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Abstract

The identifying restrictions of an earlier VAR model are validated to assess the macroeconomic impact of the risk-taking channel of monetary policy in the U.S. Structural shocks are obtained by exploiting the nonnormality of residuals. The data is found to object to the previously imposed recursive ordering, but a different recursive ordering is supported. Based on the resulting impulse responses, there is no strong and significant evidence of the risk-taking channel during the sample period. This finding is in contrast with both the predictions of the underlying theoretical model and previous empirical findings.

JEL Classification: C32, C46, E44, G01

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1 Introduction

The financial crisis of 2007-2009 has revived researchers' interest in monetary policy transmission through the banking sector by raising the question whether low levels of interest rates induce excessive risk-taking in the financial sector. Brunnermeier and Sannikov (2012) claim that since monetary policy affects financial institutions' balance sheets through asset prices, monetary policy has direct effects on financial stability. They further state

“ Policy rules that ignore financial stability fail to lean against the build up of imbalances and systemic risk in normal times and are not credible in crisis times. Several times financial turmoil has forced central banks to intervene in markets to stabilize financial sector, potentially compromising long-run price stability.” (Brunnermeier and Sannikov 2012, 34)

In the same vein, Borio and Zhu (2012) argue that the potential existence of a so-called risk-taking channel poses a problem to monetary policy. If it exists but is ignored, unsustainable economic expansions may show up first in the form of financial imbalances rather than in the form of rising inflation.

Even though literature related to different “banking channels” has evolved rather rapidly in recent years¹, surprisingly little attention has been paid to the institutional features underlying the risky behavior. Understanding the mechanism at work is a prerequisite for successful intervention. In addition, macro-level studies on this important topic are rather scarce. Financial intermediaries' risk-taking behavior as a transmission channel for monetary policy and its macro-economic impact in the US has been studied by Adrian and Shin (2010), Adrian, Moench and Shin (2010), and more recently Bruno and Shin (2013). The need for a better understanding of the risk-taking channel of monetary policy has also been recognized by Monacelli (2012), and recently by Bayomi, Dell'Ariccia, Habermeier, Mancini-Griffoli and Valencia (2014), who discuss the new shape of monetary policy after the crisis. As the future of central banking, monetary policy and financial stability is widely debated right now, this paper contributes to a discussion of direct practical relevance.

In order to fill in the gap in the literature, the present paper takes the empirical analysis of Adrian, Moench and Shin (2010) as a benchmark to assess empirically the macroeconomic impact of the link between monetary policy, banks' balance sheet management and measures of risk. The empirical

¹See Section 2 for a literature review.

analysis in Adrian *et al.* is based on a theoretical model due to Shin (2010), which explicitly focuses on the behavior of the banking sector and illustrates that the financial intermediary sector has an active role in the business cycle through the pricing of risk. Shin's (2010) theoretical model suggests the following mechanism: monetary policy induced balance sheet adjustment by financial intermediaries leads to a lower price of risk and higher real activity in the economy. Empirical assesment of this mechanism is the main interest of this paper.

The vector autoregression (VAR) and impulse response (IR) -analysis of Adrian *et al.* (2010) indicates that there is a connection between rapid growth of intermediary balance sheets, lower risk premiums and higher real activity. For methodological reasons however, as acknowledged by the authors, the results from nonstructural VARs cannot be taken as conclusive (Adrian *et al.* 2010, 197). As is commonly done, Choleski decomposition is used to identify the economic shocks and IRs of interest. Since there is not enough theory to determine a correct ordering for the variables, the ordering is essentially arbitrary. This is of concern because in a recursively identified model with zero restrictions on the impact effects, the ordering of the variables in the VAR matters for the results. Without further identifying restrictions one cannot be sure that the shocks and IRs tell us about the underlying economic processes we are essentially interested in – in this case, whether the balance sheet mechanism postulated by the theory is backed up by data. This gives reason for further research.

Lanne and Lütkepohl (2008, 2010) and Rigobon (2003) among others have pointed out that sometimes statistical properties of the data can yield further information for identification in an SVAR framework. Even when economic theory suffices to identify the shocks of interest, often there is no over-identifying information to test theories against data. Examples of such statistical properties are residual distribution and structural breaks. For example, Rigobon (2003), Lanne and Lütkepohl (2008), Lanne, Lütkepohl and Maciejowska (2010) and Lütkepohl and Netšunajev (2013) have exploited residual heteroskedasticity to extract further identifying information from the data. Rigobon (2003) and Lanne and Lütkepohl (2008) assume that changes in the volatility of shocks are determined exogeneously and partition the sample period accordingly, while Lanne *et al.* (2010) as well as Lütkepohl and Netšunajev (2013) model the changes in volatility endogenously as Markov switching (MS) regimes.

Since theories on the risk-taking channel are relatively scarce (Dell’Arriccia, Laeven and Marquez 2013, Diamond and Rajan 2012, Disyatat 2011, Shin 2010), there is not much additional theory to put structure in the empirical model. Therefore statistical identification strategies are clearly invoked. This paper applies the approach by Lanne and Lütkepohl (2010), where shock identification is based on nonnormality of the residuals. The residuals are assumed to follow a mixture of two normal distributions where, similarly to the MS approach, the regimes cannot be determined beforehand but are assigned endogenously. In addition to being relatively simple, the chosen method allows to exploit the fact that in applied work VAR residuals are often found to be nonnormal (Lanne and Lütkepohl 2010). For the data at hand, normality of residuals was strongly rejected by statistical tests, which supports the proposed identification strategy.² Hence the nonnormality of residuals can be exploited to test whether the just-identifying restrictions of the benchmark paper are consistent with the data. Testing the imposed restrictions against the data enables one to get rid of arbitrary restrictions and, more importantly, to test empirically the relationship of interest.

Even though the Lanne and Lütkepohl (2010) method only guarantees a statistical identification i.e. it delivers orthogonalized shocks but does not give an economic interpretation, the method allows us to perform a statistical test to find a recursive ordering, which is not rejected by the data. The statistical identification of shocks enables us to learn about the impact effects between the variables from the data instead of ruling out some of the effects *ex ante*. Although different from the benchmark paper, the ordering supported by the data is compatible with the suggested mechanism. However, based on the resulting impulse responses, there is no strong and significant evidence for the risk-taking channel during the sample period.

The contribution of the present paper is twofold. First, a recent econometric methodology is applied to VAR. The study by Adrian *et al.* (2010) is reconsidered and the issue of shock identification is addressed. The previously imposed indentifying restrictions can be tested against the data. This is important to properly assess the dynamic properties of the variables and to conclude whether the mechanism suggested by the theory is backed up by empirical evidence. Second, it complements existing studies with macro dynamics between monetary policy, financial intermediary sector and the least studied monetary policy transmission channel, the risk-taking channel.

²See Section 4 for details.

The rest of the paper is organized as follows. In Section 2 a brief overview of the literature on monetary policy transmission through the banking sector is given. Technical details of the empirical method are put forward in Section 3. Section 4 covers the empirical analysis and Section 5 concludes.

2 Related Literature

Literature on monetary policy transmission through the banking sector can be subdivided into two broad categories. The line of research following Bernanke and Getler (1995) emphasizes the channel through *demand* for credit and borrowers' balance sheet, while the bank lending channel studied by Bernanke and Blinder (1992) focuses on the impact of policy rate on credit *supply*. In both cases banking sector is put at the heart of monetary policy transmission. The transmission channel studied here has common features with the latter branch of research: interest lies in the passage of the policy rate through the asset side of the banks' balance sheets.

What makes these two channels distinct however is the mechanism that links the policy rate to banks' balance sheets. In Bernanke and Blinder (1992) it is binding reserve requirements of commercial banks. According to Adrian and Shin (2010), this approach is not applicable to the current crisis because reserve requirements have not been binding (e.g. Martin, McAndrews and Skeie 2012, 1) and because credit contraction did not originate from the commercial banking sector. Shin (2010) shows theoretically how financial intermediaries actively manage their balance sheets in response to changes in the market-determined risk premium, which in turn adjusts to changes in the monetary policy interest rate. This suggests that the mechanism linking the policy rate and the asset side of the balance sheets is the pricing of risk. This mechanism has been called the risk-taking channel of monetary policy (Borio and Zhu 2012, 242).

The link between monetary policy and risk-taking behavior of commercial banks has been theoretically studied by Dell'Arriccia, Laeven and Marquez (2013), Diamond and Rajan (2012), Disyatat (2011). Empirical research first started in the U.S. (Lown and Morgan 2006, Adrian and Shin 2009, Adrian, Moench and Shin 2010) but was soon extended to the countries of the Euro area (Jimenez, Onenga, Peydró and Saurina 2014, Altunbas, Gambacorta and Marquez-Ibanez 2010, Maddaloni and Peydró 2011). A common finding of the empirical studies at the micro level is that lax monetary policy in-

creases the riskiness of new loans by commercial banks. Using an extremely large, confidential micro-level data set for Spain Jimenez *et al.* (2014) find, that in an environment of low interest rates, the riskiness of bank portfolios is affected by both higher collateral values and search for yield. In the short run, the default probability of bank loans decreases, while it is found to increase in the long run when the search for yield effect prevails. Building on this Altunbas *et al.* (2010) construct various proxies for bank default risk and analyze a panel dataset that covers banks operating in 16 OECD countries. They find that interest rates below the Taylor rule increase the default probability of banks. Maddaloni and Peydró (2011) use the European Central Bank's Bank Lending Survey to explore the determinants of bank lending standards in the Euro Area. According to their panel regression a monetary expansion leads to lower credit standards for both corporate and personal loans. More recently De Santis and Surico (2013) have studied heterogeneity of bank lending across euro area countries. They use BankScope data in panel regressions, and focus on heterogeneity across four countries and bank typologies. The results indicate that the bank lending channel in the eurozone is highly heterogeneous. Finally, Buch, Eichenmeier and Prieto (2011) use a factor-augmented vector autoregressive (FAVAR) model for macro-level data for the U.S. and find that small domestic banks respond to expansionary monetary shock by increasing the amount of risky loans, but there is no evidence of increased risk-taking for the banking system as a whole. The authors suspect that aggregate data might mask differences at the banking group level.

These examples of research done to date show some of the empirical challenges in studying the topic. First, irrespectively of the empirical approach, all research on monetary policy has to come to terms with the endogeneity of policy rates. Second, the concept of risk is unobservable, hence hard to measure, and can be defined in a variety of ways. Third, sometimes data on important variables is confidential so that only people working at e.g. central banks have access to it, or it can be nonexistent like data on variations in the supply of bank loans not driven by changes in demand. Some samples are also quite small, such as data coming from surveys. The availability of data in turn sets restrictions on the empirical methodology.

According to Borio and Zhu (2012, 245), the risk-taking channel has always existed but its importance may have increased for two reasons. First, the financial system has evolved in a way that incentivizes the use of external finance and leverage. As a consequence, spending decisions are more driven

by wealth and risk than previously. Second, current accounting practices based on fair value measures (as opposed to historical cost accounting) are more sensitive to changes in interest rates and risk premia.

These observations are consistent with Adrian and Shin (2009) and Allen and Carletti (2010), who argue that nowadays capital markets play a crucial role in the supply of credit to the economy. The former provide empirical evidence that among all financial intermediaries it was credit supply by market-based intermediaries,³ not traditional commercial banks that saw the most rapid growth before the crisis - as well as the most dramatic contraction afterwards. Because the main source of funding for market-based intermediaries is short term borrowing through repurchase agreements or issuance of commercial paper, the funding is highly sensitive to changes in capital markets. Moreover, their balance sheets being marked-to-market, asset price changes translate immediately into changes in their net worth. On the other hand, most of the liabilities are long term. Since the business of these institutions is to borrow short term and lend long term, the spread between the short and long term interest rates is indicative of their expected profits. This is in contrast to the traditional view, where a bank is thought to intermediate between depositors and borrowers and the effectiveness of monetary policy is assessed by its impact on long rates only. If the supply of credit in the US economy has shifted from the traditional banking sector to market-based institutions, the distinction between the two has to be taken into account in an empirical study of monetary policy transmission and its macroeconomic impact.

A central element of the risk-taking channel is changing perceptions and attitudes towards risk and risk premia (Borio and Zhu 2012, 247). Accordingly, in the theoretical model due to Shin (2010), monetary policy induced balance sheet adjustment by financial intermediaries leads to a lower price of risk and higher real activity in the economy. Since default as well as lending and borrowing between financial intermediaries are ruled out in the model, fluctuations in the price of risk cannot arise from chains of default. When asset prices change e.g. due to monetary policy changes, in addition to the normal valuation effect there is an additional quantity adjustment of balance sheets. This sets in motion the amplifying effect of financial intermediaries

³Market-based intermediaries include broker-dealers, issuers of asset-backed securities, finance companies and funding corporations, the last three of which are called shadow banks. See Appendix for further details.

on the boom-bust cycle. The mechanism has been empirically assessed by Adrian *et al.* (2010), who find a connection between rapid growth of intermediary balance sheets, lower risk premiums and higher real activity. Bruno and Shin (2013) further suggest that banking sector leverage is a candidate channel for the transmission of monetary policy to exchange rate changes.

3 SVAR Model with Nonnormal Residuals to Test Identification Restrictions

Following Lütkepohl (2007, Ch 9), consider first a standard K -dimensional reduced form stable VAR with p lags:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t \quad (1)$$

where y_t is a $(K \times 1)$ vector of observable time series variables, the A_j 's ($j = 1, \dots, p$) are $(K \times K)$ coefficient matrices and the error term u_t is K -dimensional white noise with $u_t \sim (0, \Sigma_u)$. In the presentation of this section deterministic terms are excluded since they don't affect structural modelling and impulse response functions. Since a VAR is a system of simultaneous equations, all variables are endogenous and the error terms in different equations are likely to be correlated. Usually the purpose is to conduct impulse response analysis, which means representing a stationary VAR -process in the following Wold MA form:

$$y_t = u_t + \Phi_1 u_{t-1} + \Phi_2 u_{t-2} + \dots \quad (2)$$

where

$$\Phi_s = \sum_{j=1}^s \Phi_{s-j} A_j, \quad s = 1, 2, \dots \quad \text{with } \Phi_0 = I_k \quad (3)$$

Interest then lies in the elements of the Φ_j , the MA coefficient matrices, which contain the impulse responses of the system: responses of a variable to an impulse in another. If the error terms are contemporaneously correlated – Σ_u is not a diagonal matrix – it means that shocks come in a bunch. In this case setting all other error terms to zero to trace out single impulses can be misleading. Impulses may not correctly reflect the relations between the variables in the VAR. On the other hand if the error terms of different variables are uncorrelated then it is reasonable to assume that a shock occurs

in one variable at a time. Therefore orthogonalizing the error terms implies identifying single shocks and impulses.

In a so-called B-model (see Lütkepohl 2007, chapter 9), to orthogonalize the error term of the reduced form model means deriving shocks $\varepsilon_t \sim (0, I_K)$ such that $u_t = B\varepsilon_t$. In other words we want to find a matrix B such that

$$\varepsilon_t = B^{-1}u_t \tag{4}$$

and

$$E(u_t u_t') = \Sigma_u = B \Sigma_\varepsilon B' = B B'. \tag{5}$$

As the covariance matrix is symmetric, these equations only define $\frac{K(K+1)}{2}$ equations, while B contains K^2 elements. Hence $K^2 - \frac{K(K+1)}{2} = \frac{K(K-1)}{2}$ additional restrictions on B are needed to identify all of its K^2 elements. A common choice of B is a lower triangular matrix obtained from a Choleski decomposition of Σ_u because it yields exactly the right number of restrictions. This is done by decomposing the covariance matrix Σ_u as $\Sigma_u = P P'$ where P is a lower triangular matrix. Then by defining $P = B$ and $\Theta_i = \Phi_i P (i = 0, 1, 2, \dots)$ one obtains shocks $\varepsilon_t = P^{-1}u_t$ and the corresponding VMA representation

$$y_t = \Theta_0 \varepsilon_0 + \Theta_1 \varepsilon_1 + \Theta_2 \varepsilon_2 + \dots \tag{6}$$

Since the components of ε_t are uncorrelated with unit variance, it is possible to interpret the jk -th element of the matrix Θ_i as capturing the effect on variable j of a unit shock in variable k that occurred i periods ago. This identification strategy based on Choleski decomposition is easily and often used. However the B matrix obtained with Choleski decomposition depends on the order of the variables in the vector y_t . This implies that there can be several triangular matrices that do the orthogonalization equally well. Moreover as the B matrix contains instantaneous effects of the shocks on the variables ($\Theta_0 = B$), different choices of B can yield different results in terms of impulse responses.

The fact that the choice of B has an impact on results means that non-statistical information is needed to impose restrictions. This requires economic theory that describes the relationships of interest. In the case of Choleski decomposition this means determining, which variables do not have an instantaneous impact on some others and then ordering the variables in

the vector y_t accordingly. Other popular identification methods include the use of inequality or sign restrictions (Canova and De Nicolò, 2002; Uhlig, 2005), where a whole variety of shocks of a predetermined sign are admitted, or the exclusion of instantaneous or long-run effects of variables (Blanchard and Quah, 1989; Lütkepohl 2005), where zero effects of some variables are assumed. The resulting VARs with restrictions on the transformation matrix obtained from economic theory are called structural VARs. In the B -model the error terms u_t of the estimable reduced form VAR are seen as linear functions of some meaningful economic disturbances, ε_t , called structural shocks. In other words the information content of reduced form dynamics is transformed into behavioral ones.

A common feature of all these identification strategies is that they identify the structural shocks but do not allow the identification to be statistically tested. Without further identifying restrictions one cannot be sure that the shocks and IRs tell us about the underlying economic processes we are essentially interested in. Furthermore sometimes there is not enough economic theory to obtain a full set of restrictions in which case arbitrary restrictions are imposed.

Instead, if there is reason to believe, or there is evidence from a VAR analysis that residuals might not be normally distributed, then this information may be useful for identification. The residual distribution might have heavy tails and produce “outliers”, which can be thought to be generated by a different distribution - from a different stochastically generated regime. By modelling a more general distribution explicitly, further identifying information can be extracted (Lanne and Lütkepohl, 2010.)

Consider again the reduced form VAR reported above. As in the model proposed by Lanne and Lütkepohl (2010), now assume the k -dimensional error term u_t to be a mixture of two serially independent normal random vectors

$$u_t = \begin{cases} e_{1t} \sim N(0, \Sigma_1) & \text{with probability } \gamma \\ e_{2t} \sim N(0, \Sigma_2) & \text{with probability } 1 - \gamma \end{cases} \quad (7)$$

where $N(0, \Sigma)$ denotes a multivariate normal distribution with zero mean and covariance matrix Σ . In the model Σ_1 and Σ_2 are $(k \times k)$ covariance matrices that are assumed to be distinct, γ is the mixture probability, $0 < \gamma < 1$, a parameter of the model. γ is only identified if $\Sigma_1 \neq \Sigma_2$ hence this is assumed to hold. If some parts of Σ_1 and Σ_2 are identical then some components

of u_t may be normally distributed. In any case there only needs to be one nonnormal component in u_t . The distribution of the reduced form error term now becomes

$$u_t \sim (0, \gamma\Sigma_1 + (1 - \gamma)\Sigma_2) \quad (8)$$

The distributional assumption for u_t allows to define a locally unique matrix B in the following way. As shown in the Appendix A by Lanne and Lütkepohl (2010), a diagonal matrix $\Psi = \text{diag}(\psi_1, \dots, \psi_k)$, $\psi_i > 0$ ($i = 1, \dots, k$) and a $(k \times k)$ matrix W exist such that $\Sigma_1 = WW'$ and $\Sigma_2 = W\Psi W'$ and W is locally unique except for a change in sign of a column, as long as all ψ_i 's are distinct. Now we can rewrite the covariance matrix of the reduced form error vector u_t as

$$\Sigma_u = \gamma WW' + (1 - \gamma)W\Psi W' = W(\gamma I_k + (1 - \gamma)\Psi)W' \quad (9)$$

Then following equation (5) a locally unique B is given by

$$B = W(\gamma I_n + (1 - \gamma)\Psi)^{1/2} \quad (10)$$

This choice of B means that the orthogonality of shocks is independent of regimes. This can be seen by applying (5) to the covariance matrices as

$$\begin{aligned} B^{-1}\Sigma_u B^{-1} &= I_k \\ B^{-1}\Sigma_1 B^{-1} &= (\gamma I_k + (1 - \gamma)\Psi)^{-1} \\ B^{-1}\Sigma_2 B^{-1} &= (\gamma I_k + (1 - \gamma)\Psi)^{-1}\Psi \end{aligned} \quad (11)$$

As the equations in (11) are all diagonal matrices, the choice of B as in (10) yields shocks that are orthogonal in both regimes.

The model is estimated with maximum likelihood (ML) method. Rewriting (1) in lag operator form

$$A(L)y_t = u_t \quad (12)$$

where $A(L) = I_n - A_1(L) - \dots - A_p L^p$ is a matrix polynomial in the lag operator L then the conditional distribution of y_t given $Y_{t-1} = (y_{t-1}, y_{t-2}, \dots, y_{t-p+1})$ can be written as

$$\begin{aligned} f(y_t|Y_{t-1}) &= \gamma \det(W)^{-1} \exp\left\{-\frac{1}{2}(A(L)y_t)'(WW')^{-1}(A(L)y_t)\right\} \\ &+ (1 - \gamma) \det(\Psi)^{-\frac{1}{2}} \det(W)^{-1} \exp\left\{-\frac{1}{2}(A(L)y_t)'(W\Psi W')^{-1}(A(L)y_t)\right\} \end{aligned} \quad (13)$$

Collecting all the parameters into the vector θ , the log-likelihood is simply

$$l_T(\theta) = \sum_{t=1}^T \log f(y_t|Y_{t-1}) \quad (14)$$

The log-likelihood function (14) can be maximized with standard nonlinear optimization algorithms.

4 Empirical Analysis of Macro Dynamics: Risk Appetite Vector Autoregression

4.1 The Data and the VAR Model

There are two important variables in the theoretical model due to Shin (2010) that are difficult to quantify: the price of risk in the economy and financial intermediaries' risk taking capacity. Adrian *et al.* (2010) manage to overcome the problem by constructing two proxy variables. This enables empirical analysis of the mechanism of interest.

The first one is called *Macro Risk Premium* and it measures the hurdle rate of return⁴ for new projects financed in the economy. It reflects the ease of credit conditions and is measured from yield spreads of fixed income securities. In this framework spreads are found to matter more than the level of interest rate because the business of financial intermediaries consists of borrowing short term and lending long term. In other words spreads are informative about the marginal profitability of lending, or supplying a new loan. Since there is credit risk involved with loans granted by banks, credit spreads are also likely to affect banks' decision to supply new loans. This fact is exploited in the construction of the first variable.

The second proxy variable is labelled *Financial Intermediary Risk Appetite Factor* as it measures the looseness of financial intermediary capital constraints. In the theoretical model this corresponds to the shadow value of capital in the leveraged intermediary sector, which gives the additional bank profit from one extra dollar of capital, or marginal profit from expanding the balance sheet. This variable is important as it enables to circumvent the problem of measuring marginal loan supply. In fact one of the challenges in the empirical assessment of the risk-taking channel is the nonexistence of

⁴Hurdle rate of return = minimum acceptable rate of return to accept a new project.

data on “extra” loans supplied, i.e. the increase in loan supply not driven by demand needed to study marginal effects.

Since there are a variety of institutions that provide credit to the real economy, the authors first choose the institutions that are most important in determining risk premiums. In the US those turn out to be broker-dealers and shadow banks, whose liabilities are short term and marked to market. When balance sheets are marked to market, funding conditions are more promptly reflected in the balance sheets. This is mostly not the case with traditional banks. These variables enable to study how monetary policy actions, that affect the risk taking capacity of banks, will lead to shifts in the supply of credit to the economy. Hence balance sheet measures of these institutions have been used in the analysis.

The same set of variables as well as the exactly same dataset analyzed by Adrian, Moench and Shin (2010) is used here. The data consists of quarterly US data for the period of 1985:1 - 2010:4 and it was provided by the authors. The original source of data for GDP growth and PCE (Personal Consumption Expenditures) inflation is Bureau of Economic Analysis, S&P’s corporate bond ratings are from Standard & Poor’s, financial institutions’ balance sheet measures are from Federal Reserve’s Flow of Funds and the Federal Funds target rate as well as Treasury constant maturity yields originate from H.15 Release of the Federal Reserve Board.

The proxy variables are constructed as fitted values of the following regressions

$$GDPgrowth_t = \sum_{i=1}^7 \beta_i TreasurySpread_{it} + \sum_{i=8}^{13} \beta_i CorporateBondSpread_{it} + \varepsilon_t \quad (15)$$

where $TreasurySpread = constant\ maturity\ yield - Federal\ Fund\ target\ rate$ and $CorporateBondSpread = Yield\ of\ a\ 10\ yr.\ corporate\ bond\ for\ S\&P's\ AAA,\ AA,\ A,\ BBB,\ BB,\ B\ ratings - 10\ yr.\ constant\ maturity\ yield$. GDP growth is measured as annual growth rate. Macro risk premium obtained in this way is a weighted average of spreads, and the weights are given by the regression coefficients. This is viewed as a portfolio tracking GDP growth.

$$-\Delta MacroRiskPremium_t = \sum_{i=1}^6 \beta_i W_i * FinancialIntermediaryBalanceSheetQuantities_{it-4} - \beta_7 \Delta MacroRiskPremium_{t-4} + \beta_8 GDPgrowth_{t-4} + \varepsilon_t \quad (16)$$

where *FinancialIntermediaryBalanceSheetQuantities* = *broker-dealer leverage and equity growth, shadow bank asset and equity growth, commercial bank asset and equity growth* and *W*=*weights given by the relative size of total assets for each intermediary*. The dependent variable in the regression (16) is the negative change in macro risk premium over one year, which captures return to the premia. All dependent variables are lagged one year. Financial intermediary risk appetite factor is then obtained as fitted values of balance sheet variables only, i.e. the lagged macro premium and GDP growth are excluded.

The authors then consider the following five variable VAR:

- Δgdp_t : quarterly GDP growth
- π_t : inflation
- FFR_t : Federal Funds target rate
- mrp_t : macro risk premium
- FI_t : financial intermediary risk appetite factor

4.2 Previous Identification Restrictions

Identification in the benchmark paper is obtained with the following exclusion restrictions on the transformation matrix (B).

$$B = \begin{matrix} & * & 0 & 0 & 0 & 0 \\ & * & * & 0 & 0 & 0 \\ & * & * & * & 0 & 0 \\ & * & * & * & * & 0 \\ & * & * & * & * & * \end{matrix} \tag{17}$$

The asterisks denote unrestricted elements and the zeros are imposed so that B is lower triangular. The variable ordering

$$y_t = (\Delta gdp_t, \pi_t, FFR_t, mrp_t, FI_t)' \tag{18}$$

implies that a shock to GDP growth is allowed to have a contemporaneous effect on all other variables, whereas there is no instantaneous feedback effect from an impulse on financial intermediary risk appetite to any of the

variables. Is there a plausible economic interpretation for the exclusion restrictions required by the identification scheme? The theoretical model due to Shin (2010) illustrates how a positive shock to asset values, say a decrease in short rates, that increases the capital buffer (equity) of banks, leads to a lower risk premium and induces banks to take on additional debt to purchase more risky securities, or to supply new loans. In the model, the amount of risky assets on the balance sheets increases more than in the case of a mere valuation effect. An empirical hypothesis of interest could then be formulated as the impact of monetary policy interest rate to the risk premium and financial intermediaries' risk taking capacity. Accordingly in (17) a shock to federal funds target rate is allowed to affect contemporaneously both the macro risk premium and financial intermediary risk appetite factor, and a shock to macro risk premium is allowed to have a contemporaneous effect on risk appetite.

As Lütkepohl and Netšunajev (2013) point out, even in those cases where restrictions are derived from generally accepted economic models, the empirical and theoretical models do not necessarily coincide. As potential reasons they name measurement errors, trend and/or seasonal adjustment, and observation frequency for the data that is different from that of the theoretical model. Moreover the variables in the empirical and theoretical models might not perfectly coincide. In the present case the main challenge arises from the frequency of the data. Is it likely that there is no feedback effect from the right to the left of (18) within the same quarter? Another source of gap between the economic and empirical models stems from the fundamental differences between the two modelling approaches. A theoretical model is bound to abstract from some effects in order to describe relations within a set of variables only. To avoid problems with omitted variables, an empirical model on the other hand often requires the inclusion of variables outside of the theoretical model that are known to be important in practice (Lütkepohl and Netšunajev 2013). From this point of view, the inclusion of the first two variables in (18) is easy to justify.

Even without an appealing, justifiable theoretical reasoning a recursive identification scheme is convenient whenever there is only one shock of interest, which can be ordered at the bottom of the variable list (18). In all other cases identification via recursive ordering as in (17) necessarily implies that one is excluding certain impact effects ex-ante rather than learning about it from the data. As explained in Section 3, if it is reasonable to assume that the vector of reduced form errors u_t follows a mixed normal distribution

with covariance matrix as in (9), and if the elements of the Ψ matrix are all distinct, then these concerns become irrelevant since the validity of the restrictions in (17) can be statistically tested (Lanne and Lütkepohl 2010).

QQ-plots of the residuals of the linear VAR(1) model is shown in Figure 2. The plots feature a mostly linear pattern in the center of the data, while the tails show departures from the fitted line. Compared to a normal distribution, a slightly more S-shaped curve emerges. This kind of distribution with heavy tails and outliers can be captured by a mixture of normal distributions (Lanne and Lütkepohl 2010, 159.). The outliers can be thought to be generated by a different distribution than the rest of the observations. Then identification of the shocks is obtained from heteroskedasticity across regimes. The results of normality tests are reported in Table 1 below.

Jarque-Bera test				
variable	test statistic	p -value	skewness	kurtosis
u_1	5.97	0.0506	-0.34	4.02
u_2	14.75	0.0006	-0.19	4.89
u_3	27.23	0.0000	-0.86	4.98
u_4	510.08	0.0000	1.9	13.7
u_5	45.24	0.0000	0.49	6.24
Doornik-Hansen test		skewness	kurtosis (p -value)	
123.28 (0.000)		18.90 (0.002)	104.38 (0.000)	

Table 1: Tests for normality of residuals

The Jarque-Bera test rejects the null hypothesis of normality for each of the estimated residuals. The high overall kurtosis of the Doornik-Hansen (1994) test for multivariate normality yields further support for the mixture distribution. Hence formal tests support the proposed identification strategy, and the exclusion restrictions in (17) can be statistically tested.

4.3 Statistical Analysis

To answer the main question of interest, i.e. whether the initial effects matrix B as in (19) is supported by the data, we proceed as follows. Following the benchmark paper, lag length of one is selected according to the Bayesian Information Criterion (BIC). We first estimate an *unrestricted* Risk Appetite VAR(1) model with variable ordering (18) assuming that the error term u_t

follows a mixture of normal distributions as in (7). The estimation results are reported in Table 2.⁵ In this case identification is obtained with a distributional assumption, and the restrictions in (17) become over-identifying if the ψ_i 's are distinct. Therefore we first need to ensure that a statistical identification of the shocks has been obtained. Although the standard errors in Table 2 indicate a fairly good estimation precision, pairwise equality of the ψ_i 's has been tested with Wald tests. Since the estimators have the usual normal limiting distributions, the Wald tests have asymptotic χ^2 -distributions. The null hypothesis and the resulting p -values are listed in Table 4. The first column shows that the equality of all ψ_i 's can be rejected at the 5 % significance level and hence statistical identification of shocks has been obtained.

Now a statistical test of the exclusion restrictions used by Adrian *et al.* (2010) can be performed. To this end we next estimate a *restricted* model by imposing the recursive ordering (17).⁶ The statistical test then takes the form of a simple LR test, which has an asymptotic $\chi^2(N)$ distribution, where N is the number of restrictions. The hypotheses are H_0 : restricted B and H_1 : unrestricted B . The estimation results together with the LR test value (computed assuming $N=10$) and the associated p -value are also reported in the second column of Table 2. As the LR-test rejects the H_0 at all significance levels, we conclude that the restrictions are not compatible with the data. Note that the Wald tests for the restricted model in the second column of Table 4 reveal that the pairwise equality of ψ_1 and ψ_2 or ψ_3 and ψ_4 cannot be rejected, which implies that the LR statistic has less than 10 degrees of freedom. Given the high value for the LR, it still leads to rejection.

As pointed out in Section 4.2, a challenge that arises from the variable ordering (18) is that no feedback effect from the right to the left within the same quarter is allowed. Since our method essentially allows us to test, whether the statistically identified shocks satisfy any recursive ordering, we

⁵The computations were done with GAUSS programs. To compute the ML estimates, the BHHH procedure of the Gauss CMLMT library was used. In a first step, VAR coefficients were estimated from a linear model. In a second step, these estimates were used as starting values to estimate the parameters of the *unrestricted* model with a mixed normal distribution. Finally, the parameter estimates of the unrestricted model were used as starting values of the *restricted* model. To ensure nonsingularity of the covariance matrices, their determinants are bounded away from zero. Also the diagonal elements of the Ψ matrix are bounded away from zero.

⁶In practice this is done with restrictions on the W matrix in $B = W(\gamma I_n + (1-\gamma)\Psi)^{1/2}$.

can order the variables as

$$y_t = (\pi_t, FFR_t, mrp_t, FI_t, \Delta gdp_t)' \quad (19)$$

In (19) the ordering of FFR_t (Federal Funds target rate), mrp_t (macro risk premium) and FI_t (financial intermediary risk appetite) still conforms with the theory, while the inclusion of Δgdp_t (quarterly GDP growth) and π_t (inflation) is again justified to avoid omitted variable bias. The main difference with (18) is that now changes in the price of risk and financial intermediaries' risk appetite are allowed to affect economic fluctuations within the same quarter already. The generally accepted view that changes in monetary policy are reflected in GDP growth earlier than in inflation holds here as well. The estimation results for this model are shown on the right hand side of Table 2. Again, p -values of pairwise equality tests of the ψ_i 's are shown in Table 4. The LR test indicates that the H_0 : restricted B cannot be rejected even at the 10 % significance level. Once again taking into account that the equality of ψ_3 and ψ_4 cannot be rejected, there is still no strong evidence against the imposed restrictions. Therefore we conclude that the data at hand does not strongly object to a recursive ordering implied by (19). Inability to reject (19) simply tells us that during the sample period monetary policy has been promptly transmitted from the financial sector to the real economy. As the columns of a triangular matrix cannot be permuted, the ordering of the shocks corresponds to the lower-triangular B -matrix so that the statistically identified shocks can be economically labelled in line with the ordering in equation (19).

4.4 Robustness Check

To analyze the sensitivity of the results with respect to the proxy variables being used, the models were additionally estimated with an alternative risk premium measure, the *Excess Bond Premium* (ebp) of Gilchrist and Zakrajsek (2012). The ebp variable has been constructed to capture cyclical changes in the relationship between measured default risk and credit changes, and an increase in the excess bond premium reflects a reduction in the effective risk-bearing capacity of the financial sector (Gilchrist and Zakrajsek 2012, 2), and is therefore suitable for our purposes. The estimation procedure is as in Section 4.3. The model with the ebp variable was first estimated with variable ordering as in Adrian *et al.* (2010), or (18), and then according

to (19). The estimation results are reported in Table 3. Given the high value of the LR in the first case, the test rejects the imposed restrictions at all significance levels even if some of the ψ_i 's were identical. Also in the second case some of the ψ_i 's may not be distinct, which would decrease the p -value of LR-test. One would still not be able to reject the restrictions at usual significance levels. As these results conform perfectly with those of the baseline case, we conclude that the results are robust to the alternative proxy variable.

4.5 Model Diagnostic

In models based on mixtures of distributions, statistical tests based on conventional residuals cannot be used to check the model specification. In these cases, Kalliovirta (2012) proposes a test based on quantile residuals, which are obtained by two transformations of the estimated residuals. First, the estimated cumulative distribution function (CDF) implied by the model is used to transform the observations into approximately independent, uniformly distributed random variables. Second, the inverse of the CDF of the standard normal distribution is used to get variables that are approximately independent with standard normal distribution.

These results assume that the model is correctly specified and parameters consistently estimated. Therefore quantile residuals, that exhibit departures from these properties, provide evidence of model misspecification. This approach has been generalized to multivariate models in Kalliovirta and Saikkonen (2010), where tests based on univariate *joint* quantile residuals are developed. Model misspecification can then be detected with normality, autocorrelation and conditional heteroskedasticity tests of the joint quantile residuals.

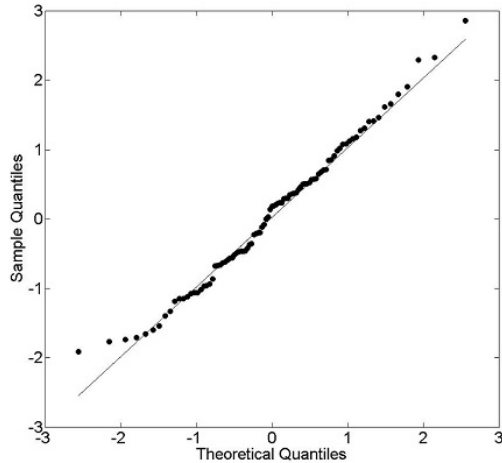


Figure 1: Joint quantile residuals, QQ plot

Figure 1 shows the QQ-plot of the joint quantile residuals obtained from the mixture VAR. Apart from a few outliers at both tails, the normality assumption seems to hold reasonably well. A formal test of normality yields a p-value of 0.38, while autocorrelation and heteroskedasticity tests for different lags range from 0.23 to 0.90 and from 0.18 to 0.99, respectively. As a conclusion, the diagnostic tests provide clear support for our model specification, where a mixed-normal distribution is assumed.

4.6 Impulse Response Analysis

Given that economically meaningful shocks have been identified, impulse responses (IRs) based on the VAR(1) model with nonnormal residuals can be computed. Because of the difficulties with the optimization of the likelihood function, confidence intervals for the IRs cannot be easily computed with classical residual based bootstrap methods. As documented in Herwartz and Lütkepohl (2014), one has to ensure that only bootstrap replications in the area of the parameter space of the original estimation step are considered, and the same sign and ordering of the shocks is preserved. To this end, the diagonal elements of Ψ and the transition probability γ are not subjected to resampling. Bootstrap IRs are obtained by nonlinear optimization of the log-likelihood with linear estimates as starting values. The bootstrap confidence intervals are the 16th and 84th quantiles of 1000 bootstrap replications.

Finally we are ready to analyze the macro effects of changing risk perceptions and risk tolerance by financial intermediaries. The IRs most important from the point of view of the mechanism of interest are displayed in Figure 3 together with 68 % bootstrap confidence intervals.

The first picture in Figure 3 shows that a unit shock to financial intermediaries' risk appetite has a positive impact on GDP growth and the effect lasts for several quarters. Based on the theory, a way to interpret this is that when financial intermediaries more easily obtain funding, they increase the supply of credit, which contributes to higher GDP growth.

The second picture in the first row plots the response of risk appetite to a positive monetary policy shock. The IR would suggest that a sudden monetary policy tightening decreases intermediaries' risk appetite for several periods, but given the wideness of the confidence bands, one has to conclude that the sign and magnitude of the reaction is ambiguous.

The first picture in the bottom row displays the response of macro risk premium to a positive risk appetite shock. Again, given the broadness of the confidence bands, no clear-cut conclusions about the sign of the effect can be made.

Finally, plotted in the second picture of the bottom row is the negative effect on GDP growth of a higher macro risk premium. As the macro risk premium measures the hurdle rate of return required to finance new projects in the economy, this can be interpreted as tighter credit conditions having an adverse effect on GDP growth.

To sum up, changes in either financial intermediaries' risk appetite or the macro risk premium are found to affect economic activity measured by quarterly GDP growth. However, there is no strong evidence in favor of a positive and significant reaction of financial intermediaries' risk appetite to lax monetary policy during the sample period. Also macro risk premiums do not appear to be significantly driven by financial intermediaries' balance sheet adjustment as measured by the risk appetite factor. The last two observations are in contradiction with the predictions of the underlying theory on the risk-taking channel and the previous empirical study. Although some of the bootstrap confidence bands shown here are relatively large, they tend to give a more precise picture of the estimation uncertainty of the coefficients in a small sample.

As a conclusion, the balance sheet adjustment by financial intermediaries and fluctuations in the price of risk have both separately contributed to economic fluctuations during the sample period, but the link between the

two and monetary policy is found to be weak.

5 Conclusions

In this paper the macroeconomic effects of the risk-taking channel of monetary policy are empirically analyzed by reconsidering the VAR study of Adrian *et al.* (2010). As proposed by Lanne and Lütkepohl (2010), statistical properties of the data are exploited to identify shocks needed to study dynamic relationships between the variables without imposing any restrictions. Even though the Lanne and Lütkepohl (2010) method only guarantees a statistical identification i.e. it delivers orthogonalized shocks without attaching economic labels to them, the method allows us to perform a statistical test and find a recursive ordering that is not rejected by the data.

Being able to identify a previously unidentified nonstructural VAR model allows to check the interpretation in Adrian *et al.* that, in the US, monetary policy can affect the balance-sheet management of financial intermediaries, the determination of risk premiums, and eventually the level of real activity.

Although the resulting impulse responses are similar to those reported by Adrian *et al.*, the wideness of the confidence bounds does not allow us to conclude that there is strong and significant evidence in support of the risk-taking channel. The confidence bounds are obtained from bootstrap estimates of a more complex empirical model based on nonnormality of residuals. Although the downside of the complexity is that it makes estimation computationally intensive, it is expected to yield better results for two reasons. First, because the nonnormality of residuals is a feature encountered in the data, estimation is based on a more realistic assumption. Second, the bootstrap method should improve the precision of the confidence intervals in a small sample like the one analyzed here.

As a conclusion, according to the impulse response analysis based on the statistically identified shocks, there is no strong evidence in favor of a positive and significant reaction of financial intermediaries' risk appetite to lax monetary policy during the sample period. Also risk premiums in the economy do not appear to be significantly driven by financial intermediaries' balance sheet adjustment as measured by the risk appetite factor. These observations are in contradiction with the predictions of the underlying theory on the risk-taking channel and the benchmark empirical study.

References

- [1] Adrian T., & Shin H. (2010). *Financial Intermediaries and Monetary Economics*, in: Friedman, B., Woodford, M. (eds.), *Handbook of Monetary Economics*. New York, N.Y.: Elsevier, 601-650.
- [2] Adrian T., & Shin H. (2009). Money, Liquidity and Monetary policy. *American Economic Review*, **99**(2): 600-605.
- [3] Adrian T., Moench E., & Shin H. S. (2010). Macro Risk Premium and Intermediary Balance Sheet Quantities. *IMF Economic Review* **58**(1).
- [4] Allen F., & Carletti E. (2010) An Overview of the Crisis: Causes, Consequences and Solutions. *International Review of Finance* **10**(1): 1-26.
- [5] Altunbas, Gambacorta, & Marques-Ibanes (2010). Bank Risk and Monetary Policy. *Journal of Financial Stability* **6**(3): 121-129.
- [6] Bayoumi T., Dell’Ariccia G., Habermeier K., Mancini-Griffoli T., & Valencia F, and an IMF Staff Team (2014). Monetary Policy in the New Normal. IMF SDN/14/3.
- [7] Bekaert G., Hoerova M., & Lo Duca M. (2012) Risk, Uncertainty and Monetary Policy. *European Central Bank Working Paper* 1565.
- [8] Bernanke B., & Blinder A. (1992). The Federal Funds Rate and the Channel of Monetary Transmission. *American Economic Review* **79**: 14-31.
- [9] Bernanke B., & Getler M. (1995). Inside the Black Box: the Credit Channel of Monetary Policy Transmission. *Journal of Economic Perspectives* **9**: 27-48.
- [10] Blanchard O., & Quah D. (1989). The Dynamic Effects of Aggregate Demand and Supply Disturbances. *American Economic Review* **79**: 655-673.
- [11] Borio C., Zhu H. (2012). Capital Regulation, Risk-Taking and Monetary Policy: A Missing Link in the Transmission Mechanism? *Journal of Financial Stability* **8**: 236-251.

- [12] Brunnermeier M.K., & Sannikov Y. (2012). Redistributive Monetary Policy. Policy Forum of the Federal Reserve Bank of Kansas City in Jackson Hole 2012.
- [13] Bruno V., & Shin H. (2013). Capital Flows and the Risk Taking Channel of Monetary Policy. *NBER Working Paper 18942*, April.
- [14] Buch C., Eickmeier S., & Prieto E. (2011) In Search for Yield? Survey-Based Evidence of Bank Risk Taking. *Deutsche Bundesbank Discussion Paper* 10/2011
- [15] Canova F., & De Nicoló G. (2002). Monetary Disturbances Matter for Business Fluctuations in the G-7. *Journal of Monetary Economics* **49**: 1131-1159.
- [16] Dell’Arriccia G., Laeven L., & Marquez R. (2014) Real Interest Rates, Leverage, and Bank Risk-Taking. *Journal of Economic Theory* **149**: 65-99
- [17] De Santis R., & Surico P. (2013). Bank Lending and Monetary Transmission in the Euro Area. *Economic Policy* **28**(75): 423-457.
- [18] Diamond, D., & Rajan R. (2012). Illiquid Banks, Financial Stability and Interest Rate Policy. *Journal of Political Economy*, **129**: 552-591.
- [19] Disyatat P. (2011). The Bank Lending Channel Revisited. *Journal of money, credit and banking* **43**(4).
- [20] Gilchrist S., & Zakrajšek E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review* **102**(4): 1692-1720.
- [21] Goncalves, S., & Kilian, L. (2004). Bootstrapping Autoregressions with Conditional Heteroskedasticity of Unknown Form. *Journal of Econometrics* **123**: 89-120.
- [22] Herwartz H., & Lütkepohl H. (2014). Structural Vector Autoregressions with Markov Switching: Combining Conventional with Statistical Identification of Shocks. *Journal of Econometrics* **183**(1): 104-116.
- [23] Jimenez G., Ongena S., Peydro J., & Saurina J. (2014). Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank

- Loans Say About the Effects of Monetary Policy on Credit Risk-Taking? *Econometrica* **82**(2): 463-505.
- [24] Kalliovirta, L. (2012). Misspecification Tests Based on Quantile Residuals. *Econometrics Journal* **15**(2): 358-93.
- [25] Kalliovirta, L., & Saikkonen P. (2010). Reliable Residuals for Multivariate Nonlinear Time Series Models. Available at <http://blogs.helsinki.fi/lkvaisan/files/2010/08/ReliableResiduals.pdf>.
- [26] Lanne M., & Lütkepohl H. (2008). Identifying Monetary Policy Shocks via Changes in Volatility. *Journal of Money, Credit and Banking* **40**: 1131-1149.
- [27] Lanne M., & Lütkepohl H. (2010). Structural Vector Autoregressions with Non-Normal Residuals. *Journal of Business & Economic Statistics* **28**: 159-168
- [28] Lanne M., & Lütkepohl H. and Maciejowska K. (2010). Structural Vector Autoregressions with Markov Switching. *Journal of Economic Dynamics and Control* **34**: 121-131.
- [29] Lütkepohl H. (2005). *New Introduction to Multiple Time Series Analysis*, Springer-Verlag, Berlin.
- [30] Martin A., McAndrews J., & Skeie D. (2013). Bank Lending in Times of Large Bank Reserves. *Federal Reserve Bank of New York Reports* **497**.
- [31] Maddaloni A., & Peydró J.L. (2011). Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the U.S. Lending Standards. *Review of Financial Studies* **24**: 2121-2165.
- [32] Monacelli T. (2012). Discussion during Economic Policy Panel, Nicosia, 19–20 October, 2012. <http://onlinelibrary.wiley.com/doi/10.1111/1468-0327.12015/full>
- [33] Rigobon R. (2003). Identification Through Heteroskedasticity. *Review of Economics and Statistics* **85**: 777-792.
- [34] Shin H.S. (2010). *Risk and Liquidity*. Clarendon Lectures in Finance. Oxford University Press, London.

- [35] Uhlig H. (2005). What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure. *Journal of Monetary Economics* **52**: 381-419.

Appendix A. Description of market-based financial intermediaries

The following description of market-based financial intermediaries is for the most part a direct quotation from the Board of Governors of the Federal Reserve System.

5.1 Issuers of asset-backed securities (ABS)

ABS issuers are special purpose vehicles (SPVs) that hold pools of assets (usually loans) in trust and use them as collateral for issuance of ABS. Most of these SPVs are formed by depository institutions, real estate investment trusts, and finance companies to move assets off their balance sheets into bankruptcy-remote entities. Assets in the pools include home, multifamily, and commercial mortgages; consumer credit (such as automobile and student loans and credit card receivables), trade credit, Treasury securities, agency- and GSE-backed securities, nonfinancial business loans securitized by depository institutions and finance companies, and syndicated loans to nonfinancial corporate businesses. Liabilities of this sector are the securities issued by the SPVs and are typically medium- to long-term corporate bonds and commercial paper. These securities are largely pass-through securities, in which purchasers receive any interest, amortization and principal payments on the underlying collateral.

5.2 Finance companies

This sector includes both finance companies and mortgage companies. Finance companies are defined as companies in which 50 percent or more of assets are held in the following types of loan or lease assets: outstanding balances on real estate, business loans and leases for commercial and industrial purposes, consumer credit and leases for household, family, and other personal expenditures. Finance companies do not include U.S.-chartered depository institutions, cooperative banks, credit unions, investment banks, or industrial loan corporations.

5.3 Security brokers and dealers

These are firms that buy and sell securities for a fee, hold an inventory of securities for resale, or do both. Brokers and dealers are an important link in the transmission of funds from savers to investors because they are a means of distributing both new security issues and those being resold on the secondary market. Dealers in U.S. government securities that stand ready to buy from or sell to the Federal Reserve System assist in the implementation of monetary policy conducted through open market operations. The major assets of the sector are collateral repayable from funding corporations in connection with securities borrowing, securities held for redistribution, and security credit provided to customers. Operations are financed largely by net transactions with parent companies, customer credit balances, security repurchase agreements, and security credit from private depository institutions.

5.4 Funding corporations

The sector consists of five types of financial institutions and entities: 1. Subsidiaries of foreign bank and nonbank financial firms that raise funds in the U.S. commercial paper market and transfer the proceeds to foreign banking offices in the United States or to foreign parent companies abroad. 2. Financial holding companies 3. Custodial accounts, which are bookkeeping entities established to hold cash collateral put up by security dealers to back securities they borrow to cover short sales and delivery failures. 4. Limited liability companies, that the Federal Reserve created in the beginning of 2008, and to which loans were extended to help stabilize the financial system. 5. Loans extended by the federal government to the Term Asset-Backed Securities Loan Facility, and to funds associated with the Public-Private Investment Program.

Appendix B. Tables and figures

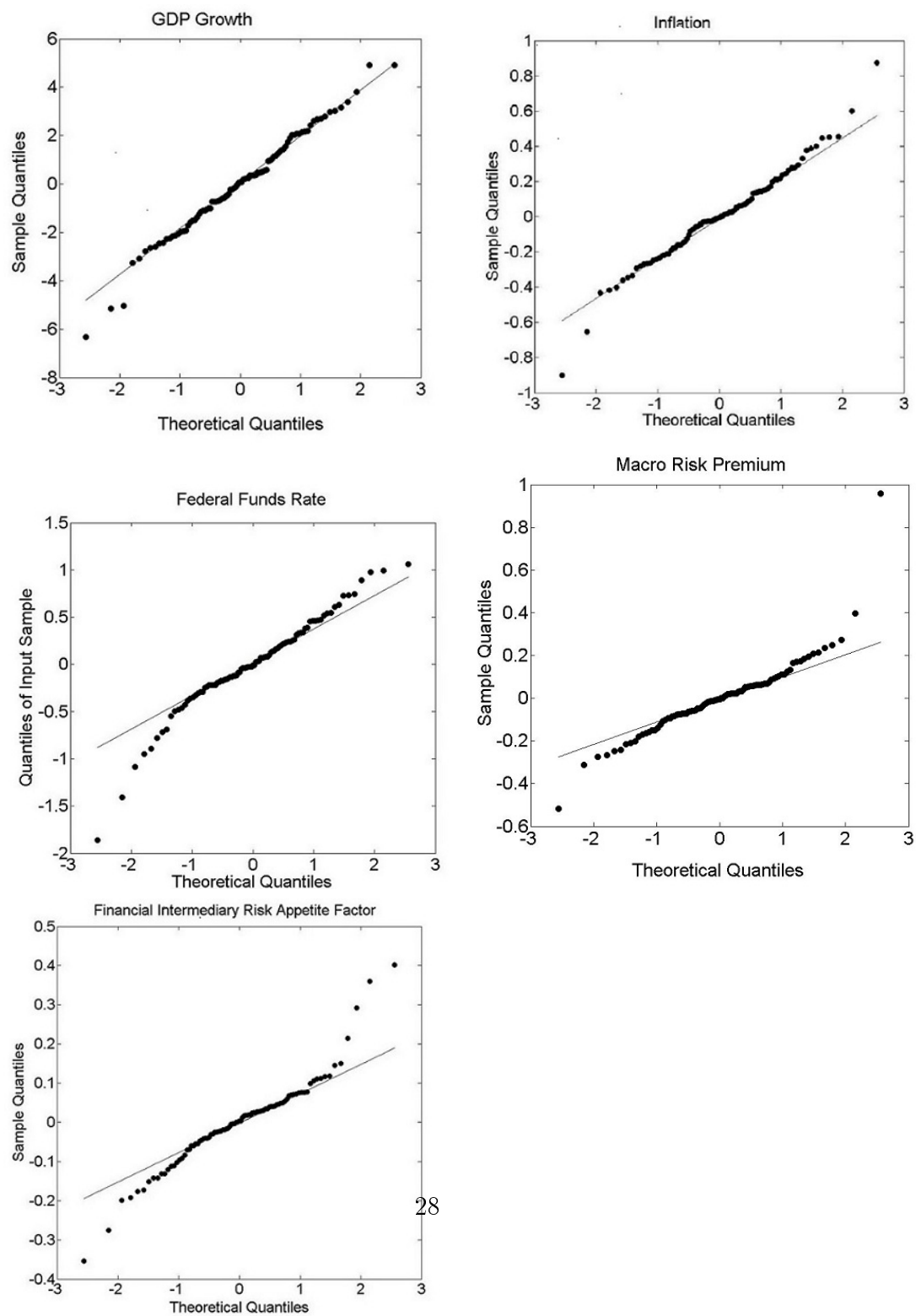


Figure 2: Residuals of the linear VAR(1) model, QQ plot

	$y_t = (\Delta gdp_t, \pi_t, FFR_t, mrp_t, FI_t)'$		$y_t = (\pi_t, FFR_t, mrp_t, FI_t, \Delta gdp_t)'$	
Parameter	Unrestricted B	Restricted B	Unrestricted B	Restricted B
$\hat{\gamma}$	0.801 (0.042)	0.866 (0.035)	0.438 (0.060)	0.408 (0.074)
$\hat{\psi}_1$	0.310 (0.118)	0.306 (0.205)	2.043 (0.734)	1.233 (0.507)
$\hat{\psi}_2$	0.044 (0.018)	0.057 (0.028)	0.078 (0.025)	0.083 (0.032)
$\hat{\psi}_3$	0.003 (0.001)	0.002 (0.001)	0.140 (0.054)	0.298 (0.102)
$\hat{\psi}_4$	0.006 (0.002)	0.0034 (0.0016)	0.049 (0.017)	0.075 (0.023)
$\hat{\psi}_5$	2.094 (0.811)	1.976 (1.180)	0.307 (0.102)	0.198 (0.101)
$\max l_T(\theta)$	255.067	228.083	248.891	241.008
LR		53.968		15.766
p -value		0.0000		0.1065

NOTE: Standard errors in parenthesis are obtained from the inverse Hessian of the log-likelihood function.

LR = $2(\log L_T - \log L_T^r)$ where L_T^r denotes the maximum likelihood under H_0 : restricted B and L_T denotes the maximum likelihood for the model under H_1 : unrestricted B . p -values were computed assuming asymptotic $\chi^2(10)$ distribution for the LR test statistic.

Table 2: Estimation results for the VAR(1) model with nonnormal residuals

Parameter	$y_t = (\Delta gdp_t, \pi_t, FFR_t, EBP_t, FI_t)'$		$y_t = (\pi_t, FFR_t, EBP_t, FI_t, \Delta gdp_t)'$	
	Unrestricted B	Restricted B	Unrestricted B	Restricted B
$\hat{\gamma}$	0.551 (0.057)	0.438 (0.145)	0.551 (0.058)	0.512 (0.063)
$\hat{\psi}_1$	0.511 (0.179)	0.530 (0.344)	1.335 (0.426)	0.910 (0.315)
$\hat{\psi}_2$	0.089 (0.030)	0.381 (0.197)	0.089 (0.030)	0.078 (0.028)
$\hat{\psi}_3$	0.026 (0.009)	0.155 (0.000)	0.079 (0.025)	0.068 (0.024)
$\hat{\psi}_4$	0.079 (0.024)	0.070 (0.044)	0.026 (0.009)	0.078 (0.025)
$\hat{\psi}_5$	1.335 (0.426)	1.264 (2.197)	0.511 (0.185)	0.639 (0.253)
$\max l_T(\theta)$	191.488	165.528	191.488	184.646
LR		51.92		13.68
p -value		0.0000		0.1881

NOTE: Standard errors in parenthesis are obtained from the inverse Hessian of the log-likelihood function.

LR = $2(\log L_T - \log L_T^r)$ where L_T^r denotes the maximum likelihood under H_0 : restricted B and L_T denotes the maximum likelihood for the model under H_1 : unrestricted B . p -values were computed assuming asymptotic $\chi^2(10)$ distribution for the LR test statistic.

Table 3: Robustness of the estimation results for the VAR(1) model with nonnormal residuals to an alternative proxy variable.

$y_t = (\Delta gdp_t, \pi_t, FFR_t, mrp_t, FI_t)'$			$y_t = (\pi_t, FFR_t, mrp_t, FI_t, \Delta gdp_t)'$	
H_0	Unrestricted B	Restricted B	Unrestricted B	Restricted B
$\psi_1 = \psi_2$	0.024	0.152	0.007	0.023
$\psi_1 = \psi_3$	0.009	0.089	0.001	0.065
$\psi_1 = \psi_4$	0.001	0.090	0.007	0.022
$\psi_1 = \psi_5$	1.22e-051	1.93e-015	0.018	0.041
$\psi_2 = \psi_3$	0.023	0.049	0.013	1.83e-011
$\psi_2 = \psi_4$	0.035	0.054	0.246	0.803
$\psi_2 = \psi_5$	0.000	0.000	5.19e-020	0.000
$\psi_3 = \psi_4$	0.003	0.317	0.092	0.029
$\psi_3 = \psi_5$	0.000	0.000	0.002	0.327
$\psi_4 = \psi_5$	0.000	0.000	5.06e-052	8.9e-008

Table 4: p -values of Wald tests for equality of ψ_i 's for models from Table 2

$y_t = (\Delta gdp_t, \pi_t, FFR_t, EBP_t, FI_t)'$			$y_t = (\pi_t, FFR_t, EBP_t, FI_t, \Delta gdp_t)'$	
H_0	Unrestricted B	Restricted B	Unrestricted B	Restricted B
$\psi_1 = \psi_2$	0.018	0.665	0.003	0.008
$\psi_1 = \psi_3$	0.007	0.276	0.003	0.008
$\psi_1 = \psi_4$	0.016	0.181	0.002	0.008
$\psi_1 = \psi_5$	4.16e-006	0.033	0.053	0.389
$\psi_2 = \psi_3$	0.036	0.251	0.739	0.721
$\psi_2 = \psi_4$	0.739	0.114	0.036	1.000
$\psi_2 = \psi_5$	0.000	7.39e-006	6.09e-045	2.69e-089
$\psi_3 = \psi_4$	3.89e-0.09	0.000	0.034	0.677
$\psi_3 = \psi_5$	0.000	0.000	6.65e-067	4.07e-125
$\psi_4 = \psi_5$	0.000	3.66e-162	0.000	1.60e-111

Table 5: p -values of Wald tests for equality of ψ_i 's for models from Table 3

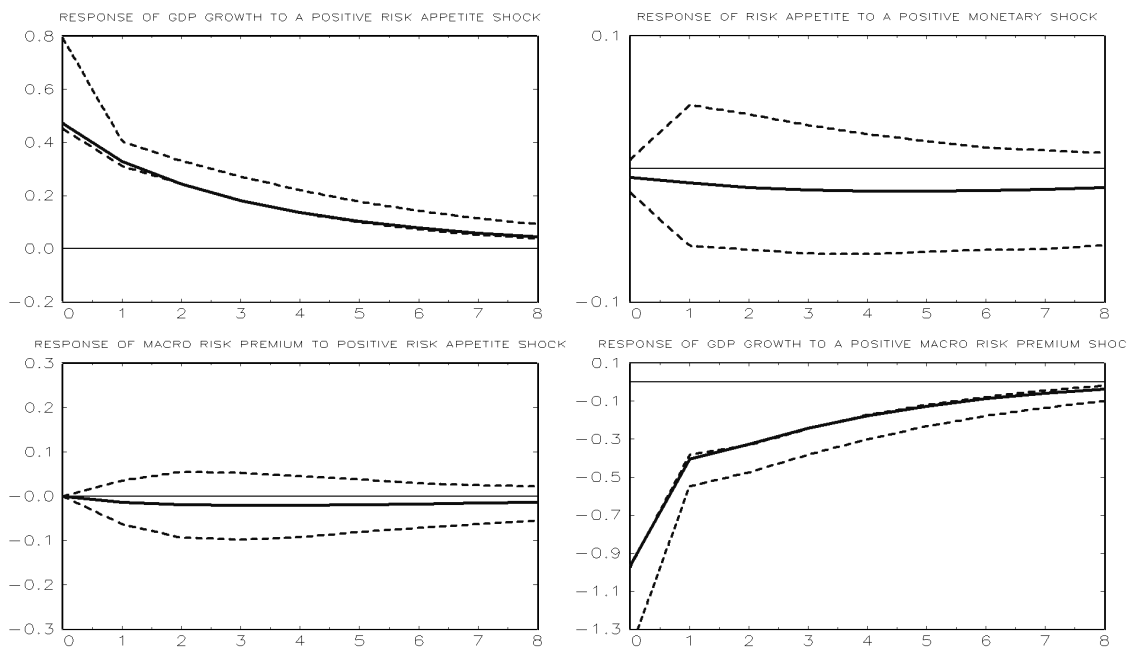


Figure 3: Impulse responses based on the VAR(1) model with nonnormal residuals and restricted B with 68 % bootstrap confidence intervals from 1000 replications.