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Geert Bekaert, Marie Hoerova and Marco Lo
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Geert Bekaert, Columbia University and CEPR
Marie Hoerova, European Central Bank
Marco Lo Duca, European Central Bank

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Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

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ABSTRACT

Risk, Uncertainty and Monetary Policy*

We document a strong co-movement between the VIX, the stock market option-based implied volatility, and monetary policy. We decompose the VIX into two components, a proxy for risk aversion and expected stock market volatility ("uncertainty"), and analyze their dynamic interactions with monetary policy in a structural vector autoregressive framework. A lax monetary policy decreases risk aversion after about five months. Monetary authorities react to periods of high uncertainty by easing monetary policy. These results are robust to controlling for business cycle movements. We further investigate channels through which monetary policy may affect risk aversion, e.g., through its effects on broad liquidity measures and credit.

JEL Classification: E32, E44, E52, G12 and G20

Keywords: business cycle, monetary policy, option implied volatility, risk aversion, stock market volatility dynamics and uncertainty

Geert Bekaert
Graduate School of Business
Columbia University
Uris Hall, Room 802
3022 Broadway
New York, NY 10027
USA

Email: gb241@columbia.edu

Marie Hoerova
Financial Research Division
European Central Bank
Kaiserstr. 29
D-60311 Frankfurt
GERMANY

Email: marie.hoerova@ecb.int

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Marco Lo Duca
Financial Research Division
European Central Bank
Kaiserstrasse 29
D - 60311 Frankfurt
GERMANY

Email: marco.lo_duca@ecb.int

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I. Introduction

A popular indicator of risk aversion in financial markets, the VIX index, shows strong co-movements with measures of the monetary policy stance. Figure 1 considers the cross-correlogram between the real interest rate (the Fed funds rate minus inflation), a measure of the monetary policy stance, and the logarithm of end-of-month readings of the VIX index. The VIX index essentially measures the “risk-neutral” expected stock market variance for the US S&P500 index. The correlogram reveals a very strong positive correlation between real interest rates and future VIX levels. While the current VIX is positively associated with future real rates, the relationship turns negative and significant after 13 months: high VIX readings are correlated with expansionary monetary policy in the medium-run future.

The strong interaction between a “fear index” (Whaley (2000)) in the asset markets and monetary policy indicators may have important implications for a number of literatures. First, the recent crisis has rekindled the idea that lax monetary policy can be conducive to financial instability. The Federal Reserve’s pattern of providing liquidity to financial markets following market tensions, which became known as the “Greenspan put,” has been cited as one of the contributing factors to the build up of a speculative bubble prior to the 2007-09 financial crisis.¹ Whereas some rather informal stories have linked monetary policy to risk-taking in financial markets (Rajan (2006), Adrian and Shin (2008), Borio and Zhu (2008)), it is fair to say that no extant research establishes a firm empirical link between monetary policy and risk aversion in asset markets.²

Second, Bloom (2009) and Bloom, Floetotto and Jaimovich (2009) show that heightened “economic uncertainty” decreases employment and output. It is therefore conceivable that the monetary authority responds to uncertainty shocks, in order to affect economic outcomes. However, the VIX index, used by Bloom (2009) to measure uncertainty, can be decomposed into a component that reflects actual expected stock market volatility (uncertainty) and a residual, the so-called variance premium (see, for

¹ Investors increasingly believed that when market conditions were to deteriorate, the Fed would step in and inject liquidity until the outlook improved. The perception may have become embedded in asset pricing in the form of higher valuations, narrower credit spreads, and excessive risk-taking. See, for example, “Greenspan Put may be Encouraging Complacency,” *Financial Times*, December 8, 2000.

² For recent empirical evidence that monetary policy affects the riskiness of loans granted by banks see, for example, Altunbas, Gambacorta and Marquéz-Ibañez (2010), Ioannidou, Ongena and Peydró (2009), Jiménez, Ongena, Peydró and Saurina (2009), and Maddaloni and Peydró (2010).

example, Carr and Wu (2009)), that reflects risk aversion and other non-linear pricing effects, perhaps even Knightian uncertainty. Establishing which component drives the strong comovements between the monetary policy stance and the VIX is therefore particularly important.

Third, analyzing the relationship between monetary policy and the VIX and its components may help clarify the relationship between monetary policy and the stock market, explored in a large number of empirical papers (Thorbecke (1997), Rigobon and Sack (2004), Bernanke and Kuttner (2005)). The extant studies all find that expansionary (contractionary) monetary policy affects the stock market positively (negatively). Interestingly, Bernanke and Kuttner (2005) ascribe the bulk of the effect to easier monetary policy lowering risk premiums, reflecting both a reduction in economic and financial volatility and an increase in the capacity of financial investors to bear risk. By using the VIX and its two components, we test the effect of monetary policy on stock market risk, but also provide more precise information on the exact channel.

This article characterizes the dynamic links between risk aversion, economic uncertainty and monetary policy in a simple vector-autoregressive (VAR) system. Such analysis faces a number of difficulties. First, because risk aversion and the stance of monetary policy are jointly endogenous variables and display strong contemporaneous correlation (see Figure 1), a structural interpretation of the dynamic effects requires identifying restrictions. Monetary policy may indeed affect asset prices through its effect on risk aversion, as suggested by the literature on monetary policy news and the stock market, but monetary policy makers may also react to a nervous and uncertain market place by loosening monetary policy. In fact, Rigobon and Sack (2003) find that the Federal Reserve does systematically respond to stock prices.³

Second, the relationship between risk aversion and monetary policy may also reflect the joint response to an omitted variable, with business cycle variation being a prime candidate. Recessions may be associated with high risk aversion (see Campbell and Cochrane (1999) for a model generating counter-cyclical risk aversion) and at the same

³ The two papers by Rigobon and Sack (2003, 2004) use an identification scheme based on the heteroskedasticity of stock market returns. Given that we view economic uncertainty as an important endogenous variable in its own right with links to the real economy and risk premiums, we cannot use such an identification scheme.

time lead to lax monetary policy. Our VARs always include a business cycle indicator. Third, measuring the monetary policy stance is the subject of a large literature (see, for example, Bernanke and Mihov (1998a)); and measuring policy shocks correctly is difficult. Models featuring time-varying risk aversion and/or uncertainty, such as Bekaert, Engstrom and Xing (2009), imply an equilibrium contemporaneous link between interest rates and risk aversion and uncertainty, through precautionary savings effects for example. Such relation should not be associated with a policy shock. However, our results are robust to alternative measures of the monetary policy stance and shocks.

The remainder of the paper is organized as follows. In Section II, we use a simple analytical framework and a series of numerical examples to provide intuition on how the VIX is related to the actual expected variance of stock returns and to risk preferences. While the literature has proposed a number of risk appetite measures (see Baker and Wurgler (2007) and Coudert and Gex (2008)), we show that our measure is monotonically increasing in risk aversion in a variety of economic settings. This motivates our empirical strategy in which we split the VIX into a pure volatility component (“uncertainty”) and a residual, which should be more closely associated with risk aversion. In Section III, we analyze the dynamic effects of monetary policy on risk aversion and uncertainty and vice versa, under various identification schemes. In Section IV, we conduct a long series of robustness tests. In the final section, we empirically examine various channels through which monetary policy may affect risk aversion and private sector risk-taking behavior, as suggested by recent research. Specifically, we consider the effects through the balance sheet of financial intermediaries (as proxied by repo growth and the growth rates of broad money aggregates) and through the expansion of credit (using the growth of credit and credit-to-GDP ratio).

Our main findings are as follows. A lax monetary policy decreases risk aversion in the stock market after about five months. This effect is persistent, lasting for two years. Moreover, monetary policy shocks account for a significant proportion of the variance of risk aversion. On the other hand, periods of high uncertainty are followed by a looser monetary policy stance. The effect of monetary policy on risk aversion is independent and does not necessarily run through repo or credit growth. Finally, it is the risk aversion

component of the VIX that has the strongest effect on the business cycle, not the uncertainty component.

II. Interpreting the VIX

The VIX represents the option-implied expected volatility on the S&P500 index with a horizon of 30 calendar days (22 trading days). This volatility concept is often referred to as “implied volatility.” The computation of the VIX index relies on theoretical results showing that option prices can be used to replicate any bounded payoff pattern; in fact, they can be used to replicate Arrow-Debreu securities (Breedon and Litzenberger (1978), Bakshi and Madan (2000)). Britten-Jones and Neuberger (2000) and Bakshi, Kapadia and Madan (2003) show how to infer “risk-neutral” or “risk-adjusted” expected volatility for a stock index from option prices. The VIX index measures implied volatility using a weighted average of European-style S&P500 call and put option prices that straddle a 30-day maturity and cover a wide range of strikes (see CBOE (2004) for more details). Importantly, this estimate is model-free and does not rely on an option pricing model.

Measuring Risk Aversion and Uncertainty

While the VIX obviously reflects stock market uncertainty, its link to option prices means it also harbours information about risk and risk aversion. Indeed, financial markets often view the VIX as a measure of risk aversion and fear in the market place. Because there are well-accepted techniques to measure the physical expected variance, we can split the VIX into a measure of stock market or economic uncertainty, and a residual that should be more closely associated with risk aversion. In the context of an external habit model, Bekaert, Engstrom and Xing (2009) show how “risk aversion” and “economic uncertainty” may have different effects on asset prices. These differences may be important to acknowledge in monetary policy transmission.

The difference between the squared VIX and an estimate of the conditional variance is typically called the variance premium (see, e.g., Carr and Wu (2009)).⁴ The variance premium is nearly always positive and displays substantial time-variation. Recent finance models attribute these facts either to non-Gaussian components in fundamentals and

⁴ In the technical finance literature, the variance premium is actually the negative of the variable that we use. By switching the sign, our indicator increases with risk aversion, whereas the variance premium becomes more negative with risk aversion.

(stochastic) risk aversion (see, for instance, Bekaert and Engstrom (2009), Bollerslev, Tauchen and Zhou (2009), Drechsler and Yaron (2009)) or Knightian uncertainty (see Drechsler (2009)).

In the empirical analysis, we use end-of-month VIX levels. To decompose the VIX index into its two components, we borrow a measure of the conditional variance of stock returns from Bekaert and Engstrom (2009). They project monthly realized variances (computed using squared 5-minute returns) on the past realized variance, the past (squared) VIX, the dividend yield and a real short interest rate. The fitted value of this regression, which is primarily driven by the past realized variance and the VIX, is the estimated physical expected variance. We call the logarithm of this estimate “uncertainty” (uc_t). We call the logarithm of the difference between the squared VIX and this conditional variance, “risk aversion” (ra_t). We plot the two series in Figure 2.

The VIX and Risk

To obtain intuition how the VIX is related to the actual (“physical”) expected variance of stock returns and to risk preferences, we analyze a one-period discrete state economy. Imagine a stock return distribution with three different states x_i , as follows:

Good state: $x_g = \mu + a$ with probability $(1 - p)/2$,

Bad state : $x_b = \mu - a$ with probability $(1 - p)/2$,

Crash state: $x_c = c$ with probability p ,

where $\mu > 0$, $a > 0$ and $c < 0$ are parameters to be determined. We set them to match statistics in the data for the US stock market - the mean, the variance (standard deviation) and the skewness - while fixing the crash return at an empirically plausible number.

The mean is given by:

$$\bar{X} = \frac{1-p}{2}x_g + \frac{1-p}{2}x_b + pc = (1-p)\mu + pc. \quad (1)$$

The variance is given by:

$$V \equiv \sigma^2 = \frac{1-p}{2}(\mu + a - \bar{X})^2 + \frac{1-p}{2}(\mu - a - \bar{X})^2 + p(c - \bar{X})^2 \quad (2)$$

and the skewness (Sk) by:

$$V^{\frac{3}{2}}Sk = \frac{1-p}{2}(\mu + a - \bar{X})^3 + \frac{1-p}{2}(\mu - a - \bar{X})^3 + p(c - \bar{X})^3. \quad (3)$$

Consider a one-period world such that the investor has a power utility function over wealth and in equilibrium she invests her entire wealth in the stock market:

$$U(\tilde{W}) = E\left[\frac{(W_0\tilde{R})^{1-\gamma}}{1-\gamma}\right], \quad (4)$$

where \tilde{R} is the gross return on the stock market, W_0 is initial wealth and γ is the coefficient of relative risk aversion.

The “pricing kernel” in this economy is given by marginal utility, denoted by m , and is proportional to $\tilde{R}^{-\gamma}$. Hence, the stochastic part of the pricing kernel moves inversely with the return on the stock market. When the stock market is down, marginal utility is relatively high and vice versa.

The physical variance of the stock market is exogenous in this economy, and is simply given by V . This variance is computed using the actual probabilities. The VIX represents the “risk-neutral” conditional variance. It is computed using the so-called “risk-neutral probabilities,” which are simply probabilities adjusted for risk.

In particular, for a general state probability π_i for state i , the risk-neutral probability is:

$$\pi_i^{RN} = \pi_i \frac{m_i}{E[m]} = \pi_i \frac{R_i^{-\gamma}}{E[m]}. \quad (5)$$

So, for a given γ , we can easily compute the risk-neutral probabilities since $R_i = x_i + 1$.

For an economy with K states, the risk-neutral variance is then given by:

$$VIX^2 = \sum_{i=1}^K \pi_i^{RN} (x_i - \bar{X})^2 \quad (6)$$

and the variance premium is:

$$VP = VIX^2 - V = \sum_{i=1}^K (\pi_i^{RN} - \pi_i)(x_i - \bar{X})^2. \quad (7)$$

In our economy, the risk-neutral probability puts more weight on the crash state and the crash state induces plenty of additional variance, rendering the variance premium positive. The higher is risk aversion, the more weight the crash state gets, and the higher

the variance premium will be. The expression for the variance premium has a particularly simple form:

$$VP = (\pi_g^{RN} - \frac{1-p}{2})(x_g - \bar{X})^2 + (\pi_b^{RN} - \frac{1-p}{2})(x_b - \bar{X})^2 + (\pi_c^{RN} - p)(x_c - \bar{X})^2 \quad (8)$$

where $\pi_g^{RN} = \frac{1-p}{2} \frac{(\mu+a+1)^{-\gamma}}{E[m]}$, $\pi_b^{RN} = \frac{1-p}{2} \frac{(\mu-a+1)^{-\gamma}}{E[m]}$ and $\pi_c^{RN} = p \frac{(c+1)^{-\gamma}}{E[m]}$.

Numerical Examples

Suppose the statistics to match are as follows: $\bar{X} = 10\%$, $\sigma = 15\%$, both on an annualized basis; $Sk = -1$ and $c = -25\%$, the latter two being monthly numbers. This crash return is in line with the stock market collapses in October 1987 and October 2008. The implied crash probability to match the skewness coefficient of -1 is given by $p = 0.5\%$. With a monthly investment horizon, the crash probability implies a crash every 200 months, or roughly once every two decades. Panel A of Table 2 provides, for different values of the coefficient of relative risk aversion γ , the values for the VIX on an annualized basis in percent (VIX), the log of the VIX on a monthly basis (LVIX), i.e., $\log(VIX/\sqrt{12})$, the annualized variance premium (VP), and our risk aversion proxy computed on a monthly basis (RA), i.e., $\log(VIX^2/12 - \sigma^2/12)$. Note that the variance premium and our risk aversion measure are monotonically increasing in the coefficient of relative risk aversion γ .

In structural models, γ is typically assumed to be time-invariant, and the time variation in the variance premium is generated through different mechanisms. For example, in Drechsler and Yaron (2009), who formulate a consumption-based asset pricing model with recursive preferences, the variance premium is directly linked to the probability of a “negative jump” to expected consumption growth. Barro’s (2006) work on the asset pricing effects of “disaster risk” could likewise yield time-variation in the variance premium in equilibrium by assuming that the probability of a consumption crash varies through time. The analogous mechanism in our simple economy would be a decrease in skewness of the return distribution implying an increase in the crash probability p . This obviously represents “risk” instead of “risk aversion”. Yet, it is the interaction of risk aversion and skewness that gives rise to large readings in our risk

aversion proxy. To illustrate, let us consider an example with lower skewness. Setting skewness equal to -2 requires a higher crash probability of $p = 1\%$. Panel B of Table 2 shows that the VIX increases, and increases more the higher the coefficient of relative risk aversion, both in absolute and in relative terms. The variance premium roughly doubles for all γ levels, whereas our risk aversion proxy increases by about 0.7.

In Bekaert and Engstrom (2009), when a recession becomes more likely, the representative agent also becomes more risk averse through a Campbell-Cochrane (1999)-like external habit formulation. The recession fear then induces high levels of the VIX. We can informally illustrate such a mechanism in our one-period model. Imagine that the utility function is over wealth relative to an exogenous benchmark wealth level W_{bm} . Normalizing the initial wealth W_0 to 1, the pricing kernel is now given by $(\tilde{R} - W_{bm})^{-\gamma}$, and the coefficient of relative risk aversion is $\gamma \tilde{R} / (\tilde{R} - W_{bm})$. Consequently, risk aversion is state dependent and increases as \tilde{R} decreases towards the benchmark level. It is easy to see how a dynamic version of this economy, for instance with a slow-moving W_{bm} , could generate risk aversion that is changing over time as return realizations change the distance between actual wealth and the benchmark wealth level.

To illustrate this mechanism, Panel C considers three different benchmark levels for W_{bm} (0.05, 0.25 and 0.5) with γ fixed at 4, $Sk = -1$ and $p = 0.5\%$. The second column shows expected relative risk aversion in the economy (CRRA), weighting the three possible realizations for risk aversion with the actual state probabilities. The other columns are as in the panels above. Clearly, for $W_{bm} = 0$, CRRA = 4 and we replicate the values in Panel A for $\gamma = 4$. Keeping γ fixed and increasing W_{bm} , effective risk aversion increases. For example, CRRA increases from 4.21 to 7.97 as W_{bm} increases from 0.05 to 0.5. The VIX increases from 17.87 to 27.93 and our risk aversion proxy RA increases from 2.06 to 3.83. In sum, our risk aversion measure monotonically increases with true risk aversion in the underlying economy.

III. Risk, Uncertainty and Monetary Policy

We begin our analysis with a four-variable VAR on risk aversion, uncertainty, a measure of monetary policy, and a business cycle indicator, using monthly data for the United States from January 1990 to July 2007. We exclude recent data on the crisis, which presents special challenges. Table 1 describes all the variables we use and assigns them a short-hand label.

To measure the monetary policy stance, we use the real interest rate (RERA), i.e., the Fed funds end-of-the-month target rate minus the CPI inflation rate. In Section IV, we consider alternative measures of the monetary policy stance for robustness. The robustness analysis also includes a standard VAR specification featuring the nominal Fed funds rate as the measure of monetary policy stance and price level measures (consumer and producer price indices) as separate variables.

It is conceivable that the intriguing links between the VIX and monetary policy simply reflect monetary policy and implied volatility jointly reacting to business cycle conditions. For example, news indicating weaker than expected growth in the economy may make a cut in the Fed funds target rate more likely, but at the same time cause people to be effectively more risk averse, for example because a larger number of households feel more constrained in their consumption relative to “habit,” or because people fear a more uncertain future. To analyze business cycle effects, denoted by bc_t , we use the log-difference of non-farm employment (DEMP) in our benchmark VAR.

While our main focus is on the links between risk, uncertainty and monetary policy, our analysis may also provide important inputs to a rapidly growing macroeconomic literature linking business cycles to the stock market. Beaudry and Portier (2006), for example, present empirical evidence suggesting that business cycle fluctuations may be driven to a large extent by changes in stock market expectations, which anticipate total factor productivity movements. Bloom (2009) shows that “economic uncertainty” has real effects, in particular it generates a sharp drop in employment and output, which rebounds in the medium term, and a mild long-run overshoot. He explains these facts in the context of a production model where uncertainty increases the region of inaction in hiring and investment decisions of firms facing non-convex adjustment costs. In his empirical work, Bloom uses the VIX index to create an index of “exogenous” volatility

shocks. However, as the VIX reflects both uncertainty and risk aversion, it is conceivable that it is the risk aversion component of the VIX index that generates the real effects, not the economic uncertainty component. Moreover, these shocks may be simply correlated with business cycles, as predicted by external habit models, for example.⁵ In a recent Economist article, Blanchard (2009) describes the VIX index as an indicator of Knightian uncertainty, arguing that such uncertainty may prolong the current crisis. In both cases, the implication is that monetary policy may want to respond strongly to uncertainty shocks, in Bloom's case to economic uncertainty shocks, in Blanchard's case to what we call risk aversion shocks.

We collect the four variables in the vector $Z_t = [bc_t, mp_t, ra_t, uc_t]'$ where bc_t is a business cycle indicator, mp_t is a measure of monetary policy stance, and ra_t and uc_t are our risk aversion and uncertainty proxies, RA and UC. Without loss of generality, we ignore constants. Consider the following structural VAR:

$$A Z_t = \Phi Z_{t-1} + \varepsilon_t \quad (9)$$

where A is a 4x4 full-rank matrix and $E[\varepsilon_t \varepsilon_t'] = I$. Of main interest are the dynamic responses to the structural shocks ε_t .

Of course, we start by estimating the reduced-form VAR:

$$Z_t = B Z_{t-1} + C \varepsilon_t \quad (10)$$

where B denotes $A^{-1} \Phi$ and C denotes A^{-1} . Moreover, let us define Σ to be the variance-covariance matrix of the reduced-form residuals, i.e., $\Sigma = E[(C \varepsilon_t) (C \varepsilon_t)'] = C C'$.

The first-order VAR in Equations (9) and (10) is useful to illustrate the identification problem: Equation (10) yields 26 coefficients in the matrices B and Σ , but Equation (9) has 32 unknowns. Hence, we need 6 restrictions on the VAR to identify the system. In general, for a VAR of order k with N variables, we have $(k+1)N^2$ parameters to identify and we can estimate $kN^2 + N(N+1)/2$ parameters. Hence, we need $N(N-1)/2$ restrictions to identify the system. We later use formal selection criteria to select the correct order of the VAR.

Reduced-form Statistics

Before we explore structural identification, Table 3 reports some reduced-form VAR statistics. Panel A produces three lag-selection criteria: Akaike (AIC), Hannan-Quinn

⁵ To be fair, Bloom (2009) attempts to identify exogenous shocks to the VIX, which are less likely to be of a cyclical nature.

(HQIC) and Schwarz (SBIC). While the Schwarz criterion selects a VAR with one lag, the AIC and HQIC criteria both select a VAR with three lags. We focus the remainder of the analysis in this section on the three-lag VAR. Panel B reports Granger causality tests. We find strong overall Granger causality in the risk aversion and real interest rate equations. While significance is high for all the variables in the risk aversion equation, monetary policy has the strongest effect. In the real rate equation, employment and uncertainty are significant at 5% and 10% level, respectively. Granger causality is not significantly present in either the employment or uncertainty equations. The strongest relation is risk aversion predicting or anticipating employment significantly at the 5% level. The real rate predicts or anticipates employment and uncertainty (both at the 10% significance level).⁶

Finally, Panel C reports some specification tests on the residuals of the VAR. These tests (see Johansen (1995)) test for autocorrelation in the residuals of the VAR at lag j ($j=1,2,3$). The VAR with 3 lags clearly eliminates all serial correlation in the residuals.

Identification

To obtain structural identification, we investigate two types of restrictions: exclusion restrictions on contemporaneous responses (setting coefficients in A to zero) and long-run restrictions.

Our first set of restrictions uses a Cholesky decomposition of the estimate of the variance-covariance matrix. We order the business cycle variable first, followed by the real interest rate, with risk aversion and uncertainty ordered last. This captures the fact that risk aversion and uncertainty, stock market based variables, respond instantly to the monetary policy shocks, while the business cycle variable is relatively more slow-moving. Effectively, this imposes six exclusion restrictions on the contemporaneous matrix A :

$$A = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \quad (11)$$

⁶ In the three-lag VAR, reporting the feedback coefficients is not very informative. In a first-order VAR, laxer monetary policy predicts lower risk aversion next period whereas higher uncertainty predicts laxer monetary policy next month. Both coefficients are significant at the 1% level.

The other set of restrictions combines five contemporaneous restrictions (also imposed under the Cholesky decomposition above) with the assumption that monetary policy has no long-run effect on the level of employment. This long-run restriction is inspired by the literature on long-run money neutrality: money should not have a long run effect on real variables. Bernanke and Mihov (1998b) and King and Watson (1992) marshal empirical evidence in favor of money neutrality using data on money growth and output growth.

Following Blanchard and Quah (1989), the model with a long-run restriction (LR) involves a long-run response matrix, denoted by D:

$$D \equiv (I - B)^{-1} C. \quad (12)$$

It follows that $D D' = (I - B)^{-1} C C' [(I - B)^{-1}]' = (I - B)^{-1} \Sigma [(I - B)^{-1}]'$. Hence, using the estimates of B and Σ from the reduced-form VAR, we obtain D, and thus $A^{-1} = C$.⁷ The system with five contemporaneous restrictions and one long-run exclusion restriction corresponds to the following contemporaneous matrix A and long-run matrix D:

$$A = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \quad (13)$$

$$D = \begin{bmatrix} d_{11} & 0 & d_{13} & d_{14} \\ d_{21} & d_{22} & d_{23} & d_{24} \\ d_{31} & d_{32} & d_{33} & d_{34} \\ d_{41} & d_{42} & d_{43} & d_{44} \end{bmatrix} \quad (14)$$

Recently, the use of long-run restrictions to identify VARs has come under attack (see, for example, Chari, Kehoe and McGrattan (2008)). However, Christiano, Eichenbaum and Vigfusson (2006) show that many of the problems can be overcome by using long-run information (rather than a parsimonious VAR) to identify the long-run restrictions. Although they advocate using a non-parametrically estimated spectral density matrix, a VAR with a relatively long lag-length effectively uses long-run information to identify the restrictions. We therefore also checked that our results remain

⁷ To facilitate interpretation of the impulse responses, we adopt a sign normalization requiring that the diagonal elements of A^{-1} be positive.

robust to the use of a longer VAR lag-length. We did not go beyond four lags, as otherwise the saturation ratio (data points to parameters) drops below 10.⁸

Both identification schemes satisfy necessary and sufficient conditions for global identification of structural vector autoregressive systems (see Rubio-Ramírez, Waggoner and Zha (2009)).

Structural Evidence

We couch our main results in the form of impulse-response functions (IRFs henceforth), estimated in the usual way. We compute 90% bootstrapped confidence intervals based on 1000 replications, and focus our discussion on significant responses. We report the resulting structural impulse-response functions in Figure 3.

A one standard deviation negative shock to the real rate corresponds to a 33 basis points decrease in both models. It lowers risk aversion by 0.05 after 4 months in the model with contemporaneous restrictions and by 0.04 after 5 months in the model with contemporaneous/long-run restrictions. The impact reaches a maximum of 0.09 after 12 and 17 months, respectively. It remains significant up and till lag 34 in the model with contemporaneous restrictions and till lag 39 in the model with contemporaneous/long-run restrictions. So, laxer monetary policy lowers risk aversion under both identification schemes. The impact of a one standard deviation positive shock to risk aversion (equivalent to 0.33 in both models) on the real rate is mostly negative but not statistically significant.

A positive shock to the real rate lowers uncertainty in the short-run (between lags 0 and 3) but increases it in the medium-run (between lags 25 and 39 in the model with contemporaneous restrictions and 29 - 42 in the model with contemporaneous/long-run restrictions). The maximum positive impact is 0.04 at lag 25 and 0.05 at lag 29 in the models with contemporaneous and contemporaneous/long-run restrictions, respectively. In the other direction, the real rate decreases in the short-run following a positive one standard deviation shock to uncertainty (equivalent to 0.50). In both models, the impact reaches a maximum of 5 basis points in period 1 and is not statistically significant

⁸ We also estimated a VAR with 1 lag, as selected by the Schwarz (SBIC) criterion. Our results were unaltered.

thereafter. Hence, we find a structural effect of uncertainty on the subsequent monetary policy stance.

As for interactions with the business cycle variable (Panels E - J), a contractionary monetary policy shock leads to a decline in employment growth after about 28 (23) months, with the effect being (borderline) significant up and till lag 47 (57) in the model with contemporaneous restrictions (contemporaneous/long-run restrictions). In the other direction, monetary policy reacts as expected to business cycle fluctuations: a one standard deviation positive shock to employment growth, equivalent to 0.0009, leads to a higher real rate. Specifically, in the model with contemporaneous restrictions, the real rate increases by a maximum of 22 basis points after 13 months, with the impact being significant between lags 0 and 33. The impact is also positive in the model with contemporaneous/long-run restrictions, and it is (borderline) statistically significant between lags 29 and 38. Higher risk aversion decreases employment growth in both models (Panel G). In the other direction, higher employment growth decreases risk aversion in the short-run (between lags 1 and 2). Such effect is consistent with habit-based theories of countercyclical risk aversion as in Campbell and Cochrane (1999). While positive uncertainty shocks do not have a statistically significant impact on employment growth, higher employment growth has a negative effect on uncertainty in the short-run (between lags 2 and 9 in the model with contemporaneous restrictions and between lags 5 and 10 in the model with contemporaneous/long-run restrictions). These results potentially shed new light on the analysis in Bloom (2009), who found that uncertainty shocks generate significant business cycle effects, using the VIX as a measure of uncertainty. Our results suggest that the link between the VIX and the business cycle may well be driven by the risk aversion rather than the uncertainty component of the VIX.⁹

Finally, increases in risk aversion predict future increases in uncertainty under both identification schemes (Panel L). Uncertainty has a positive, albeit short-lived effect on risk aversion (Panel K).

⁹ Popescu and Smets (2009) analyze the business cycle behavior of measures of perceived uncertainty and financial risk premia in Germany. They also find that positive financial risk aversion shocks have a large and persistent negative impact on the economy and are more important in driving business cycles than uncertainty shocks.

Our main result is that monetary policy has a medium-run statistically significant effect on risk aversion. This effect is not only statistically but also economically significant. In Figure 4, we show what fraction of the structural variance of the four variables in the VAR is due to monetary policy shocks. They account for over 30% of the variance of risk aversion at horizons longer than 24 months in the model with contemporaneous restrictions, and for over 40% of the variance of risk aversion at horizons longer than 28 months in the model with contemporaneous/long-run restrictions.

IV. Robustness

In this section, we consider five types of robustness checks: 1) measurement of the monetary policy stance; 2) measurement of the business cycle variable; 3) identification of monetary policy shocks; 4) identification of uncertainty shocks; and 5) general identification.

Measuring Monetary Policy

Our first alternative measure of the monetary policy stance is the Taylor rule residual, i.e., the difference between the nominal Fed funds rate and the Taylor rule rate (TR rate). The TR rate is estimated as in Taylor (1993):

$$TR_t = Inf_t + NatRate_t + 0.5*(Inf_t - TargInf) + 0.5*OG_t \quad (15)$$

where Inf is the annual inflation rate, $NatRate$ is the “natural” real Fed funds rate (consistent with full employment), which Taylor assumed to be 2%, $TargInf$ is a target inflation rate, also assumed to be 2%, and OG (output gap) is the percentage deviation of real GDP from potential GDP. We assume that the growth of potential GDP is 3% per year. As additional measures of the monetary policy stance, we consider the nominal Fed funds rate instead of the real rate, and (the growth rate of) the monetary aggregate M1, which is commonly assumed to be under tight control of the central bank.¹⁰ When we estimate a VAR with M1 in levels, we also use employment instead of employment growth.

Table 4 reports summary statistics on the interaction of monetary policy with risk aversion (Panel A) and with uncertainty (Panel B). The results confirm that looser monetary policy stance lowers risk aversion in the short to medium run. This effect is

¹⁰ We consider the negative of the M1 (growth) so that a positive shock to this variable corresponds to monetary policy tightening, in line with all other measures of monetary policy we use.

persistent, lasting for about two years. Risk aversion has no statistically significant effect on monetary policy. As for the effect of monetary policy on uncertainty, monetary tightening increases uncertainty in the medium run. In the other direction, higher uncertainty leads to laxer monetary policy in all specifications. The statistical significance of the last two effects is less robust.

Measuring Business Cycle Variation

We consider the log-difference of industrial production, the log-difference of hours worked and the level of jobless claims as alternative business cycle indicators. Unlike employment, industrial production and hours worked, jobless claims is a stationary variable, implying that VAR shocks do not have a long run effect on it. Our long-run restriction on the effect of monetary policy is thus stronger when applied to jobless claims: it restricts the total effect of monetary policy on jobless claims to be zero. Nevertheless, our main results from Section III are confirmed for each specification with an alternative business cycle variable. Detailed results are available upon request.

Identification of Monetary Policy Shocks

To check robustness with respect to the identification of monetary policy shocks, we consider two specifications in which the Fed funds rate and the price level variable enter separately (rather than jointly through the real interest rate). We estimate a five-variable VAR with the consumer price index (CPI), employment, Fed funds rate, risk aversion and uncertainty and a six-variable VAR adding the producer price index (PPI) to the above list.¹¹ To identify monetary policy shocks, we use a Cholesky ordering with CPI and employment ordered first, followed by the Fed funds rate and PPI (in the six-variable VAR), with risk aversion and uncertainty ordered last. This strategy follows Christiano, Eichenbaum and Evans (1999).

We present impulse-responses to monetary policy shocks in Figure 5. A positive monetary policy shock corresponds to a 16 basis points increase in the Fed funds rate in both specifications. A contractionary monetary shock leads to a decrease in the CPI after 3 months in both models. The effect is significant up and till lag 16 and lag 25 in the model with CPI and CPI/PPI, respectively. Furthermore, employment declines following

¹¹ We estimate both models with four lags, as suggested by the Akaike criterion. All variables are in logarithms except for the Fed funds rate. Note that employment now also enters the VAR in levels.

a monetary contraction, although this effect is only statistically significant in the model with CPI (after about 30 months).

Importantly, the reactions of both risk aversion and uncertainty are remarkably similar to those uncovered in the previous section. Risk aversion decreases following a monetary easing in both specifications. The effect reaches a maximum at lag 16 and 15 in the model with CPI and CPI/PPI, respectively, and remains statistically significant till lag 24 and 28. The effects remain economically important as monetary policy shocks account for over 16% (26%) of the variance of risk aversion at horizons longer than 30 months in the model with CPI (CPI/PPI), see Figure 6. As for uncertainty, a higher Fed funds rate lowers uncertainty in the short-run (between lags 2 and 14 in the model with CPI and between lags 2 and 10 in the model with CPI/PPI). However, in the medium-run, uncertainty increases in the model with CPI/PPI, which is also consistent with our previous findings.

Identification of Uncertainty Shocks

As an alternative to our identification of uncertainty shocks, we follow Bloom (2009). We construct an indicator of large, “exogenous” uncertainty shocks, i.e., a 0-1 variable which takes on a value of one if uncertainty is more than 1.65 standard deviations above the Hodrick Prescott (HP) detrended ($\lambda = 129,600$) mean of the uncertainty series and zero otherwise. We isolate five shocks during our sample period. They are associated with terror, war and financial crises.¹² When uncertainty is above its mean for several consecutive months, we assign a value of one to the chronologically first month in which uncertainty was high and zero to the other months. The idea is that a high reading of uncertainty in the first month represents an initial shock, while the remaining high values reflect propagation of the initial shock. We then estimate a four-variable system with four lags (as selected by the Akaike criterion), imposing contemporaneous restrictions, with the uncertainty indicator ordered first, followed by employment, the real interest rate and risk aversion. We also estimate a five-variable model, which includes the CPI, using the following Cholesky ordering: uncertainty indicator, CPI, employment, Fed funds rate and risk aversion.

¹² The five events are: first Gulf war (August 1990), Asian crisis (October 1997), Russian/LTCM crisis (August 1998), 9/11 terrorist attack (September 2001), Corporate scandals (July 2002).

We present impulse-responses to such uncertainty shocks in Figure 7. The interest rate decreases following a positive shock to uncertainty, with the effect being statistically significant until lag 12 and 19 in the two respective models. It reaches a maximum decrease of 10 basis points at lag 5 in the model with the real rate and 11 basis points at lag 10 in the model with the Fed funds rate/CPI. Consequently, this identification scheme leads to stronger, longer-lasting effects of uncertainty on monetary policy. As in the previous section, higher uncertainty leads to higher risk aversion in the short-run. Uncertainty shocks do not have a statistically significant impact on employment.

General Identification

We tried alternative identification schemes, while always preserving a structure that satisfies necessary and sufficient conditions for global identification. For Cholesky decompositions, we reversed the order of risk aversion and uncertainty in all our VARs, and employment and CPI in our 5- and 6-variable VARs. We experimented with imposing solely long-run restrictions, as well as with alternative combinations of contemporaneous and long-run restrictions. We consistently found that looser monetary policy lowers risk aversion in the medium-run. Results are available upon request.

We conclude that a lax monetary policy decreases risk aversion significantly, with the effect being most pronounced in the medium run, while the interest rate tends to decrease in response to high uncertainty. So, our previous results are robust to alternative ways of identifying monetary policy and uncertainty shocks, and to other variations in identification.

V. Channels

We have unearthed some intriguing interactions between the component in the VIX index not related to actual stock market volatility, and the stance of monetary policy. If monetary policy indeed affects risk aversion, our results could be important in the current debate about the origins of the 2007-2009 crisis. While pinpointing in detail how monetary policy affects risk aversion is beyond the scope of the article, we use this section to empirically analyze some potential channels, discussed in a number of recent articles.

Adrian and Shin (2008) suggest that the link between monetary policy and asset prices runs through the balance sheets of financial intermediaries and that repo growth rates adequately proxy for the riskiness of balance sheets. Using US data, they find that the growth of outstanding repos forecasts the difference between implied and realized volatility and that rapid growth in repos is associated with loose monetary policy (defined as the Fed funds rate).

To examine the Adrian-Shin channel in our structural framework, we use a four-variable VAR as in Section III but with repo growth replacing the business cycle variable. First, we examine whether introduction of this variable eliminates the effect of the real interest rate on risk aversion we uncovered in the previous section. Table 5, Panel A summarizes the results. Lax monetary policy is still associated with lower risk aversion after 5 months. This effect is persistent. In the opposite direction, the responses are not statistically significant. In Table 5, Panel B we investigate the interaction between the real rate and uncertainty. Consistent with our previous findings, higher rates lower uncertainty initially, while the real rate decreases following a positive shock to uncertainty (though the latter effect is not statistically significant).

Second, we analyze the direct link between repo growth and risk aversion. Higher repo growth has a negative effect on risk aversion but this effect is only statistically significant in the model with contemporaneous restrictions (between lags 17 and 42). In that specification, a shock to the real interest explains over 40% of the variance of risk aversion beyond lag 25, while a repo shock explains not more than 6.5% at any of the 60 lags considered. In sum, our VAR suggests that the monetary policy – risk aversion link does not only run through repo growth.

Many commentators have noted a rather large build up of liquidity through money growth prior to financial crises (see also Adalid and Detken (2007), Alessi and Detken (2009)). We thus use the growth rates of a broad money aggregate as a “channel” variable, replacing the business cycle variable in the four-variable VAR. In particular, we consider the growth rate of M2 net of M1. This part of the money growth is arguably less under control of a central bank and rather reflects activities in the financial sector.

Using this set-up, we confirm our finding that lower real rates lead to lower risk aversion in both specifications considered (see Table 5, Panel A). We also confirm that

positive uncertainty shocks lower the real rate in the short-run (Table 5, Panel B). As for the interaction between money growth and risk aversion, we find a structural link from risk aversion to M2-M1: when risk aversion increases, M2-M1 increases in the short run. This finding can be related to flights-to-safety effects in that risk-averse investors may flee to relatively safe assets during crisis times. Such assets are incorporated in the M2 measure (e.g., money market and time deposits).

According to Borio and Lowe (2002), medium-term swings in asset prices are associated with a rapid credit expansion. Moreover, they stress that such financial imbalances may build up in a low inflation environment and that in some cases it is appropriate for monetary policy to respond to these imbalances. Consequently, they suggest a link between credit growth and monetary policy. It is conceivable that periods of high risk appetite coincide with periods of rapid credit expansion, suggesting a channel for the effect of monetary policy on risk aversion.

To investigate the role of credit, we consider two separate four-variable VAR systems, with (private) credit growth and the first-difference of the credit-to-GDP ratio replacing the business cycle variable. The significant impact of monetary policy on risk aversion is present again (see Table 5, Panel A). Higher uncertainty decreases the real rate in all specifications (see Table 5, Panel B). We do not find statistically significant effects of credit developments on risk aversion in the stock market.

While our results are robust to two different identification schemes, one of them relies on a long-run money neutrality assumption that is less palatable for our channel variables than it is for the business cycle variable, to which it was applied in Section III. We therefore examine an alternative identification scheme, using the Cholesky ordering with CPI, a channel variable, the Fed funds rate, risk aversion and uncertainty. We consistently find that looser monetary policy lowers risk aversion. In sum, considering channels through which monetary policy may affect risk aversion does not eliminate the direct effect of monetary policy on risk appetite.

VI. Conclusions

A number of recent studies point at a potential link between loose monetary policy and excessive risk-taking in financial markets. Rajan (2006) conjectures that in times of ample liquidity supplied by the central bank, investment managers have a tendency to

engage in risky, correlated investments. To earn excess returns in a low interest rate environment, their investment strategies may entail risky, tail-risk sensitive and illiquid securities (“search for yield”). Moreover, a tendency for herding behaviour emerges due to the particular structure of managerial compensation contracts. Managers are evaluated vis-à-vis their peers and by pursuing strategies similar to others, they can ensure that they do not under perform. This “behavioral” channel of monetary policy transmission can lead to the formation of asset prices bubbles and can threaten financial stability. Given the dramatic crisis witnessed in 2007-2009, Rajan’s story sounds prophetic. Yet, there is no empirical evidence on the links between risk aversion in financial markets and monetary policy.

This article has attempted to provide a first characterization of the dynamic links between risk, uncertainty and monetary policy, using a simple vector-autoregressive framework. We decompose implied volatility into two components, risk aversion and uncertainty, and find interactions between each of the components and monetary policy to be rather different. Lax monetary policy increases risk appetite (decreases risk aversion) in the future, with the effect lasting for about two years and starting to be significant after five months. On the other hand, high uncertainty leads to laxer monetary policy in the near-term future. These results are robust to controlling for business cycle movements. Consequently, our VAR analysis provides a clean interpretation of the stylized facts regarding the dynamic relations between the VIX and the monetary policy stance depicted in Figure 1. The primary component driving the co-movement between past monetary policy stance and current VIX levels (first column of Figure 1) is risk aversion. The uncertainty component of the VIX lies behind the negative relation in the opposite direction (second column of Figure 1).

We hope that our analysis will inspire further empirical work and research on the exact theoretical links between monetary policy and risk-taking behavior in asset markets. In particular, recent work in the consumption-based asset pricing literature attempts to understand the structural sources of the VIX dynamics (see Bekaert and Engstrom (2009), Bollerslev, Tauchen and Zhou (2008), Drechsler and Yaron (2009)). Yet, none of these models incorporates monetary policy equations. In macroeconomics, a number of articles have embedded term structure dynamics into the standard New-

Keynesian workhorse model (Bekaert, Cho, Moreno (2010), Rudebusch and Wu (2008)), but no models accommodate the dynamic interactions between monetary policy, risk aversion and uncertainty, uncovered in this article.

The policy implications of our work are potentially very important. Because monetary policy significantly affects risk aversion and risk aversion significantly affects the business cycle, we seem to have uncovered a monetary policy transmission mechanism missing in extant macroeconomic models. Fed chairman Bernanke (see Bernanke (2002)) interprets his work on the effect of monetary policy on the stock market (Bernanke and Kuttner (2005)) as suggesting that monetary policy would not have a sufficiently strong effect on asset markets to pop a “bubble” (see also Bernanke and Gertler (2001), Gilchrist and Leahy (2002), and Greenspan (2002)). However, if monetary policy significantly affects risk appetite in asset markets, this conclusion may not hold. If one channel is that lax monetary policy induces excess leverage as in Adrian and Shin (2008), perhaps monetary policy is potent enough to weed out financial excess. Conversely, in times of crisis and heightened risk aversion, monetary policy can influence risk aversion in the market place, and therefore affect real outcomes. Blanchard (2009) noted that the economy and financial markets had “nothing to fear but fear itself,” suggesting a role for policy to reduce these fears. His conclusion that markets were “fearful” was exactly inspired by unusually elevated VIX levels.

One disadvantage of our framework is that it does not really test the Rajan (2006) and related stories. Current stories about the potential pernicious effects of lax monetary policy give a prominent role to the length of the policy, and are explicitly asymmetric (they are about policy being too lax, not too contractionary). Such features are really not present in our linear VAR framework. We plan to investigate potential asymmetric and duration effects in an explicitly non-linear framework in the near future.

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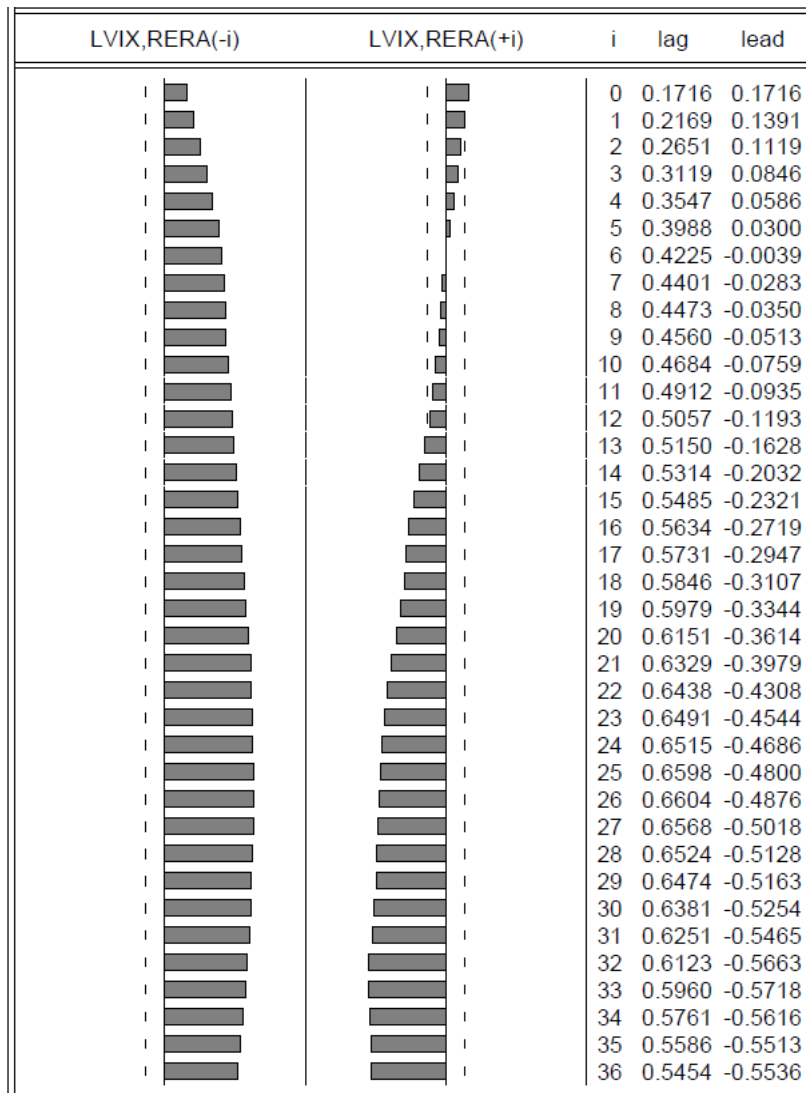
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Table 1: Description of variables

Name	Label	Description
Consumer price index	CPI	Consumer price index
Credit growth	CG	Month-on-month growth of business loans
Credit-to-GDP ratio	CGDP	Ratio of credit to GDP (intrapolated)
Fed funds rate	FED	Fed funds target rate
Hours worked	HW	Average weekly hours (private industries)
Implied volatility S&P500	LVIX	$\text{Log}(\text{VIX} / \sqrt{12})$
Industrial production	IP	Industrial production index
Jobless claims	LJOB	Log jobless claims
M1 money aggregate growth	M1	Month-on-month growth of M1
M2 net of M1 money growth	M2-M1	Month-on-month growth of (M2-M1)
(Growth of) Non-farm employment	(D)EMP	Log (difference of) employment
Producer price index	PPI	Intermediate materials
Real interest rate	RERA	FED minus annual CPI inflation rate
Repo growth	GREPO	Monthly growth in repos outstanding
Risk aversion	RA	$\text{Log}(\text{VIX}^2 / 12 - \exp(\text{UC}))$
Taylor Rule deviations	TRULE	FED minus Taylor rule rate (see p.15)
Uncertainty (conditional variance)	UC	$\text{Log}(\text{conditional variance} / 12)$
Unemployment rate	URATE	Unempl. rate minus 3-year moving average

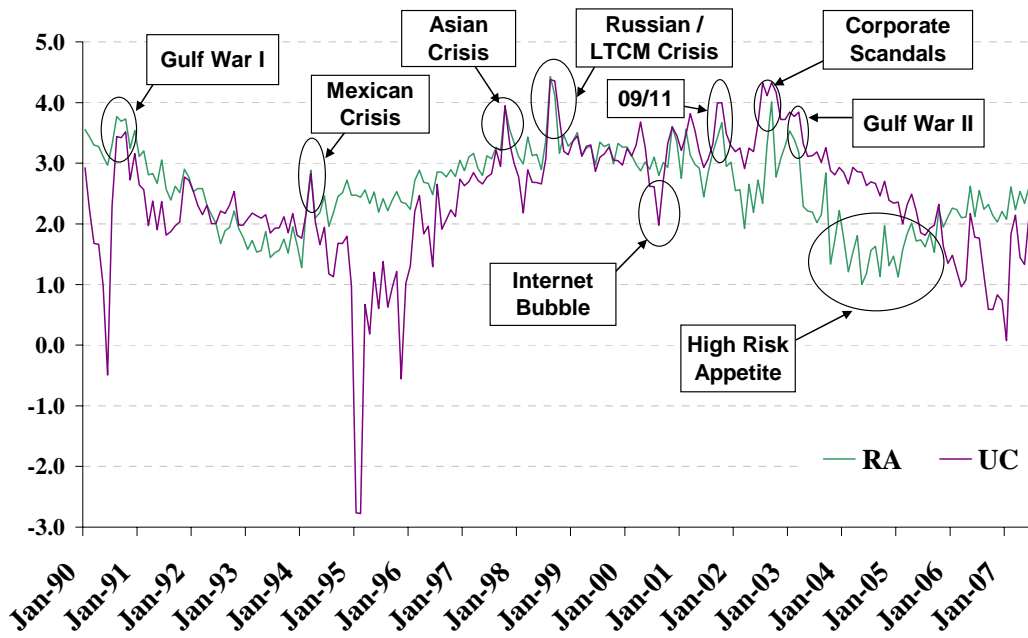
Notes: Monthly frequency, end-of-the-month data (seasonally adjusted where applicable). Source: Thomson Datastream; data on risk aversion and uncertainty are from Bekaert and Engstrom (2009).

Figure 1: Cross-correlogram LVIX RERA



Notes: The first column presents the (lagged) cross-correlogram between the log of the VIX (LVIX) and past values of the real interest rate (RERA). The second column presents the (lead) cross-correlogram between LVIX and future values of RERA. Dashed vertical lines indicate 95% confidence intervals for the cross-correlation. The third column presents the cross-correlation values. The index i indicates the number of months either lagged or led for the real interest rate variable.

Figure 2: Risk Aversion and Uncertainty



Notes: Plots of risk aversion (RA) and uncertainty (UC) for our sample period (January 1990 – July 2007).

Table 2: The VIX and Risk Aversion

Panel A: Varying γ , $Sk = -1$, $p = 0.5\%$					
Parameters	VIX	LVIX	VP	RA	
$Sk = -1, \gamma = 2$	15.9871	1.5293	0.0031	0.9357	
$Sk = -1, \gamma = 4$	17.6115	1.6261	0.0085	1.9597	
$Sk = -1, \gamma = 6$	20.1388	1.7602	0.0181	2.7112	
Panel B: Varying γ , $Sk = -2$, $p = 1\%$					
Parameters	VIX	LVIX	VP	RA	
$Sk = -2, \gamma = 2$	16.9078	1.5853	0.0061	1.6239	
$Sk = -2, \gamma = 4$	19.8412	1.7453	0.0169	2.6431	
$Sk = -2, \gamma = 6$	24.0754	1.9387	0.0355	3.3862	
Panel C: Varying W_{bm} , $\gamma = 4$, $Sk = -1$, $p = 0.5\%$					
Parameters	CRRA	VIX	LVIX	VP	RA
$\gamma = 4, W_{bm} = 0$	4.0000	17.6115	1.6261	0.0085	1.9597
$\gamma = 4, W_{bm} = 0.05$	4.2091	17.8677	1.6405	0.0094	2.0611
$\gamma = 4, W_{bm} = 0.25$	5.3234	19.5977	1.7330	0.0159	2.5844
$\gamma = 4, W_{bm} = 0.50$	7.9682	27.9344	2.0874	0.0556	3.8347

Notes: Values of the VIX on an annualized basis in percent (VIX), the log of the VIX on a monthly basis (LVIX), the annualized variance premium (VP), and our proxy for risk aversion on a monthly basis (RA) for different values of the underlying parameters, while keeping the crash return c fixed at -25%. In Panel A, the varying parameter is the coefficient of relative risk aversion γ while skewness Sk is fixed at -1. In Panel B, skewness Sk is fixed at -2. Panel C computes, for γ fixed at 4 and Sk fixed at -1, expected risk aversion (CRRA) and the other four variables for different values of the benchmark wealth level W_{bm} .

Table 3: Four-variable VAR results (DEMP, RERA, RA, UC)

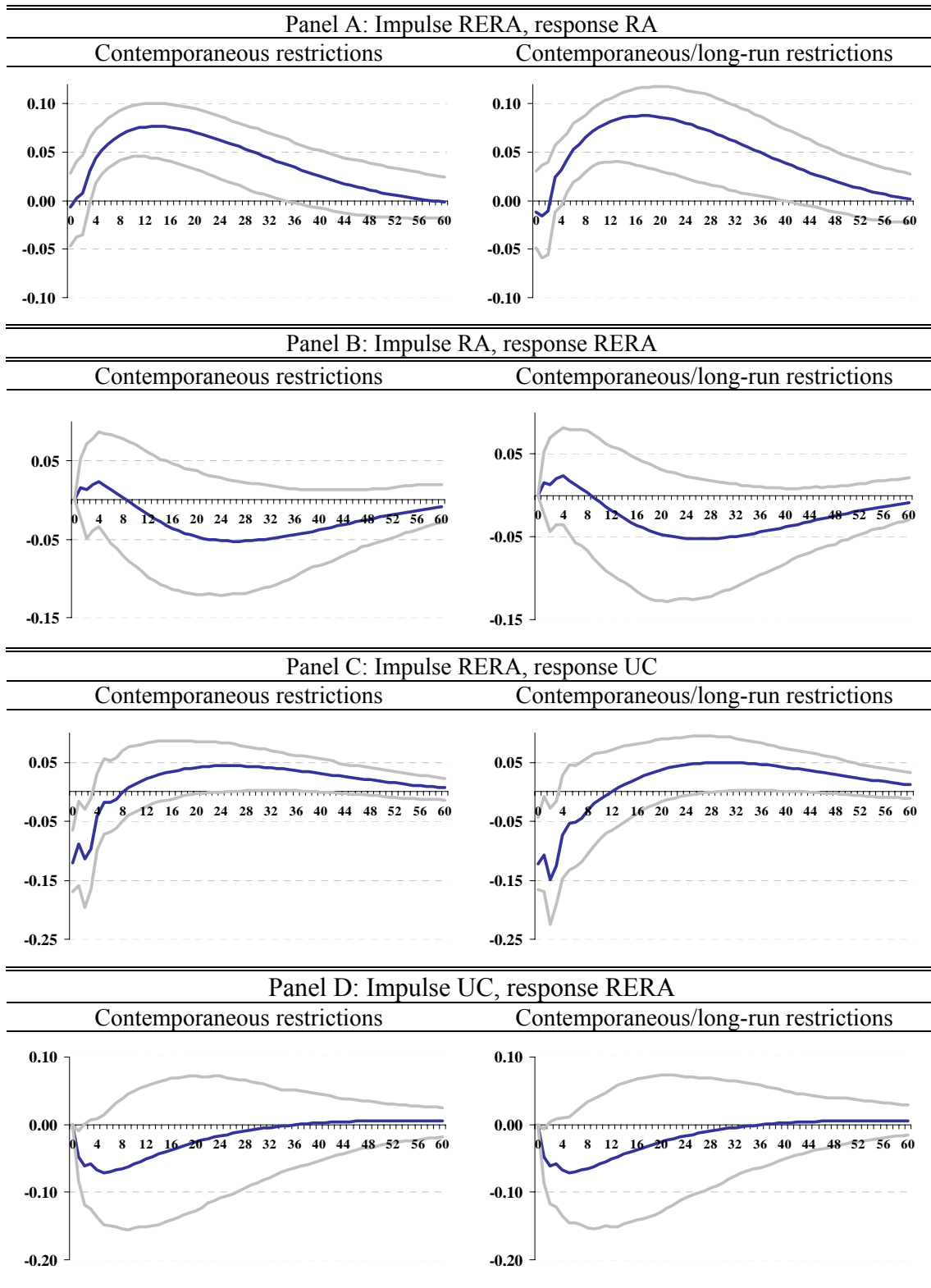
Panel A: Lag-length selection			
Lag	AIC	HQIC	SBIC
1	-8.0672	-7.9589	-7.7996*
2	-8.1979	-7.9812	-7.6627
3	-8.3350*	-8.0100*	-7.5322
4	-8.2579	-7.8246	-7.1875
5	-8.2196	-7.6779	-6.8816
6	-8.1096	-7.4595	-6.5040
7	-8.0610	-7.3027	-6.1878
8	-7.9946	-7.1279	-5.8538
9	-8.0290	-7.0540	-5.6206
10	-7.9534	-6.8700	-5.2774

Panel B: Granger causality				
Equation	Excluded	chi2	df	p-value
DEMP	RERA	6.3112	3	0.0970
DEMP	RA	8.3870	3	0.0390
DEMP	UC	5.6949	3	0.1270
DEMP	ALL	13.5410	9	0.1400
RERA	DEMP	10.2100	3	0.0170
RERA	RA	4.1227	3	0.2490
RERA	UC	6.8635	3	0.0760
RERA	ALL	18.5010	9	0.0300
RA	DEMP	7.9370	3	0.0470
RA	RERA	18.5740	3	0.0000
RA	UC	7.0723	3	0.0700
RA	ALL	31.9310	9	0.0000
UC	DEMP	6.1796	3	0.1030
UC	RERA	6.6957	3	0.0820
UC	RA	1.7631	3	0.6230
UC	ALL	12.2250	9	0.2010

Panel C: Lagrange-multiplier test			
Lag	chi2	df	p-value
1	11.9227	16	0.7493
2	20.1366	16	0.2141
3	15.2849	16	0.5039

Notes: Four-variable VAR on the log-difference of non-farm employment (DEMP), the real interest rate (RERA), risk aversion (RA) and uncertainty (UC). Panel A presents lag-length selection results based on three criteria: Akaike (AIC), Hannan-Quinn (HQIC) and Schwarz (SBIC). The star indicates the lag chosen. Panel B presents Granger causality results for the model with 3 lags (selected by Akaike and Hannan-Quinn). Panel C presents Lagrange-multiplier specification tests for the model with 3 lags (selected by Akaike and Hannan-Quinn). The null hypothesis is that there is no autocorrelation at lag order $j=1,2,3$ and the degrees of freedom are given by the square of the number of equations in the VAR, as the test examines the null hypothesis that the residuals of lag j are not jointly significant in the VAR.

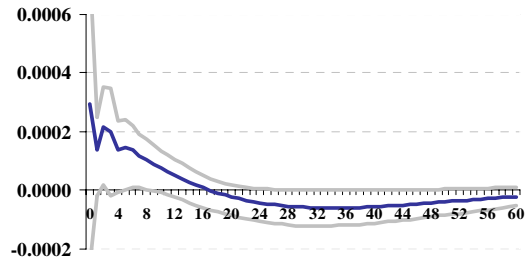
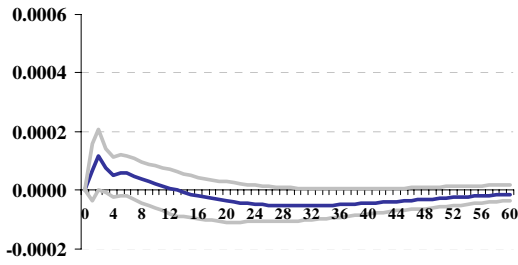
Figure 3: Structural-form IRFs for the 4-variable VAR (DEMP, RERA, RA, UC)



Panel E: Impulse RERA, response DEMP

Contemporaneous restrictions

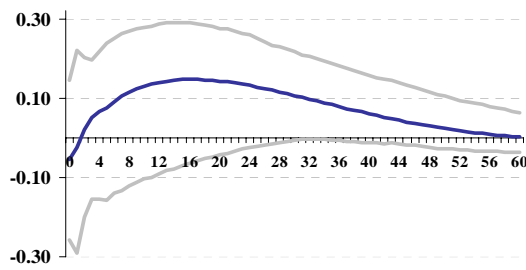
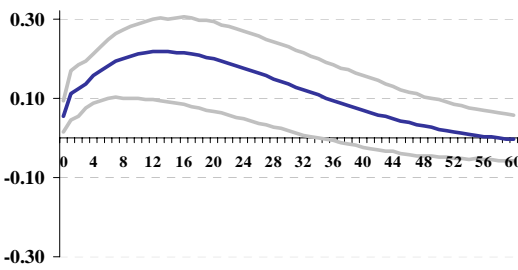
Contemporaneous/long-run restrictions



Panel F: Impulse DEMP, response RERA

Contemporaneous restrictions

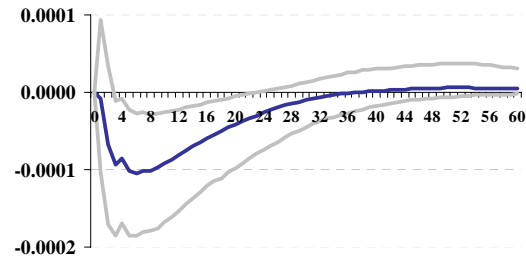
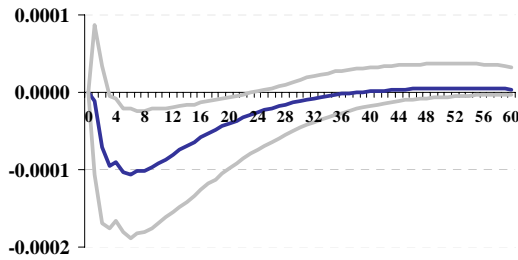
Contemporaneous/long-run restrictions



Panel G: Impulse RA, response DEMP

Contemporaneous/long-run restrictions

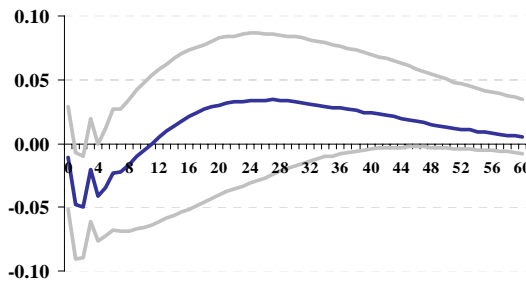
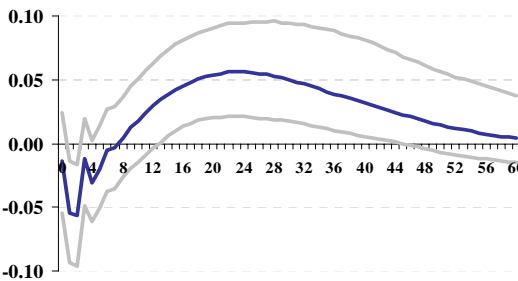
Contemporaneous/long-run restrictions

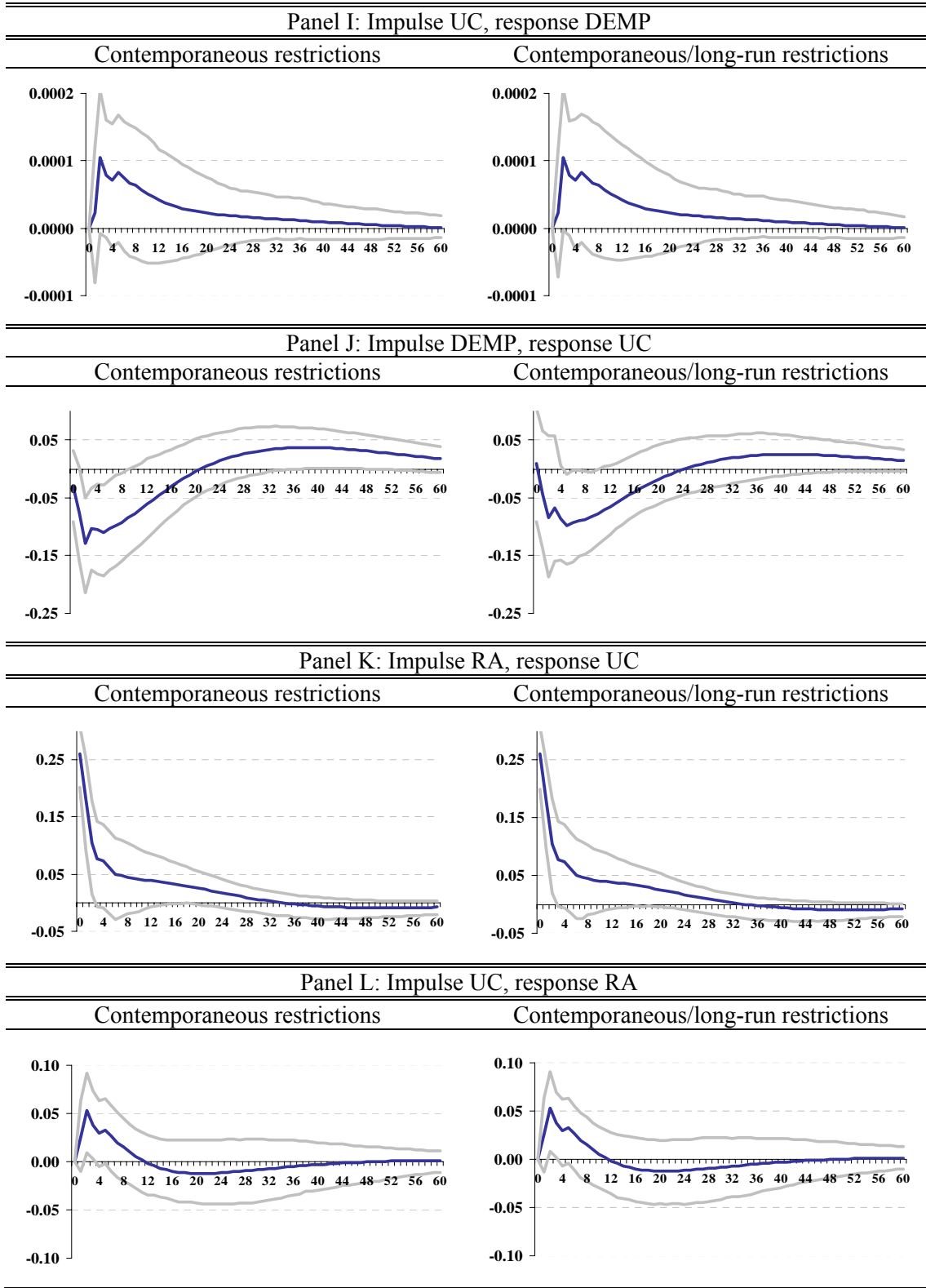


Panel H: Impulse DEMP, response RA

Contemporaneous restrictions

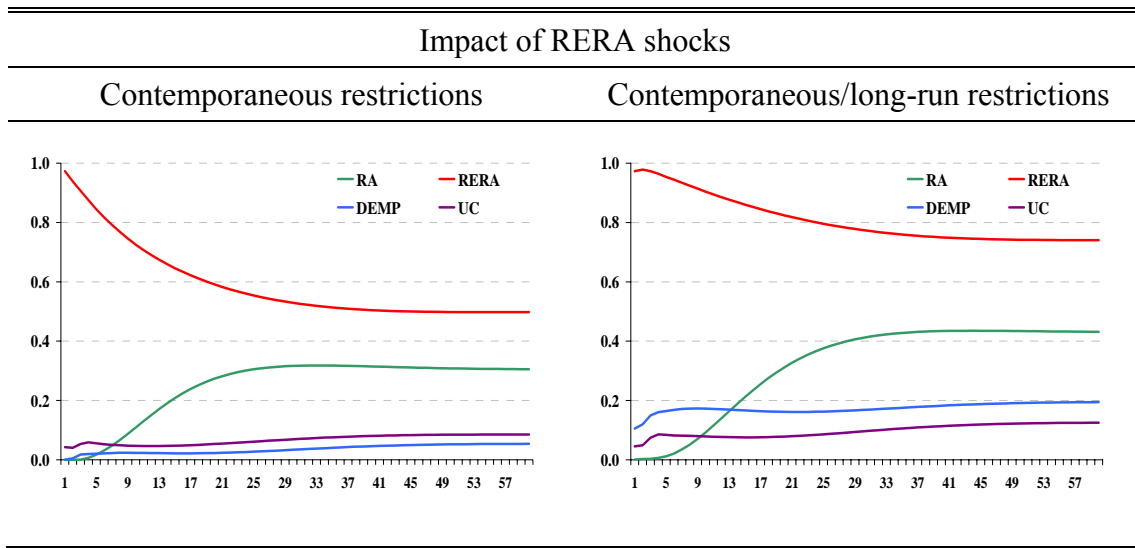
Contemporaneous/long-run restrictions





Notes: Estimated structural impulse-response functions (blue lines) and 90% bootstrapped confidence intervals (grey lines) for the model with 3 lags (selected by Akaike and Hannan-Quinn), based on 1000 replications. Panels on the left present results of the model with contemporaneous (Cholesky) restrictions, panels on the right present results of the model with contemporaneous/long-run restrictions.

Figure 4: Structural Variance Decompositions



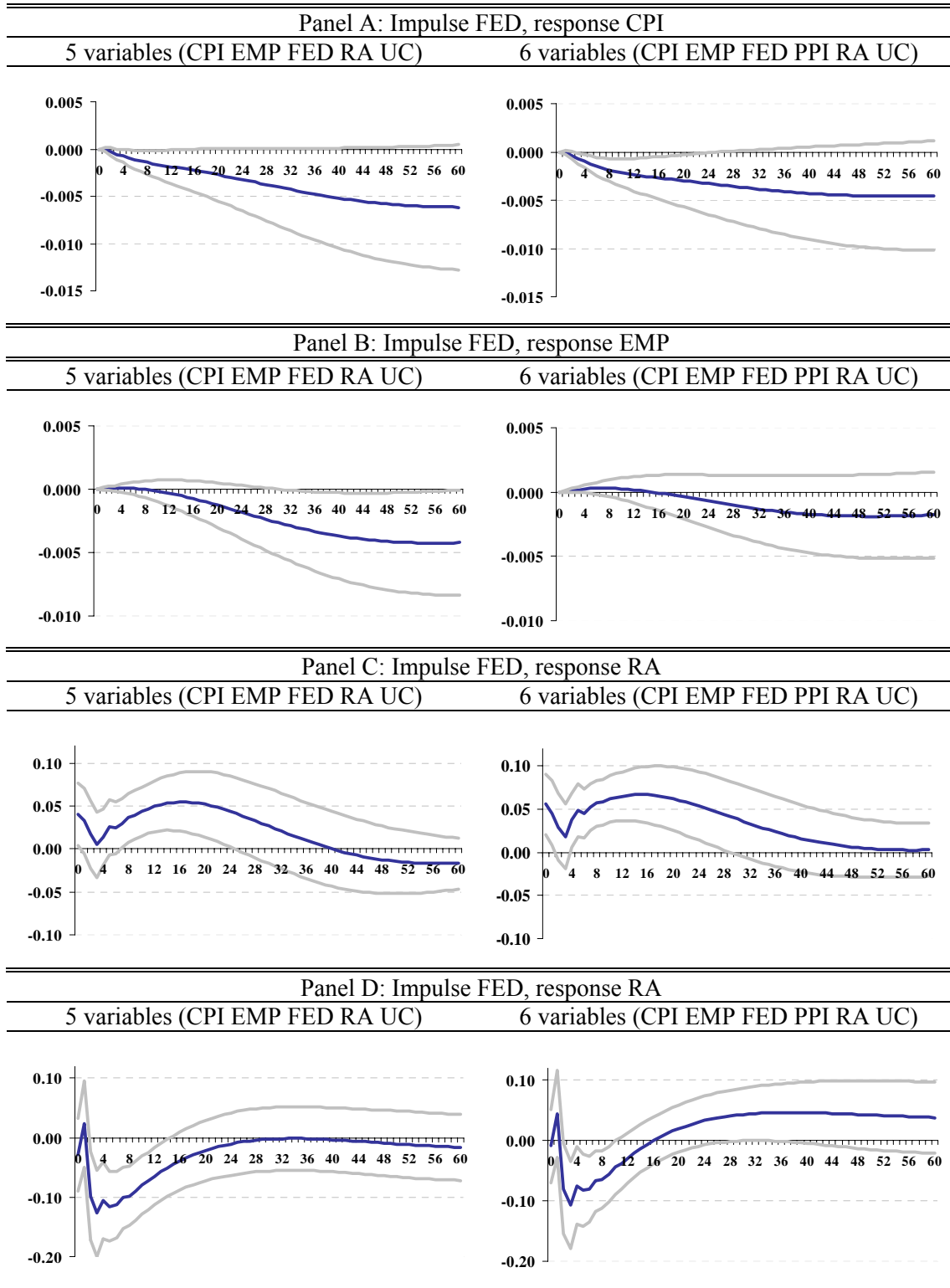
Notes: Fractions of the structural variance due to RERA shocks for the four variables DEMP, RERA, RA and UC (model with 3 lags, selected by Akaike and Hannan-Quinn). The panel on the left presents results of the model with contemporaneous restrictions, the panel on the right presents results of the model with contemporaneous/long-run restrictions.

Table 4: Robustness to monetary policy measures

Panel A: Monetary policy instrument – risk aversion pair				
MP instrument	Impulse MP, response RA		Impulse RA, response MP	
	sign	significant from-to (month)	sign	significant from-to (month)
Real interest rate				
- COR	+	4 – 34	–	--
- CLR	+	5 – 39	–	--
Taylor rule				
- COR	+	4 – 35	–	--
- CLR	+	4 – 38	–	--
Fed funds rate				
- COR	+	0, 6 – 27	–	--
- CLR	+	6 – 33	–	--
(-1)*M1 growth				
- COR	+	5 - 19	–	--
- CLR	+	14 – 30	–	--
(-1)*M1				
- COR	+	2 - 19	–	--
- CLR	+	3 – 22	–	--
Panel B: Monetary policy instrument – uncertainty pair				
MP instrument	Impulse MP, response UC		Impulse UC, response MP	
	sign	significant from-to (month)	sign	significant from-to (month)
Real interest rate				
- COR	-/+	0 - 3 (-), 25 - 39 (+)	–	0 – 1
- CLR	-/+	0 - 3 (-), 29 - 42 (+)	–	0 – 1
Taylor rule				
- COR	-/+	0 (-), 26 - 38 (+)	–	0 – 1
- CLR	-/+	0 (-), 25 - 44 (+)	–	0 – 1
Fed funds rate				
- COR	-/+	4 - 5 (-), --	–	--
- CLR	-/+	2 - 8 (-), --	–	--
(-1)*M1 growth				
- COR	-/+	--	–	--
- CLR	-/+	--	–	--
(-1)*M1				
- COR	-/+	--, 10 - 32 (+)	–	4 – 44
- CLR	-/+	--, 14 - 42 (+)	–	5 – 43

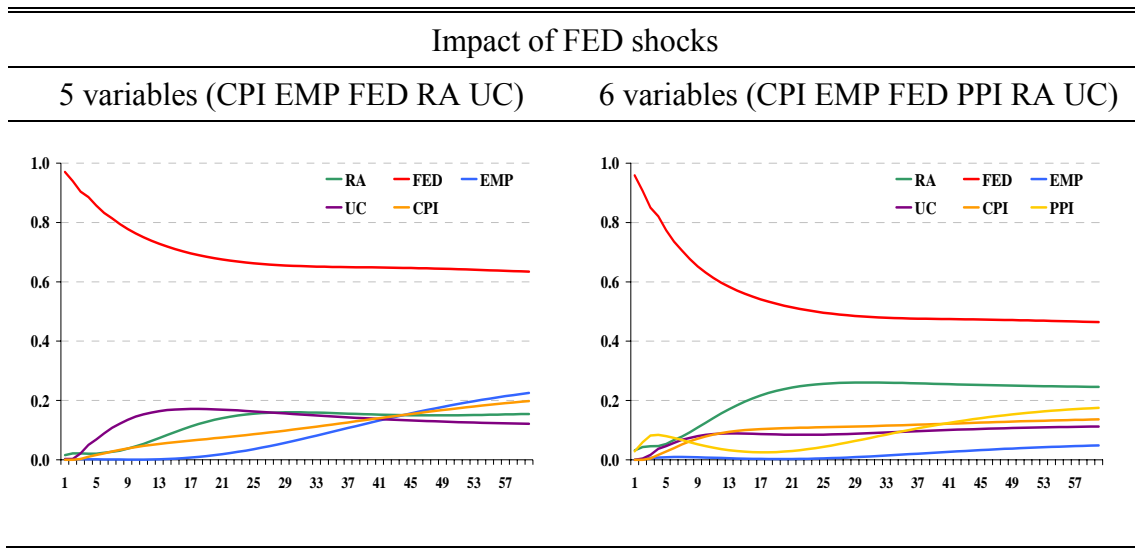
Notes: Table 4 summarizes results for the interactions between monetary policy (as represented by four different measures) and risk aversion (RA) in Panel A and between monetary policy and uncertainty (UC) in panel B in the four-variable model with DEMP, MP, RA and UC. The MP measures considered are: real interest rate, Taylor rule deviations, Fed funds rate, and the negative of the M1 growth. The last row in each panel considers a specification with M1 and employment both entering in levels rather than growth rates. Each Panel lists for how many months impulse-response functions (from the VAR with contemporaneous (COR) and contemporaneous/long-run (CLR) restrictions, respectively) were statistically significant within the 90% confidence interval in the direction indicated in the column “sign”.

Figure 5: Effects of a monetary policy shock (5 and 6-variable VARs)



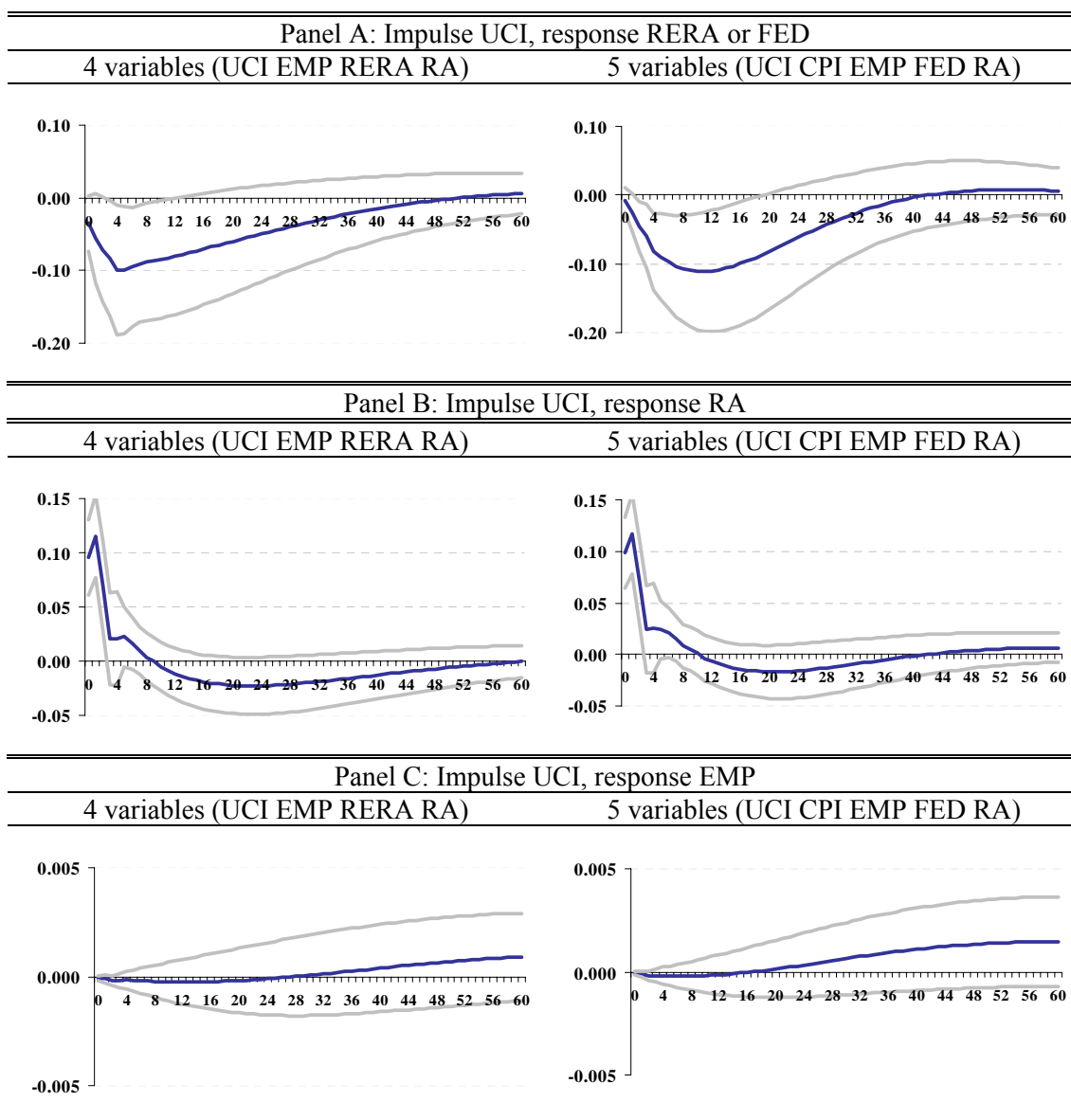
Notes: Estimated structural impulse-responses to a monetary policy shock (blue lines) and 90% bootstrapped confidence intervals (grey lines), based on 1000 replications. Panels on the left present results of the 5-variable model (Cholesky ordering in parenthesis), panels on the right present results of the 6-variable model (Cholesky ordering in parenthesis).

Figure 6: Structural Variance Decompositions (5- and 6-variable VARs)



Notes: Fractions of the structural variance due to FED shocks for the 5-variable model (Cholesky ordering in parenthesis) and the 6-variable model (Cholesky ordering in parenthesis).

Figure 7: Effects of an uncertainty shock (4- and 5-variable VARs)



Notes: Estimated structural impulse-responses to an uncertainty shock (blue lines) and 90% bootstrapped confidence intervals (grey lines), based on 1000 replications. Uncertainty (UCI) is an indicator variable taking on a value of 1 if $UC > 1.65$ standard deviations above the HP detrended mean of the UC series and 0 otherwise. Panels on the left present results of the 4-variable model (Cholesky ordering in parenthesis), panels on the right present results of the 5-variable model (Cholesky ordering in parenthesis).

Table 5: Channels

Panel A: Real interest rate – risk aversion pair				
Channel	Impulse RERA, response RA		Impulse RA, response RERA	
	sign	significant from-to (month)	sign	significant from-to (month)
Repo growth				
- COR	+	5 – 38	–	--
- CLR	+	5 – 41	–	--
(M2-M1) growth				
- COR	+	5 – 37	–	--
- CLR	+	9 – 38	–	--
Credit growth				
- COR	+	5 – 40	–	--
- CLR	+	5 – 37	–	--
Δ Credit/GDP				
- COR	+	5 – 39	–	--
- CLR	+	5 – 40	–	--
Panel B: Real interest rate – uncertainty pair				
MP instrument	Impulse RERA, response UC		Impulse UC, response RERA	
	sign	significant from-to (month)	sign	significant from-to (month)
Repo growth				
- COR	–	0 – 5	–	--
- CLR	–	0, 3	–	--
(M2-M1) growth				
- COR	–	0 – 4	–	0 – 1
- CLR	–	0 – 4	–	0 – 1
Credit growth				
- COR	–	0 – 4	–	0 – 2
- CLR	–	0 – 4	–	0 – 1
Δ Credit/GDP				
- COR	–	0 – 4	–	0 – 1
- CLR	–	0 – 4	–	0 – 1

Notes: Table 5 summarizes results for the interactions between monetary policy (as represented by the real interest rate) and risk aversion (RA) in Panel A and between monetary policy and uncertainty (UC) in Panel B in the four-variable model with a Channel variable, RERA, RA and UC. Each Panel lists the corresponding Channel variable (left column) and for how many months impulse-response functions (from the VAR with contemporaneous (COR) and contemporaneous/long-run (CLR) restrictions, respectively) were statistically significant within the 90% confidence interval in the direction indicated in the column “sign”.