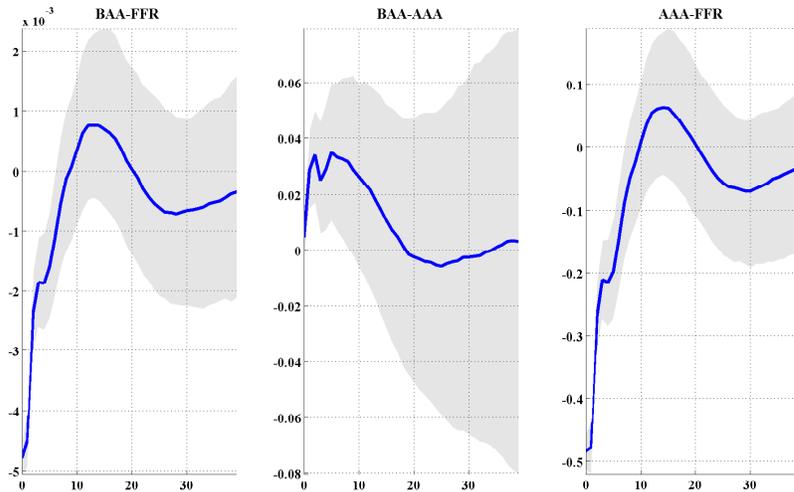

Figure 6: Spread responses to monetary policy shock in a large-scale VAR

Credit spread (BAA-FFR) and maturity mismatch spread (AAA-FFR) fall to negative values upon the impact of the shock. However, the default risk spread (BAA-AAA) jumps from a small but positive value and reaches its maximum after eight quarters upon the impact of the shock. The drop in the maturity mismatch spread comes from the sticky response of AAA bond yields to the rise in the short-term interest rate. The elasticity of corporate bond yields to the rise in the short-term interest rate decreases, as the maturity of the bonds increases. Hence, the maturity mismatch spread falls upon the impact of the contractionary monetary policy shock. The response of the default risk spread follows the financial accelerator mechanism. A rise in interest rate would impede economic activity and demand; therefore, firms' default risk rises and this would affect their cost of funding. A policy implication would be that firms issue longer maturity paper to protect their financial position in case of monetary contraction.

C. Generalized IRF and cyclicality

Generalized IRF is the IRF to a shock on real GDP, which is ordered first. It is a linear combination of shocks that have historically moved GDP. This can be interpreted as a business cycle shock and is closely linked to the notion of cyclical shock in Giannone, Lenza, and Reichlin
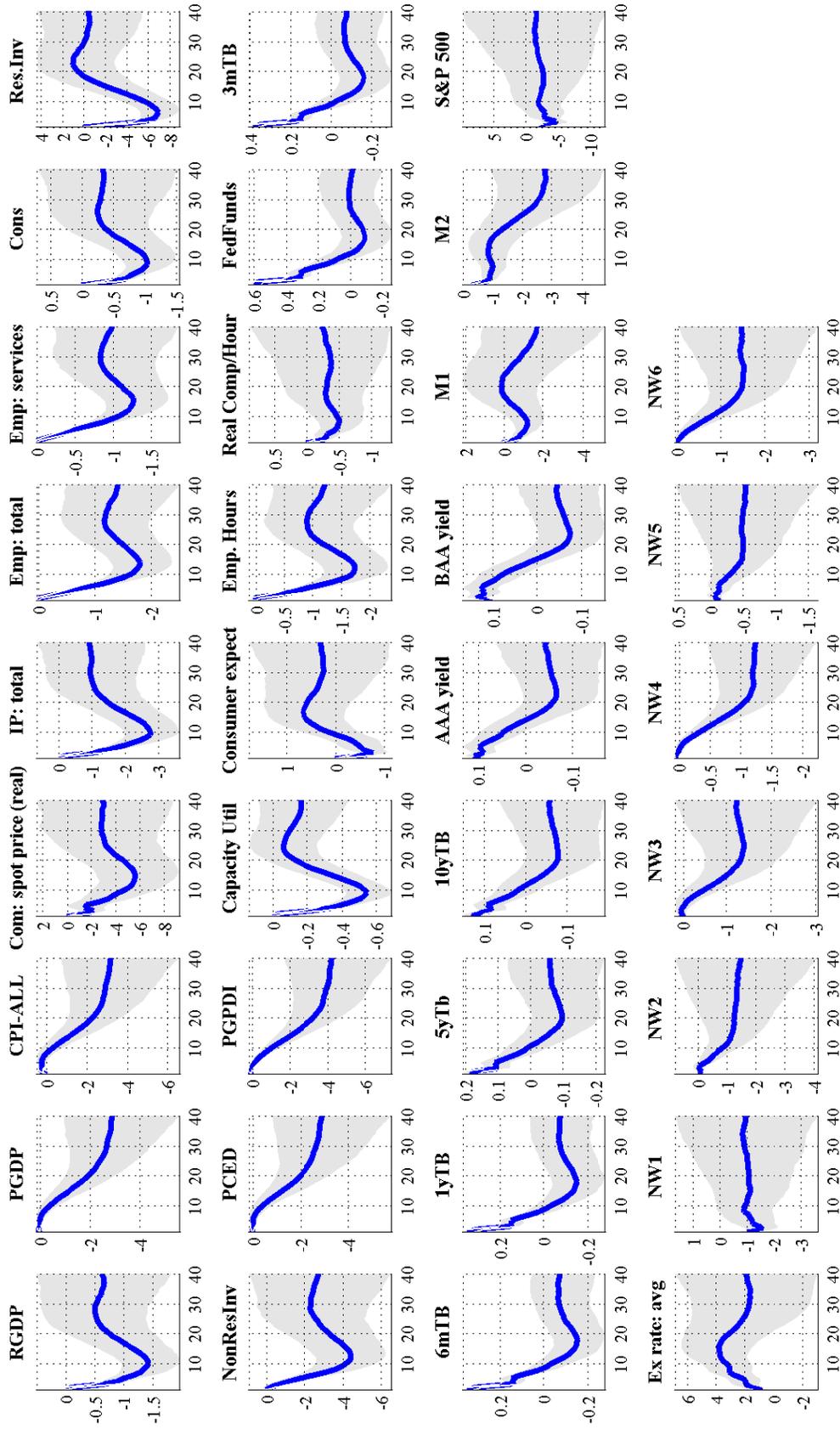
Figure 7: Monetary policy shock in a large-scale VAR

(2012). The main goal of this exercise is to uncover the relationship between the business cycle and the external finance premium. Figure 8 reports the median as well as the 16th and 84th percentiles of the posterior distribution of the impulse responses to a real GDP shock within the large-scale VAR model. In response to a positive shock to output, real economic activity, short and long rates, and net worth all exhibit a procyclical response. Bond yields go up slightly.

The responses of monetary bases are particularly interesting. While the narrow money, M1, appears to be countercyclical, M2 seems to be procyclical. M2 is a broader classification of money than M1. It additionally contains a wider range of financial assets held mainly by households, which forms banks' liabilities at longer maturity. The difference between M2 and M1 mainly consists of savings deposits and term deposits. Therefore, the analysis of the broader monetary aggregate can be instructive regarding the behavior of banks' liabilities over the business cycle. The procyclicality of M2 suggests a strong procyclical behavior of banks' liabilities at longer maturity. This is intuitive, since in a good economic climate households tend to save more and, hence, banks' deposits increase.[12] Giannone, Lenza, and Reichlin (2012) provide a comprehensive business cycle study of credit and money in the euro area, using cyclical shock analysis.

One of the contributions of this paper is to investigate the cyclical properties of the credit spread and its components. My generalized impulse response analysis shows that credit spread and both of its risk components are countercyclical. This issue is particularly interesting, as the DSGE literature does not seem to have a definitive conclusion regarding the cyclicality of the credit spread. The seminal work of Bernanke, Gertler, and Gilchrist (1999), or the recent work by Christiano, Motto, and Rostango (2013), emphasize the countercyclicality of EFP. A recent strand of DSGE literature shows that the estimated premium is not necessarily countercyclical and it depends on the model assumptions about stochastic processes and shocks, included in the model. De Garve (2008) and Glain (2010) estimates a NK-DSGE model with financial frictions for the EU and the US, respectively, using solely non-financial macroeconomic data. They show that the premium derived from their estimated model is procyclical. In Dib and Christensen (2005), the preference shock increases consumption more than it crowds out investment. They further show that this leads to a conditionally procyclical premium. The models by Faia and Monacelli (2007) and Meeks (2006) build upon the seminal work of Carlstrom and Fuerst (1997), by adding additional stochastic process. They show that adding the new shocks changes the cyclical behavior of the premium.

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[12]According to the St. Louis Fed, "M1 includes funds that are readily accessible for spending. M1 consists of: (1) currency outside the U.S. Treasury, Federal Reserve Banks, and the vaults of depository institutions; (2) traveler's checks of nonbank issuers; (3) demand deposits; and (4) other checkable deposits (OCDs), which consist primarily of negotiable order of withdrawal (NOW) accounts at depository institutions and credit union share draft accounts. M2 includes a broader set of financial assets held principally by households. M2 consists of M1 plus: (1) savings deposits (which include money market deposit accounts, or MMDAs); (2) small-denomination time deposits (time deposits in amounts of less than $100,000; and (3) balances in retail money market mutual funds (MMMFs)."
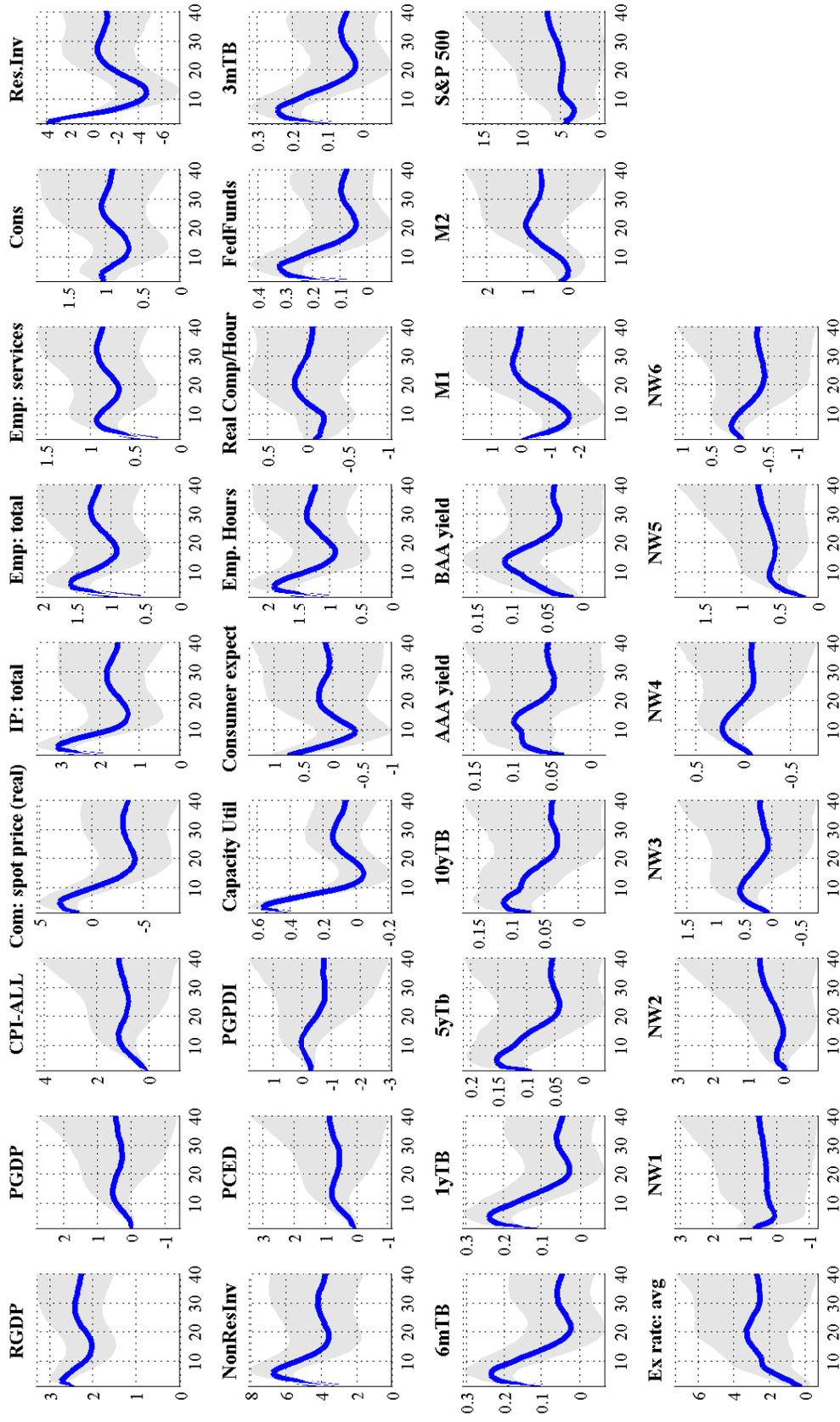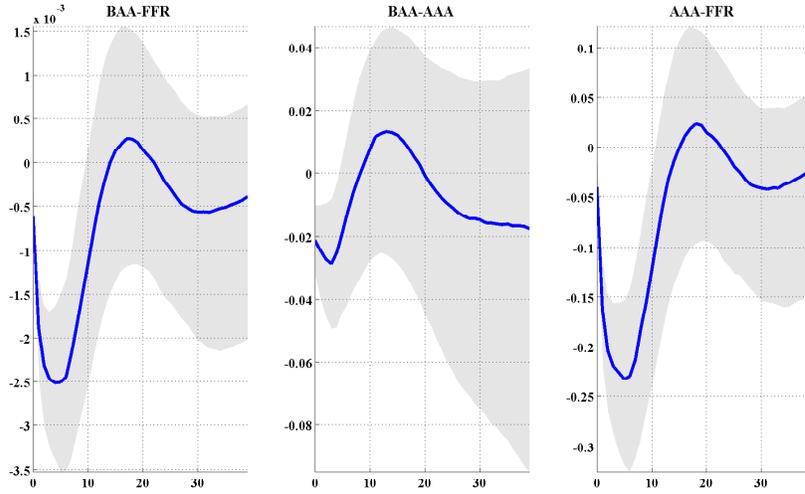
Figure 8: Generalized IRF

Figure 9: Spreads responses - Generalized IRF

Figure 9 shows that VAR analysis implies that credit spread, default risk spread, and maturity mismatch spread are countercyclical. During the great recession, credit spread rose four-fold from Dec 2007 to June 2009; during the same period default risk spread rose three-fold and liquidity risk spread rose five-fold. Thanks to the Federal Reserve's quick response to the financial disruptions and monetary easing, default risk spread returned to where it started in 2007 and as of the first quarter of 2013, its value is 0.93, while the liquidity risk spread has not decreased in response to the Fed's expansionary monetary policy; it is still as high as 3.74. The reactions of these two spreads to monetary policy is in line with the findings of this paper, as the expansionary monetary policy shock would lower the default risk spread but increase the maturity mismatch spread.

D. Spreads Shock

In this section, I identify the effects of credit shocks in order to quantify their impact and contribution in explaining fluctuations in the real economy. Changes in the spread can be seen as either changes in "default risk" or "liquidity/maturity mismatch risk". They further affect the external financing position of firms (or borrowers in general) and, hence, the cost of funding they face. Within the BGG context, EFP is the difference between the costs of raising external funds and the opportunity costs of funds raised internally. EPF is the main link between a firm's balance sheet and real output.

Inefficient shocks originating in the credit market will be fed back and amplified into the real economy. When a firm's capacity to repay their loans deteriorates, their default risk rises, which translates into a higher premium on their loans. Alternatively, when a firm's balance

sheet experiences liquidity problems, this leads to a higher cost of external financing. Hence, EFP is related to the risks faced due to the firm's financial position, namely, default and liquidity risks. An adverse credit supply shock results in a significant reduction in real economic activity. The credit channel further amplifies otherwise short-lived macroeconomic shocks and lengthens their impact.
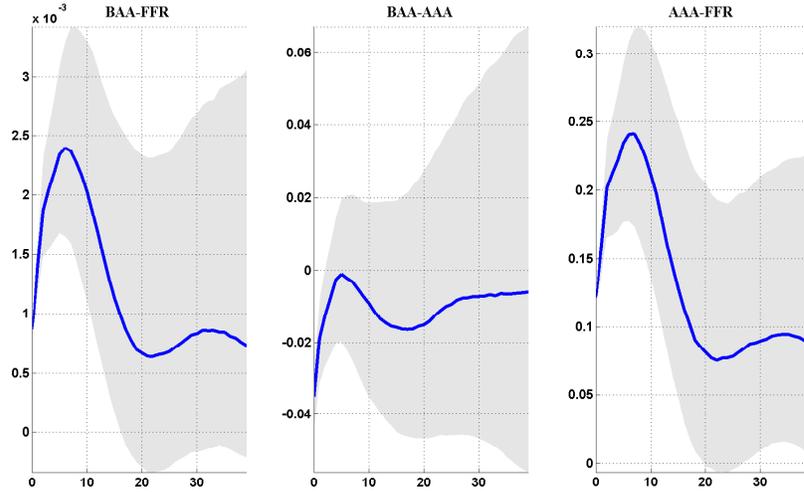

Figure 10: Spreads responses to a maturity mismatch spread (AAA-FFR) shock

Figures 10 to 13 report the median as well as the 16th and 84th percentiles of the posterior distribution of the impulse responses to a one-percent exogenous increase in either of the spread variablesmaturity mismatch spread or default risk spread. The spread shock is identified by assuming that the macro variables, prices, short and long rates, which are contained in blocks 1, 2, and 3, do not react contemporaneously to the shock. However, the financial variables and net worth respond immediately to the shock. The maturity mismatch shock can be viewed as having its roots in the balance sheets of corporates, but the default risk shock can be related to the general or firm-specific economic environment, such as demand or productivity. Figures 10 and 11 present the impulse responses to a one-standard-deviation shock to the maturity mismatch spread. Likewise, Figures 12 and 13 present the impulse responses to a one-standard-deviation shock to the default risk spread. Following a widening of the spreads, the credit channel tightens, and the cost of funding soars, which, in turn, leads to lower demand and investment.

The response of both investment and output is hump-shaped, with the peak in the response occurring at five quarters after the impact of the financial shock. The consumer expectations index goes up, peaking 10 quarters after the impact. Short and long rates go down, in accordance with the prediction of the accelerator mechanism. Monetary aggregates go up and stock prices go down. Exchange rate initially jumps but it declines quickly. The equity variables also go down.[13]

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[13]The maturity mismatch spread resembles the slope of the yield curve, as AAA is a long rate and FFR is
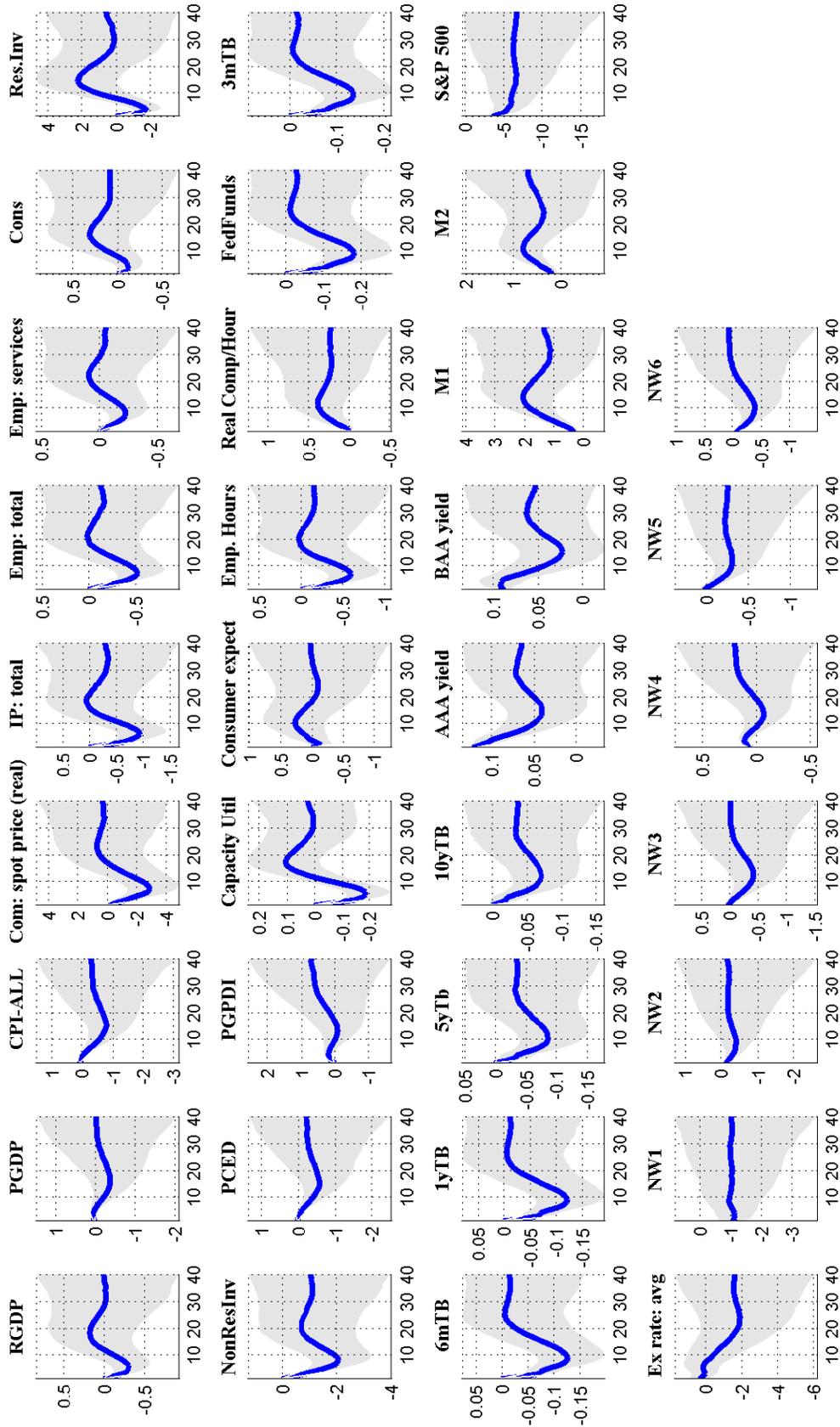
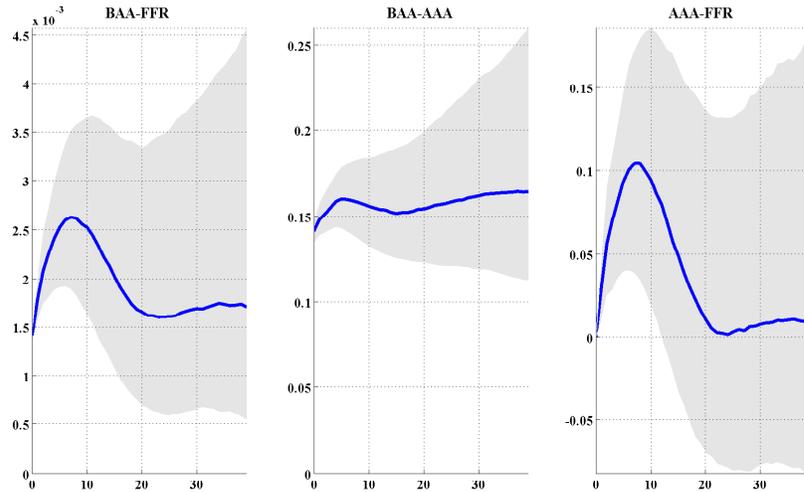Figure 11: Maturity mismatch spread (AAA-FFR) shock

Figure 12: Spreads' responses to a default risk spread (BAA-AAA) shock

Figure 14 compares the responses of these two shocks in the same chart. As is clear from the charts, the impact of a maturity mismatch shock is more severe than a default risk shock. In particular, the drop in stock prices is much more magnified when the adverse credit supply shock originates from balance sheet problems rather than from default risk. Following the exogenous widening of the default risk spread, the net worth variables do not revert to the pre-shock levels, in contrast to the scenario in which the economy is hit by a maturity mismatch spread shock. A policy implication would be that additional measures should be in place to prevent the emergence of a liquidity shortage.

To check the robustness of the identification of the spread shocks, I changed the order of variables in my VAR model. More specifically, I reverse the order of BAA and AAA in the VAR system and re-estimate the model. Then, I compute the IRF for two shocks: 1) BAA-AAA and 2) AAA-FFR. The results remain robust with respect to ordering. Regardless of the ordering of spreads in the model, negative developments in the credit market, which increase either the default risk spread or maturity mismatch spread exogenously, will produce a downturn in real economic activity.

I report the results of the robustness check in the same IRF graph, in order to allow for a more immediate visual comparison. Figure 15 shows the median and the 16th and 84th percentiles of the posterior distribution of the impulse responses to a one-percent exogenous increase in the AAA-FFR spread. The blue lines are called "check" (which is my robustness test); to compute them, I swap the order of BAA and AAA. Then I estimate the model and compute the impulse

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a short rate. During the great recession, different measures of non-standard monetary policies were employed to lower the long rates (e.g., operation twist, quantitative easings). Such policies can be seen as an exogenous shock to the maturity mismatch spread; therefore, one can conjecture the effect of such policies in the real economy using the impulse responses to this shock. For example a policy that reduces the long rate by 12% with respect to the steady state will increase real GDP by 30.7% five quarters after the impact.
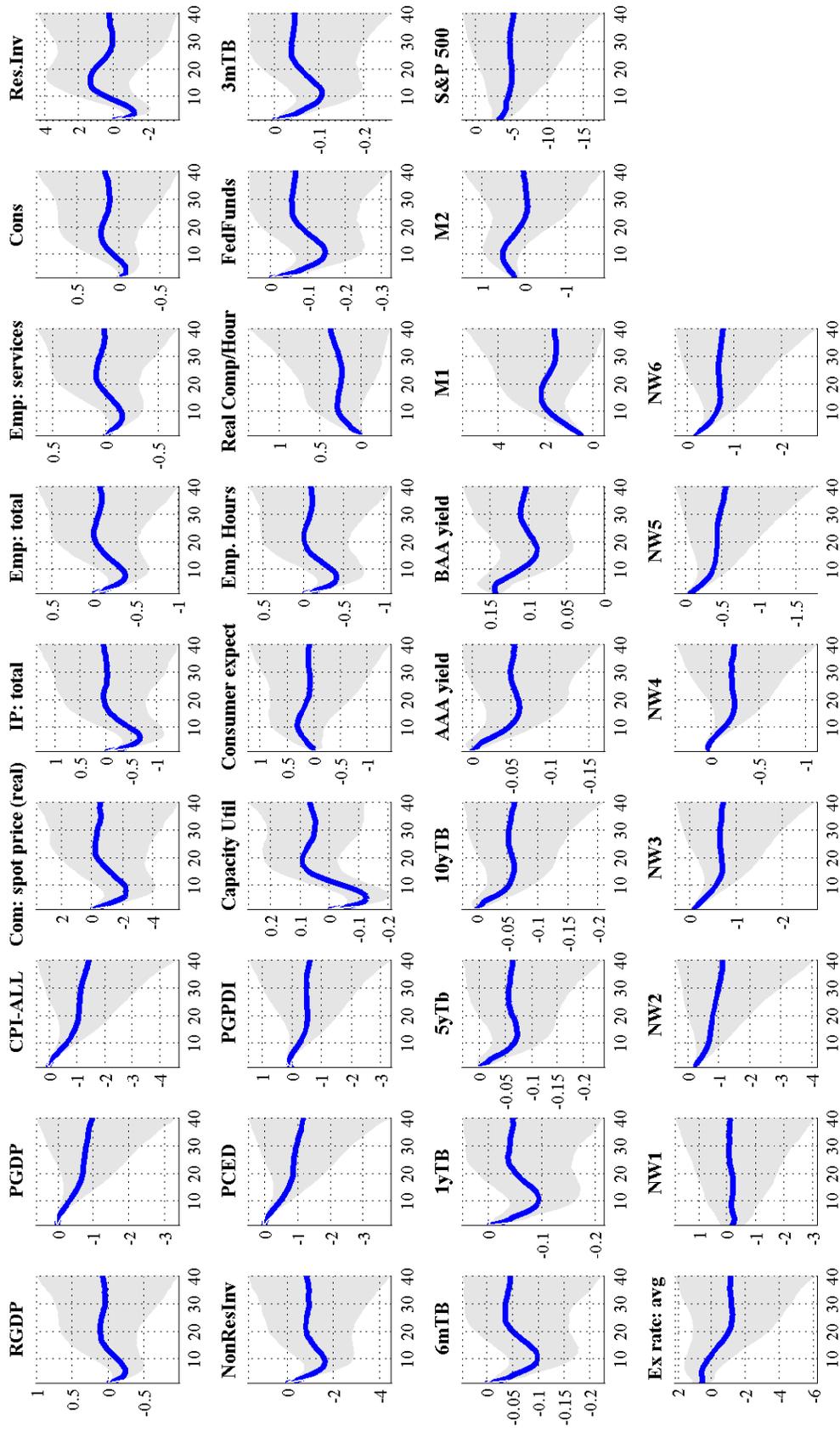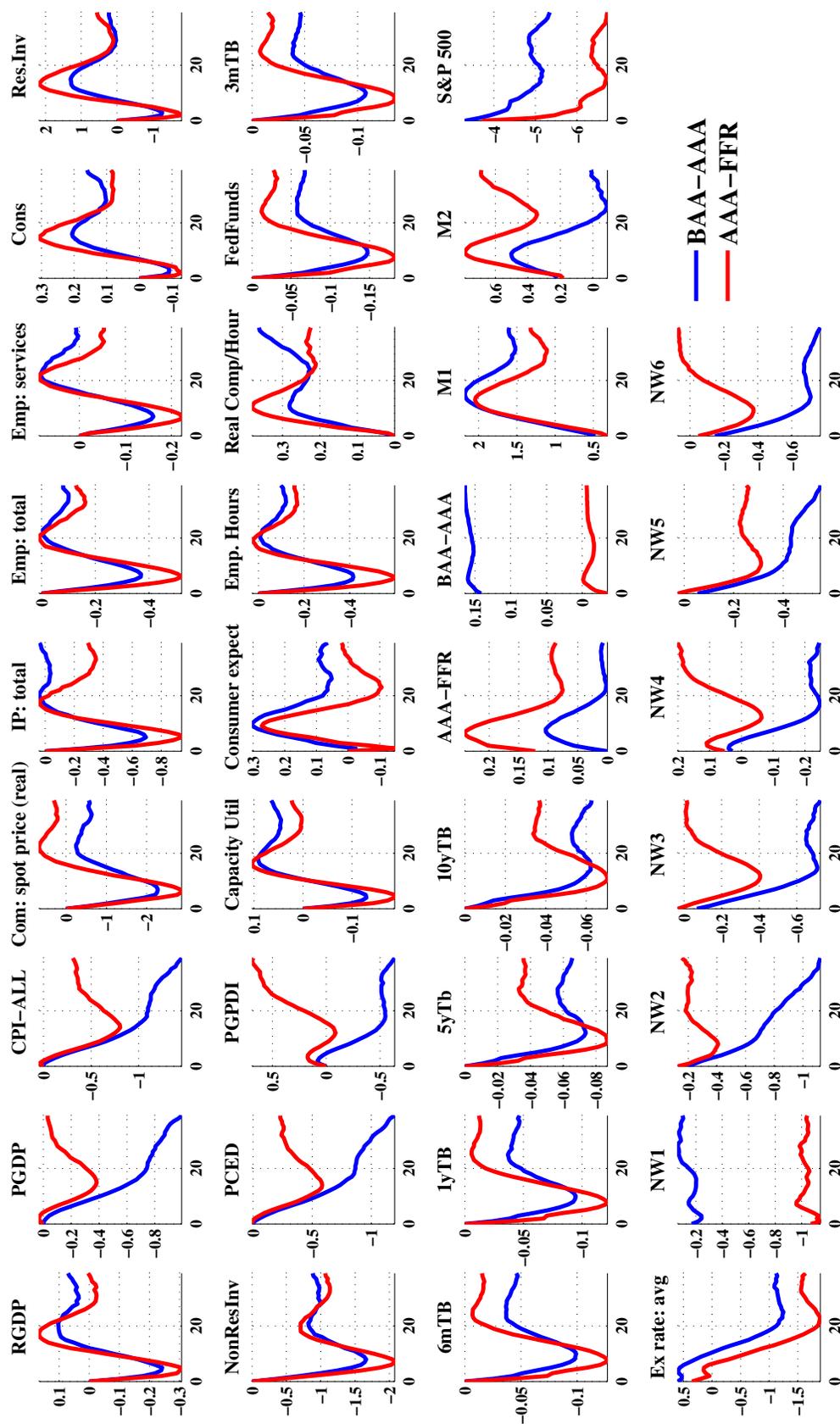
Figure 13: Default risk spread (BAA-AAA) shock

Figure 14: Default risk spread shock versus maturity mismatch spread

responses by disturbing the economy by a liquidity mismatch spread shock (AAA-FFR). As is clear from the graphs, the results are robust with respect to reversing the order of the spread variables in the VAR model.

IV.   Conclusion

In this paper, a comprehensive impulse response analysis is conducted to identify the spread shock, the business cycle shock, and the monetary policy shock in large-, medium-, and small-scale Bayesian VAR models. I investigate four issues: structural model validation, spread shock propagation into the real economy, monetary policy propagation into the credit market, and the cyclical properties of external financing premium and net worth. I find that the impulse responses of a DSGE model with financial frictions are amplified compared to a DSGE model without financial frictions. Moreover, the size of impulse responses better match those from VAR models. Evidence from a large VAR model illustrates that in response to a monetary policy shock, credit spread and maturity mismatch spread fall to negative values, while the default risk spread rises to a positive value, upon the impact of the shock. By employing a generalized IRF, I show that while the risk spreads are countercyclical, the net worth is procyclical. Finally, I propose an approach for identifying exogenous shocks to the components of credit spread in the data. The impulse response analysis further shows that the impact of the liquidity risk shock is more severe than the default risk shock.
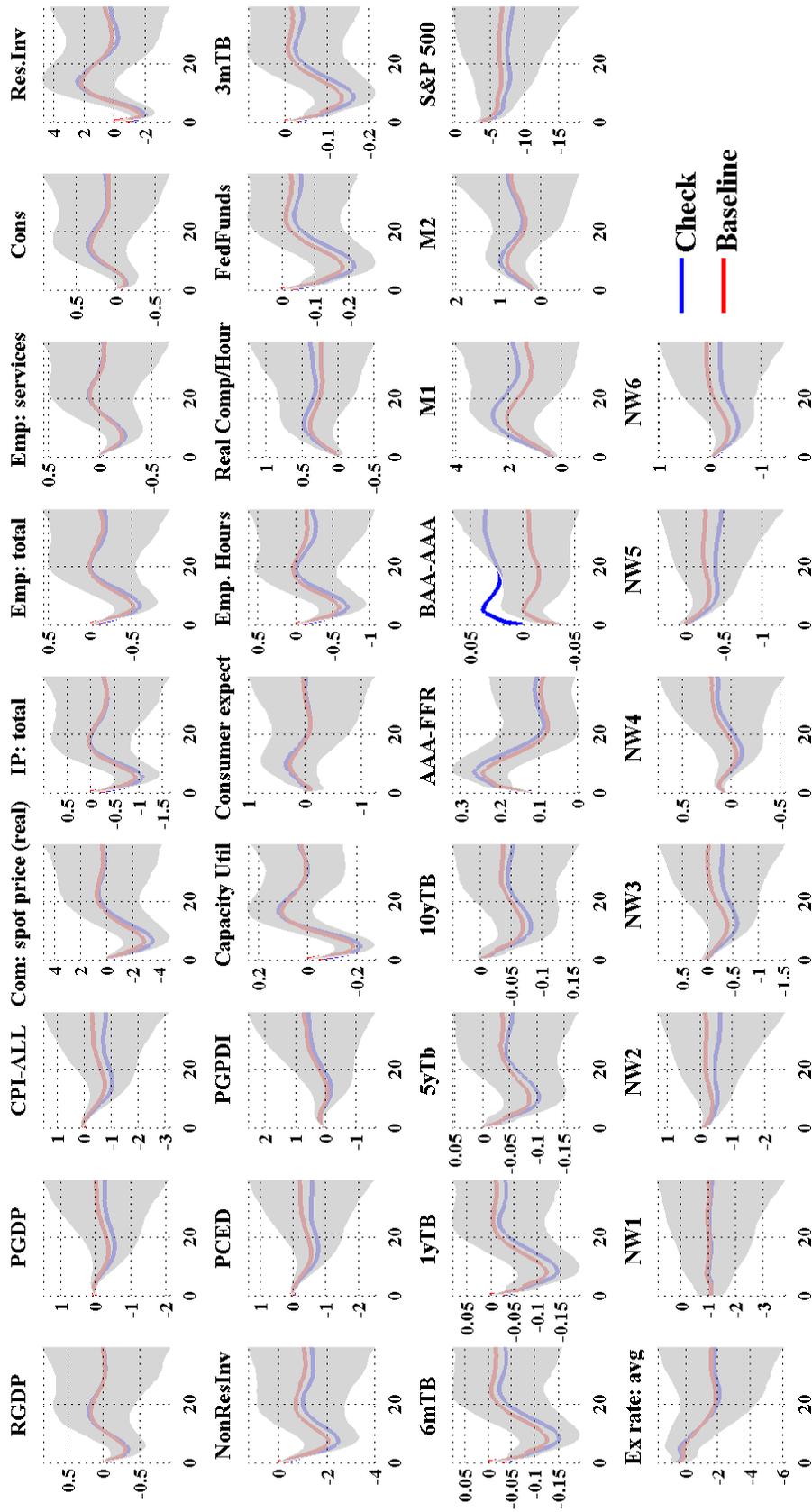
Figure 15: Robustness check - Spread Shock (AAA-FFR)

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A   Appendix - Data

1. REAL GROSS DOMESTIC PRODUCT, Quantity Index (2000=100), SAAR.

2. GROSS DOMESTIC PRODUCT PRICE INDEX.

3. CPI All Items (SA).

4. Real SPOT MARKET PRICE INDEX: BLS CRB: ALL COMMODITIES (1967=100) (PSC-COM/ PCEPILFE).

5. INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX.

6. EMPLOYEES, NONFARM - TOTAL PRIVATE.

7. EMPLOYEES, NONFARM - SERVICE-PROVIDING.

8. REAL PERSONAL CONSUMPTION EXPENDITURES, Quantity Index (2000=100), SAAR.

9. REAL GROSS PRIVATE DOMESTIC INVESTMENT - Residential, Quantity Index (2000=100).

10. REAL GROSS PRIVATE DOMESTIC INVESTMENT - Nonresidential, Quantity Index.

11. PERSONAL CONSUMPTION EXPENDITURES PRICE INDEX.

12. GROSS PRIVATE DOMESTIC PRICE INDEX.

13. CAPACITY UTILIZATION - MANUFACTURING (SIC).

14. U. OF MICH. INDEX OF CONSUMER EXPECTATIONS (BCD-83).

15. HOURS OF ALL PERSONS: NONFARM BUSINESS SEC (1982=100, SA).

16. REAL COMPENSATION PER HOUR, EMPLOYEES: NONFARM BUSINESS (82=100, SA).

17. FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM, NSA).

18. U.S. TREASURY CONST MATURITIES, 3 months.(% PER ANN, NSA).

19. U.S. TREASURY CONST MATURITIES, 6 months.(% PER ANN, NSA).

20. U.S. TREASURY CONST MATURITIES, 1-YR.(% PER ANN, NSA).

21. U.S. TREASURY CONST MATURITIES, 5-YR.(% PER ANN, NSA).

22. U.S. TREASURY CONST MATURITIES, 10-YR.(% PER ANN, NSA).

23. BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM).

24. BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM).

25. MONEY STOCK: M1(CURR, TRAV.CKS, DEM DEP, OTHER CK'ABLE DEP) (BIL$, SA)'.

26. MONEY STOCK: M2 (M1+O'NITE RPS, EURO $, G/P, B/D MMMFS, SAV, SM TIME DEP(BIL$).

27. S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10).

28. USA EFFECTIVE EXCHANGE RATE (MERM)(INDEX NO.).

29. NW1: MVEONWMVBSNNCB MARKET VALUE OF EQUITIES OUTSTANDING - NET WORTH (MARKET VALUE) - BALANCE SHEET OF NONFARM NONFINANCIAL CORPORATE BUSINESS (MVEONWMVBSNNCB), BILLIONS OF DOLLARS, QUARTERLY, NOT SEASONALLY ADJUSTED.

30. NW2: OEHRENWBSHNO OWNERS' EQUITY IN HOUSEHOLD REAL ESTATE - NET WORTH - BALANCE SHEET OF HOUSEHOLDS AND NONPROFIT ORGANIZATIONS (OEHRENWBSHNO), BILLIONS OF DOLLARS, QUARTERLY, NOT SEASONALLY ADJUSTED.

31. NW3: TNWMVBSNNCB TOTAL NET WORTH (MARKET VALUE) - BALANCE SHEET OF NONFARM NONFINANCIAL CORPORATE BUSINESS (TNWMVBSNNCB), BILLIONS OF DOLLARS, QUARTERLY, NOT SEASONALLY ADJUSTED.

32. NW4: RCSNNWMVBSNNCB REPLACEMENT-COST VALUE OF STRUCTURES: NON-RESIDENTIAL - NET WORTH (MARKET VALUE) - BALANCE SHEET OF NONFARM NONFINANCIAL CORPORATE BUSINESS (RCSNNWMVBSNNCB), BILLIONS OF DOL-LARS, QUARTERLY, NOT SEASONALLY ADJUSTED.

33. NW5: TNWHCBSNNCB TOTAL NET WORTH (HISTORICAL COST) - BALANCE SHEET OF NONFARM NONFINANCIAL CORPORATE BUSINESS (TNWHCBSNNCB), BILLIONS OF DOLLARS, QUARTERLY, NOT SEASONALLY ADJUSTED .

34. NW6: TNWBSNNB TOTAL NET WORTH - BALANCE SHEET OF NONFARM NONCOR-PORATE BUSINESS (TNWBSNNB), BILLIONS OF DOLLARS, QUARTERLY, NOT SEA-SONALLY ADJUSTED.

Table 2: Data Description and Transformation

| Block #	Position	Mnemonic	Description	Transformation	Small	Large
	1	RGDP	Real GDP	log level	X	X
	2	PGDP	GDP Price Index	log level	X	X
	3	CPI-ALL	CPI All Items	log level		X
	4	Com: spot price (real)	Commodity Price	log level		X
	5	IP: total	Industrial Production	log level		X
	6	Emp: total	Total Employment	log level		X
	7	Emp: services	Service Employment	Level		X
Block 1	8	Cons	Real Personal Consumption	log level		X
	9	Res.Inv	Residential Investment	log level		X
	10	NonResInv	NonResidential Investment	log level		X
	11	PCED	Consumption expenditures Price Index	log level		X
	12	PGPDI	Investment Price Index	log level		X
	13	Capacity Util	Capcity Utilization: Manufacturing	Level		X
	14	Consumer expect	Consumer expectation	Level		X
	15	Emp. Hours	Hours worked	log level		X
	16	Real Comp/Hour	real compensation per hours	log level		X
Block 2	17	FedFunds	Effective Federal Fund Rate	Level	X	X
	18	3mTB	Treasury Bill Rate 3 months	Level		X
	19	6mTB	Treasury Bill Rate 6 months	Level		X
Block 3	20	1yTB	Treasury Bill Rate 1 year	Level		X
	21	5yTb	Treasury Bill Rate 5 year	Level		X
	22	10yTB	Treasury Bill Rate 10 year	Level		X
Block 4	23	AAA yield	AAA Corporate Bond Yield	Level	X	X
	24	BAA yield	BAA Corporate Bond Yield	Level	X	X
	25	M1	M1	log level		X
Block 5	26	M2	M2	log level		X
	27	S&P 500	SP500	log level		X
	28	Ex rate: avg	Effective Exchange Rate	log level		X
	29	NW1	MVEONWMVBSNNCB	log level	X	X
	30	NW2	OEHRENWBSHNO	log level		X
Block 6	31	NW3	TNWMVBSNNCB	log level		X
	32	NW4	RCSNNWMVBSNNCB	log level		X
	33	NW5	TNWHCBSNNCB	log level		X
	34	NW6	TNWBSNNB	log level		X

B   Appendix - Net worth
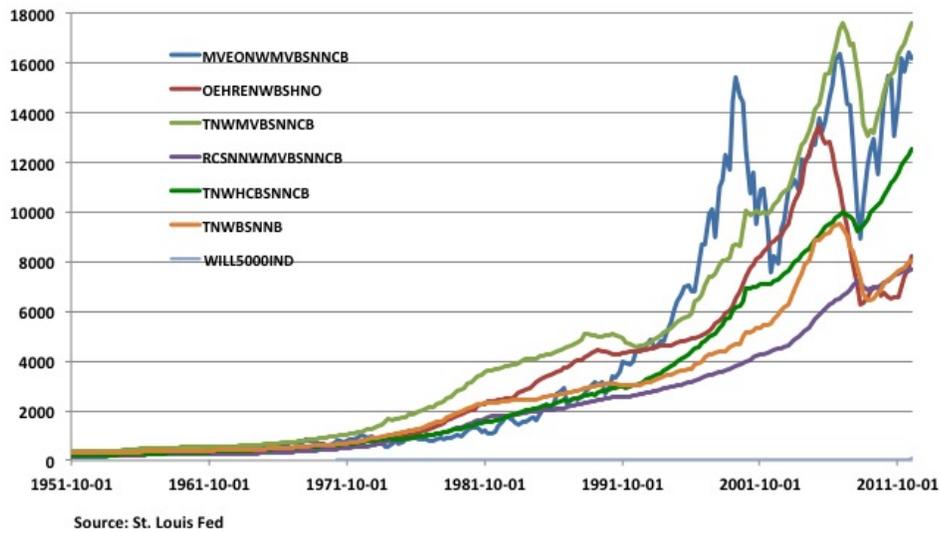
Figure 16: Net Worth time series

Table 3: Correlation Between Net worths and Whilshire 5000

Variable	NW1	NW2	NW3	NW4	NW5	NW6
Corr with Whilshire	0.996	0.916	0.944	0.939	0.971	0.934

Table 4: Series Definitions

NW1:	MVEONWMVBSNNCB	Market Value of Equities Outstanding-Corporate
NW2:	OEHRENWBSHNO	Owners' Equity in Household Real Estate
NW3:	TNWMVBSNNCB	Total Net Worth (Market Value)-Corporate
NW4:	RCSNNWMVBSNNCB	Replacement-Cost Value of Structures-Corporate
NW5:	TNWHCBSNNCB	Total Net Worth (Historical Cost)-Corporate
NW6:	TNWBSNNB	Nonfarm Noncorporate Business (Financial)