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Abstract

In this paper, we investigate the dynamic relationship between financial market volatility, macroeconomic fundamentals and investor sentiment, employing a two-factor model to decompose volatility into a persistent long-run component and a transitory short-run component. Using a structural VAR model with Bayesian sign restrictions, we show that adverse shocks to aggregate demand and supply cause an increase in the persistent component of both stock and bond market volatility, and that adverse shocks to the persistent component of either stock or bond market volatility cause a deterioration in macroeconomic fundamentals. We find no evidence of a relationship between the transitory component of volatility and macroeconomic fundamentals. Instead, we find that the transitory component is more closely associated with changes in investor sentiment. Our results are robust to a wide range of alternative specifications.

Key words: Stock and bond market volatility, two-factor volatility model, macroeconomic fundamentals, structural vector autoregression, Bayesian estimation.

JEL classification: C32, E32, E44.

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1. Introduction

It is by now well established that financial market volatility and macroeconomic fundamentals are inextricably linked. This link has been analysed from two, quite distinct perspectives. Early studies focussed on the macroeconomic determinants of financial market volatility (see, for example, Officer, 1972; Schwert, 1989), and these have been used to develop improved models for forecasting volatility, particularly over longer horizons (see, for example, Engle and Rangel, 2008; Engle, Ghysels and Sohn, 2013). Another, more recent strand of the literature has investigated the impact that financial market volatility has on the real economy, both theoretically (see, for example, Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry 2014; Basu and Bundick, 2015; Berger, Dew-Becker and Giglio, 2016; Gourio, 2013; Leduc and Liu, 2015) and empirically (see, for example, Bloom, 2009; Bloom, Baker and Davis, 2015; Gilchrist, Sim and Zakrajsek, 2014; Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2015). Both of these strands of the literature focus on total volatility. However, it is well documented that financial market volatility is characterised by a two-factor process, with a slowly varying long run component and a strongly mean-reverting short run component (see, for example, Ding and Granger, 1996; Engle and Lee, 1999; Gallant, Hsu and Tauchen, 1999; Alizadeh, Brandt and Diebold, 2002; Chernov, Gallant, Ghysels and Tauchen, 2003; Adrian and Rosenberg, 2008).

In this paper, we decompose the volatility of stock and bond returns into a long run persistent component and a short run transitory component and investigate the bidirectional relationships that each of these volatility components has with macroeconomic fundamentals and investor sentiment. We study the macroeconomic properties of the two volatility components separately for three reasons. Firstly, since the commonly used measure of total volatility conflates the two components, policy makers and practitioners are better served by utilizing a volatility measure that is more closely associated with the economy. Secondly, having a good understanding of how these volatility components interact with the economy will enable policy makers and practitioners to obtain more accurate forecasts of volatility conditional on macroeconomic shocks. Thirdly, although the financial economics literature has extensively documented that volatility is characterized by a two-component process, the macroeconomics literature has yet to investigate the economic implications of this. Following Engle and Rangel (2008) and Engle et al. (2013), we hypothesise that the long run component of volatility is related to macroeconomic fundamentals that are associated with future cash flows and discount rates, while the short run component is related to the transitory determinants of volatility, such as investor sentiment. To explore this notion, we use the semi-parametric cyclical volatility model of Harris, Stoja and Yilmaz (2011) to decompose financial market volatility into a long run persistent component and a short run transitory component. We then estimate a structural vector autoregression (SVAR) model for the components of financial market volatility, real activity (measured by output growth and inflation), monetary policy (as reflected in the short term interest rate) and investor sentiment. We impose standard a priori sign restrictions that are defined according to well established micro-based macroeconomic principles in order to identify the structural shocks. We measure the impact of adverse shocks to aggregate demand, aggregate supply and investor sentiment on both stock and bond market volatility and the impact of adverse shocks to stock and bond market volatility on macroeconomic fundamentals and investor sentiment.

The model is estimated for the U.S. using monthly data over the period July 2001 to June 2015. We show that adverse shocks to aggregate demand and aggregate supply cause an increase in both stock and bond market volatility and that adverse shocks to either stock or bond market volatility cause a deterioration in macroeconomic fundamentals. Moreover, we show that it is the persistent component, not the transitory component, that is more closely related to macroeconomic fundamentals. In light of these findings, we then estimate a smaller SVAR model to examine the dynamic relationship between changes in investor sentiment and transitory volatility. We find that an unanticipated improvement in sentiment first reduces and then increases transitory volatility. Moreover, negative shocks to transitory volatility lead to a significant improvement in sentiment. This suggests that transitory volatility and investor sentiment are closely linked. Our results are robust to a wide range of alternative model specifications.

Our work is related to Berger et al. (2016), who investigate the relationship between stock market volatility and the real economy in the U.S., using data on both realized volatility and option-implied expectations of volatility. They show that, consistent with the findings of Bloom (2009) and Basu and Bundick (2015), shocks to current realized volatility are contractionary, while shocks to expected volatility are expansionary. The authors argue that these facts are inconsistent with models in which increases in expected volatility cause contractions, but are in line with the predictions of a simple model in which aggregate technology shocks are negatively skewed. Our work differs from that of Berger et al. (2016) in a number of respects. First, we consider the bidirectional relationship between financial market volatility and the wider economy; in other words, we are interested also in the impact that conventional macroeconomic shocks have on volatility. Second, by decomposing total volatility into its long run persistent and short run transitory components, we are able to more precisely define the relationship between financial market volatility and macroeconomic fundamentals and we present evidence to support this. Moreover, it allows us to investigate the impact of non-macroeconomic determinants of volatility and in particular, to test hypotheses about the relationship between the transitory component of volatility and investor sentiment. Standard asset pricing theory suggests that sentiment has no influence on economic activity. However, De Long, Shleifer, Summers and Waldmann (1990) show that with limits to arbitrage, sentiment-based decisions of uninformed investors lead to excess volatility. Changes in sentiment can trigger strong liquidity shocks with a significant impact on volatility (Campbell, Grossman and Wang, 1993). In the short run, a change in one set of prices may influence investor sentiment triggering changes in a seemingly unrelated set of prices (Eichengreen and Mody, 1998). Indeed, Baek, Bandopadhyaya and Du (2005) argue that changes in investor sentiment explain asset price movement in the short-term better than fundamental factors.[1] Finally, while Berger et al. (2016) focus on the U.S. stock market, we examine both the stock and bond markets.

[1] Non-economic events such as weather, sport and aviation disasters can also shift sentiment leading to changes in asset prices in the short term (see, for example,

Our work is also related to Bekaert, Hoerova and Lo Duca (2013), who decompose the VIX index (which is an estimate of the risk neutral volatility of the S&P 500 index) into the conditional variance of the S&P 500 and the variance risk premium, and explore the relationship between each of these components and US monetary policy. Using a structural VAR with a variety of identification schemes for monetary policy shocks, they show that loose monetary policy leads to a sustained reduction in risk aversion and, to a lesser extent, a reduction in uncertainty. The causal link from risk aversion and uncertainty to monetary policy is shown to be much weaker. Using the same decomposition, Bekaert and Hoerova (2014) show that the variance risk premium is a good predictor of stock returns, while conditional volatility is a much better predictor of economic activity, as measured by growth in industrial production, and is also a better predictor of financial instability. While a number of our findings are consistent with the results that both Bekaert et al. (2013) and Bekaert and Hoerova (2014) report, our work is distinguished by the fact that it is concerned with the decomposition of conditional volatility into its short run transitory component and long run persistent component, and the relationship that each of these has with macroeconomic fundamentals, monetary policy and investor sentiment.

Finally, our work is related to the literature on the macroeconomic determinants of multifactor volatility. Engle and Rangel (2008) develop a Spline-GARCH model in which volatility is modelled as a combination of a low frequency component that is determined by both the level and volatility of macroeconomic variables, market development and market size, and a high frequency component that is modelled as a GARCH process. They estimate the model for a sample of developed and emerging markets and show that the Spline-GARCH model provides less noisy estimates of low frequency volatility than annual realized volatility. Engle et al. (2013) develop this idea further and propose a GARCH-MIDAS model that combines a GARCH model for daily stock return data and a MIDAS polynomial for monthly, quarterly and bi-annual macroeconomic variables. They compare the GARCH-MIDAS model with the Spline-

Hirshleifer and Shumway, 2003; Kamstra, Kramer and Levi, 2003; Edmans, Garcia and Norli, 2007; Kaplanski and Levy, 2010).

GARCH model of Engle and Rangel (2008) and a component GARCH model that combines realized volatility measured at different frequencies. They find that over a long sample of data for the U.S., the levels and volatility of output growth and inflation are useful predictors of future market volatility. Like Engle and Rangel (2008), we also recognise the component structure of volatility and use a semi-parametric approach to estimate it. However, our objective is to map the bidirectional relationships between financial market volatility and the wider economy. Moreover, the structural VAR estimation framework also allows us to better uncover the dynamics of these relationships. Additionally, while Engle and Rangel (2008) and Engle et al. (2013) focus on the low frequency long run component of volatility, which they relate to macroeconomic fundamentals, we also explore the role of the high frequency short run component of volatility and its relationship with investor sentiment. The literature contains few studies that examine this relationship. Brown (1999) shows that shifts from the average level of sentiment are positively related to volatility, while Lee, Jiang and Idro (2002) find that bullish changes in sentiment lead to decreases in volatility and vice versa. However, Wang, Keswani and Taylor (2006) find limited evidence in support of a relationship between sentiment and volatility.

The remainder of this paper is organized as follows. In the following section, we describe the decomposition of volatility into its persistent and transitory components. In Section 3, we discuss the data used in the analysis and the structural VAR methodology. Section 4 presents the empirical results of the analysis. Section 5 considers the relationship between the persistent and transient components of volatility and market sentiment. Section 6 provides a summary of the paper, some concluding comments and suggestions for further work.

2. The Cyclical Volatility Model

In this section, we outline the cyclical volatility model of Harris, Stoja and Yilmaz (2011, hereafter HSY), which we use to extract the long run persistent and short run transitory components of volatility that are used in the empirical analysis. While other models could also be used, the HSY framework offers a simple and flexible way to decompose volatility. Suppose that the natural logarithm of the asset price at time s, denoted $p(s)$, follows a continuous time diffusion given by:

$$dp(s) = \sigma^2(s)dW(s) \tag{1}$$

where $dW(s)$ is the increment of a Wiener process and $\sigma^2(s)$ is the instantaneous variance, which is strictly stationary and independent of $dW(s)$.[2] Suppose that we observe the price at intervals $t = 1, \dots, T$. Conditional on the sample path of $\sigma^2(s)$, the logarithmic return, $r_t = p_t - p_{t-1}$, is normally distributed with integrated variance defined by:

$$\sigma_t^2 = \int_{t-1}^{t} \sigma^2(s)ds \tag{2}$$

HSY assume that the integrated standard deviation follows a two-factor dynamic structure, with a persistent long run component, q_t, and a transitory short run component, c_t:

$$\sigma_t = q_t + c_t \tag{3}$$

This specification is motivated by the findings of a number of authors who show that volatility is characterised by a factor structure. For example, Engle and Lee (1999) find that the component GARCH model which decomposes volatility into a persistent long run component and a transitory short run component that is mean-reverting towards the persistent component, provides a better fit to the data than an equivalent one-factor model. Alizadeh et al. (2002) estimate both one-factor and two-factor range-based stochastic volatility models for the daily returns of a number of exchange rates and find that the evidence strongly supports a two-factor model with one highly persistent factor

[2] For convenience, we assume that the drift of the log price process is zero, which is a common assumption when dealing with short horizon returns. However, it is straightforward to relax this assumption.

and one rapidly mean-reverting factor. Similarly, Brandt and Jones (2006) estimate one-factor and two-factor range-based EGARCH models for daily returns on the S&P 500 index. They too show that volatility is well characterised by a two-factor model with one highly persistent factor and one strongly stationary factor. In contrast with these authors, however, HSY leave the precise dynamics of the long run component, q_t, unspecified and instead estimate it non-parametrically. Conditional on the trend, HSY assume that the transitory component $c_t = \sigma_t - q_t$ follows a stationary first order autoregressive process:

$$c_t = \alpha c_{t-1} + u_t \tag{4}$$

where u_t is a random error term with zero mean and constant variance. The parameter $\alpha < 1$ measures the speed of reversion of volatility to the long run trend q_t. The integrated volatility, σ_t, is unobserved, but can be easily estimated using a measure of realized volatility (see, for example, Andersen, Bollerslev and Diebold, 2004) or the intraday range (see, for example, Parkinson, 1980). HSY use the range-based cyclical model to generate multi-step out-of-sample forecasts of daily exchange rate volatility and show that it provides a significant improvement over the one-and two-factor range-based EGARCH models and the range-based FIEGARCH model of Brandt and Jones (2006).

In this paper, we use the cyclical volatility model of HSY to estimate the persistent and transitory components of the realized standard deviation of monthly stock and bond returns. Rather than applying the model directly to monthly returns, we extract the persistent component from the daily standard deviation and aggregate this to yield the persistent component of the monthly realized standard deviation. We then use this to compute the transitory component of the monthly realized standard deviation. We proxy the daily integrated standard deviation by the absolute return and, following HSY, apply the one-sided low-pass filter of Hodrick and Prescott (1997) to estimate the persistent component. We set the smoothing parameter in the Hodrick-Prescott filter to the commonly used value of 100 multiplied by the squared frequency of the data, which for daily data (assuming 240 trading days per year) is 5,760,000 (see, for example, Baxter and King, 1999). In order to prevent look-ahead bias, we apply the cyclical volatility estimator to a rolling window of 500 observations. For each iteration of the rolling window procedure, we save the estimated value of the persistent component for the most recent day, which we denote q_{t_i}, where t_i represents day *i* of month *t*. The rolling window daily persistent component is then aggregated to yield the persistent component of the standard deviation for each month *t*:

$$q_t = \left(\sum_{i=1}^{N_t} q_{t_i}^2\right)^{0.5} \tag{5}$$

where N_t is the number of days in month *t*. The transitory component of the month *t* standard deviation is then computed as:

$$c_t = \sigma_t - q_t \tag{6}$$

where the realized standard deviation of month *t* is given by:

$$\sigma_t = \left(\sum_{i=1}^{N_t} r_{t_i}^2\right)^{0.5} \tag{7}$$

The monthly persistent and transitory components are then used in the empirical analysis, as described below.[3]

[3] To check that our results are not sensitive to the precise way in which the monthly persistent and transitory components of volatility are estimated, we undertook a number of robustness tests. First, we used the realized variance, range-based variance and range-based standard deviation in place of the realized standard deviation. Second, we used a range of values for the smoothing parameter of Hodrick-Prescott filter from 10^5 to 10^7. Third, we used the band pass filter of Christiano and Fitzgerald (2003), with oscillation parameters of (2, 120), (2, 240), (12, 240), (120, 240) and (200, 240). Finally, we used alternative rolling window lengths of 250 and 750 days. In all cases, our results are qualitatively similar and our conclusions are broadly unchanged. The results of these robustness tests are available on request.

3. Data and Estimation Methodology

3.1. *Sample and Data*

Our volatility estimation sample comprises monthly data for the period January 1990 to June 2015.[4] We use the cyclical volatility model described in the previous section to estimate the persistent and transitory components of the standard deviation of aggregate stock and bond returns for the U.S. Daily return index data for equities and bonds were obtained from Datastream (codes TOTMKUS and BMUS10Y, respectively) for the period 03 February 1988 to 30 June 2015, and used to construct daily log returns. For the sake of brevity, we do not report summary statistics for the daily return series, but note that consistent with evidence reported elsewhere, for both markets, the series are highly non-normal with positive excess kurtosis and negative skewness. Returns are serially uncorrelated, but squared returns are highly autocorrelated, indicative of volatility clustering. The first 500 observations (i.e. 03 February 1988 to 02 January 1990) were reserved for initial estimation of the cyclical volatility model and then the rolling window procedure described in the previous section was used to estimate the persistent and transitory components of the monthly realized standard deviation over the estimation sample. Panel A of Figure 1 plots the realized standard deviation and the persistent component of stock market volatility, while Panel B plots the transitory component. Realized volatility displays very pronounced volatility clustering. The three periods of high volatility during the dotcom boom and bust, the 2008-2009 financial crisis and the 2010-2011 Eurozone crisis are evident, with increases in both the persistent and transitory components of volatility.[5]

[Figure 1]

[4] The SVAR estimation sample starts in July 2001 because we are constrained by the availability of the monthly Crash Confidence Index, which we discuss below.

[5] The autoregressive parameters for total, persistent and transitory stock volatility are 0.76, 0.93 and 0.33, respectively, while for bond volatility they are 0.66, 0.90 and 0.14 respectively. Results from statistical tests, including the Augmented Dickey-Fuller test and Kwiatkowski-Phillips-Schmidt-Shin test, show no evidence of a unit root in any series.

We are interested in exploring the relationship between financial market volatility and various aspects of the wider economy. In particular, we construct a model that captures the dynamics of the real economy (measured by output and prices), the monetary policy (as reflected in the short term interest rate) and investor sentiment. The data used to construct the macroeconomic variables in our model are obtained from Datastream. Real output growth (g_t) for the U.S. is measured by the monthly logarithmic change of seasonally adjusted industrial production at constant prices (code USIPTOT.G). The inflation rate (π_t) is measured by the monthly logarithmic change in the seasonally adjusted consumer price index (code CPIAUCSL). The short term interest rate (r_t) is the Federal Funds rate (codes USFDFUND). As a proxy for investor sentiment (s_t), we use the U.S. Crash Confidence Index provided by Robert Shiller.[6] Owing to the availability of this index, the estimation sample for the SVAR that includes investor sentiment starts from July 2001.

3.2. *VAR Methodology*

In order to explore the relationship between volatility and the wider economy, we employ the structural vector autoregression methodology (Sims, 1980). In particular, we consider the following VAR system:

$$Y_t = A_0 + \sum_{k=1}^{p} A_k Y_{t-k} + u_t \tag{8}$$

where $Y_t = [vol_t, g_t, \pi_t, r_t, s_t]'$ is the 5×1 vector of variables measured in month t, A_0 is an 5×1 vector of constants, A_k is the 5×5 matrix of parameters for lag k and u_t is a 5×1 vector of reduced form residuals that are assumed to be normally distributed with

[6] The U.S. Crash Confidence Index was obtained from http://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/stock-market-confidence-indices/us-crash-confidence-index. The index is based on a survey of respondents who attach a probability of less than 10 percent to a stock market crash in the next six months. Higher index values are associated with more positive investor sentiment.

mean zero and covariance matrix Σ. vol_t is, in turn, total volatility, σ_t, the long run persistent component of volatility, q_t, or the short run transitory component, c_t. We first estimate the model using OLS and employ the Schwartz Bayesian Criterion to select a lag length for the VAR of $p = 3$. Diagnostic tests suggest that the resulting model is well specified.

3.3. *Structural Shock Identification*

We adopt the Bayesian sign restriction framework to identify structural shocks (see Uhlig, 2005; Arias, Rubio-Ramirez and Waggoner, 2014). There are two advantages to this approach. First, with respect to the structural macroeconomic shocks, we are able to draw on standard theoretical predictions concerning output, prices and the short-term interest rate. Second, we remain agnostic about the responses of financial market volatility and investor sentiment to the structural macroeconomic shocks. Denoting v_t as the vector of structural shocks, we assume the following relationship between reduced-form and structural shocks:

$$v_t = S^{-1} u_t \tag{9}$$

In the current set-up, the orthogonal structural shock identification lies in the specification of the 'contemporaneous' matrix S. Technically, if P is the Cholesky decomposition of Σ such that $S^{-1} = P$ and $\Sigma = PP'$, it follows that $\tilde{S}^{-1} = PD$ also satisfies $\Sigma = PP'$ if D is orthonormal (that is $DD' = I$). In other words, we can repeatedly draw orthonormal rotation matrices D and retain those matrices $\tilde{S}^{-1} = PD$ which give impulse response functions satisfying our a priori sign restrictions.

We identify the following structural macroeconomic shocks:[7]

[7] We note that these structural shocks are not explained by any endogenous variables. Instead, they are constructed from the reduced-form residuals that are *unexplained* by the endogenous variables in the SVAR system.

- Adverse *aggregate demand* shocks drive down output growth, the inflation rate and short-term interest rate contemporaneously;

- Adverse *aggregate supply* shocks drive down output growth, but drive up the inflation rate and short-term interest rate contemporaneously;

- Adverse *monetary policy* shocks drive up the short-term interest rate but lead to lower output growth and inflation rate contemporaneously.

This way of identifying the three macroeconomic shocks is based on micro-founded macroeconomic models and is subject to a broad consensus in the macroeconomics literature (see, for example, Canova and de Nicolo, 2003). We deliberately leave out any restrictions on the contemporaneous responses of financial market volatility and investor sentiment, reflecting the fact that we are agnostic about the endogenous responses of these variables with respect to the structural macroeconomic shocks. To complete our shock identification scheme, we introduce two more shocks:

- Adverse *investor sentiment* shocks are assumed to be associated with no contemporaneous change in real activity, but its subsequent impact is unrestricted. This reflects the assumption that a shock to investor sentiment takes at least one period to be transmitted to the economy. The direction of the resulting impact on financial market volatility is unrestricted;

- Adverse *financial market volatility* shocks are assumed to be associated with no contemporaneous change in either investor sentiment or real activity, but its subsequent impact is unrestricted. This reflects our assumption that a shock to financial market volatility takes at least one period to impact investor sentiment and the real economy.

The sign restrictions associated with the three macroeconomic shocks, the investor sentiment shock and the financial market volatility shock are summarised in Table 1. The five structural shocks are orthogonal to each other by construction.

[Table 1]

3.4. *Model Estimation and Impulse Response Functions*

The model is estimated using Bayesian methods with uninformative priors. Bayesian estimation carries the advantage of incorporating both parameter and shock uncertainty during estimation. Being a simulation-based method, it is also compatible with the simulation requirement of sign restrictions. Each model is estimated with 5000 simulations, with the first 1000 draws as burn-in.

Impulse response functions, which are determined by the estimated SVAR coefficients and our structural shock identification, provide a useful way to investigate the endogenous propagation of structural shocks within an economic system. The responses are interpreted as deviations from the long run, steady-state value that prevails before the system is perturbed by the shock. Our objective is to uncover the bidirectional relationship between financial market volatility and the wider economy For this reason, we focus on two types of impulse response. The first is the endogenous responses of financial market volatility conditional on the following four adverse shocks: aggregate demand shocks; aggregate supply shocks; monetary policy shocks; and investor sentiment shocks. The second is the response of output growth, inflation, the interest rate and investor sentiment to an adverse shock to financial market volatility. As noted above, we separately consider the role of total volatility, the long run persistent component of volatility and the short run transitory component of volatility.

4. Empirical Results

In this section, we report the results of estimating the SVAR model given by (8). For the sake of brevity, we do not report the estimated parameters of the SVAR model, although these are available on request. Instead, we focus on the impulse responses that are implied by the estimated SVAR coefficients. We first present detailed results for the U.S. using stock market volatility. We then provide a brief summary of our findings using bond market volatility. For these cases, we report only a selection of the empirical results. In each case, the figure presents the response from the SVAR specified using either total volatility (the black line) or the persistent component of volatility (the blue line), Following Sims and Zha (1999), the figure shows also the associated 68 percent confidence interval (the black and blue dashed lines, respectively),[8]

Figure 2 presents the responses of output growth, inflation, the interest rate, sentiment and stock market volatility to an adverse aggregate demand (AD) shock, represented by a reduction of 35 basis points (bp) in output growth, a fall of 10 bp in inflation and a slight decrease in the interest rate on impact.[9,10] Such a shock causes significant impact to the real economy for about eight months. An AD shock has a statistically significant, positive impact on stock market volatility, with a similar magnitude for both total volatility and persistent volatility. The peak response of persistent volatility occurs later than it does for total volatility and the impact takes longer to dissipate, reflecting the smoothed nature of

[8] Sims and Zha (1999) argue that that the conventional frequentist error bands can be misleading because they mix information about parameter location with information about model fit. They propose likelihood-based bands and suggest using 68% interval bands to provide a more precise estimate of the true coverage probability (see also Blanchard and Perotti, 2002; Uhlig, 2005).

[9] Sign restrictions identify a set of models and hence do not uniquely pin own a single structural model. The estimation gives no information about the size of one standard deviation structural shocks (see Fry and Pagan, 2011; Baumeister and Hamilton, 2015).

[10] For reference, the standard deviation of the monthly industrial production growth rate in the sample is 70 basis points, whereas the standard deviation of the inflation rate is 33 basis points. At the zenith of the 2008 financial crisis, the industrial production growth rate experienced a 280 basis point fall, from -1.5% to -4.3% between September and October 2008.

the persistent component. An AD shock has a negative impact on investor sentiment, but this is only marginally statistically significant.

[Figure 2]

Figure 3 presents the impulse responses of the five variables to an adverse aggregate supply (AS) shock, represented by an initial reduction in output growth by 43 bp and an increase in inflation of 20 bp, as well as a short-lived rise in the interest rate. The response pattern following an AS shock is very similar to that following an AD shock. In particular, it yields a statistically significant increase in both total volatility and persistent volatility, and a reduction in investor sentiment. In contrast with the AD shock, the reduction in investor sentiment becomes statistically significant after four months. As with an AD shock, the peak response for persistent volatility occurs somewhat later than for total volatility. The conclusion from Figures 2 and 3, therefore, is that macroeconomic shocks, whether to demand or supply, significantly increase stock market volatility and that the response of persistent volatility lasts longer than that of total volatility.

[Figure 3]

Figure 4 presents the impulse response functions for the five variables to an adverse monetary policy (MP) shock, which is associated with a 3 bp increase in the interest rate. An MP shock yields a small and marginally significant reduction in output growth and inflation, although in both cases, the impact is short lived. Both investor sentiment and volatility increase, but in neither case is the impact statistically significant.

[Figure 4]

Figure 5 shows the responses to an adverse sentiment shock. The effect on volatility is insignificant and very short lived. This supports the hypothesis that sentiment shocks do not lead to significant changes in either volatility or macroeconomic fundamentals.

[Figure 5]

Having considered the causal links from macroeconomic fundamentals to financial market volatility, we now consider the links in the reverse direction, as many other papers do in the literature. Figure 6 presents the impulse response functions for the five variables for an adverse volatility shock. To facilitate comparison of the responses caused by shocks in total and persistent volatility, we normalise the size of the volatility shock to be 0.007, which is the size of a one standard deviation shock that would otherwise be obtained using the recursiveness assumption. Increasing volatility – whether total volatility or persistent volatility – leads to a significant drop in output growth, inflation and sentiment. The key difference is that shocks to persistent volatility lead to deeper economic contractions, which can be explained by its protracted rise in magnitude after the shock. The interest rate displays a sustained reduction but this is not statistically significant. These results are consistent with the burgeoning empirical evidence on the impact of financial volatility shocks on the macroeconomy.

[Figure 6]

We now turn to the SVAR analyses for transitory volatility. Figure 7 displays the responses of transitory volatility (the green line) to macroeconomic and investor sentiment shocks. We find little evidence that these shocks lead to a significant increase in transitory volatility. Figure 8 shows the responses of the economic system to transitory volatility shocks. Apart from a very short-lived fall in prices and real activity, these shocks do not in general cause a significant macroeconomic response.

[Figure 7]
[Figure 8]

To summarize, we provide empirical evidence to support the hypothesis that persistent volatility is closely associated with macroeconomic fundamentals. We first show that traditional macroeconomic structural shocks cause significant responses in persistent volatility but not in transitory volatility. We then show that shocks to persistent volatility lead to macroeconomic fluctuations, but transitory volatility shocks do not have this effect. This provides support to the hypothesis that it is the persistent component of volatility that is linked to the market's expectations of future cash flows and discount rates. We also differentiate the dynamic responses between total volatility and persistent volatility subject to various shocks.

Results Using Bond Market Volatility

In this section, we present results for the SVAR analysis for bond market volatility. Again, rather than reporting all of the impulse response functions, we focus on the role of volatility. Figure 9 reports the response of U.S. bond market volatility to adverse shocks to aggregate demand, aggregate supply, monetary policy and sentiment. The results using bond market volatility are very similar to those using stock market volatility. In particular, there is a significant increase in volatility following an adverse shock to AD, AS and MP, and for an AD or AS shock, the response is statistically significant. Following an adverse sentiment shock, volatility rises, but not significantly so.

[Figure 9]

Figure 10 reports the response of output growth, inflation, the interest rate and sentiment to an adverse shock to U.S. bond market volatility. An adverse shock to volatility leads to a reduction in sentiment and the interest rate, but neither is statistically significant. There is an initial increase in output growth followed by a sharper reduction, which is marginally significant. The effect in inflation mirrors this, with an initial reduction followed by a larger increase. The impact on inflation is greater for the persistent component of volatility than it is for total volatility.[11]

[11] We also find that transitory volatility in the bond market is not significantly associated with macroeconomic shocks. In the interests of space we do not report these results, but they are available on request.

[Figure 10]

Further Robustness Tests

As a further robustness check, we conducted the same SVAR analysis for the U.K. and Germany. We also conducted the SVAR analysis without the U.S. Crash Confidence Index, which allows us to extend the sample back to January 1990. We additionally undertook the analysis using alternative estimates of the persistent component of volatility, as described in Section 3. In particular, we tried different values of the smoothing parameter in the HP filter, the Christiano-Fitzgerald band pass filter with different oscillation bounds and different rolling window lengths in each case. For all the robustness tests, the results are qualitatively similar and the conclusions unchanged. The results of these additional analyses are available on request.

5. Volatility and Investor Sentiment

In the previous section, we have shown that adverse shocks to the long run persistent component of volatility have a measurable and economically significant impact on the real economy. Moreover, the association between volatility and the real economy is stronger for the persistent component of volatility than it is for total volatility, supporting our hypothesis that it is the persistent component of volatility that is linked to the market's expectations of future cash flows and discount rates. We also provide evidence that transitory volatility is largely unrelated to macroeconomic fundamentals. This is consistent with and indeed provides support for, the economic model of volatility presented by Engle et al. (2013).

De Long et al. (1990) show that sentiment-based decisions of uninformed investors may lead to excess volatility and Campbell et al. (1993) argue that *changes* in investor sentiment can trigger strong liquidity shocks with a significant impact on volatility. In this section, we test this hypothesis by further exploring the dynamic relationship between transitory volatility and investor sentiment. To that end, we estimate an SVAR model including transitory volatility and the *change* in investor sentiment, defined as the first difference in the investor sentiment index. We do not include macroeconomic variables in this system because our empirical results in the previous section suggest that neither investor sentiment nor transitory volatility is significantly related to macroeconomic fundamentals. We also include persistent volatility in the system in order to control for the possible interaction between the two volatility factors. The model is again estimated with three lags with non-informative priors. [12]

Adopting the Cholesky decomposition approach to identify structural shocks, we place the changes in investor sentiment as the first variable. As in Berger et al (2015), we do not literally interpret this as reflecting the timing of shocks, but rather that shocks to changes in investor sentiment will transmit to volatility within the same time period but not the other way round. Figure 11 presents the relevant impulse responses. Conditional on positive shocks to investor sentiment (Panel A), we find a significant drop in persistent volatility for the first five months. Transitory volatility decreases slightly, although insignificantly, on impact, followed by a significant rise between three and four months after the shock. One reason for this may be that a positive change in investor sentiment affects noise traders who enter the market and increase the transitory volatility in the process. Conversely, negative shocks to transitory volatility cause stronger and more persistent improvement in sentiment than persistent volatility shocks do (Panel B).

[Figure 11]

Overall the empirical evidence suggests that changes in investment sentiment are associated with both volatility factors. However, the causal link from transitory volatility to changes in investment sentiment is stronger. We also uncover interesting dynamics resulting from sentiment shocks: while an improvement in sentiment tends to lower persistent volatility, the transitory volatility experiences a short-lived increase.

[12] The results reported below are robust against (i) different orderings of the variables and (ii) using macroeconomic variables as control variables. These results are available upon request.

6. Conclusion

The link between financial market volatility and the real economy has been well studied in the literature from both a theoretical and empirical perspective. In this paper, we add to this literature by examining the dynamic relationships between the real economy, investor sentiment and stock and bond market volatility. Noting that volatility is characterised by a two-factor process and that changes in the real economy should be associated with the slowly-varying factor of volatility, we employ the cyclical volatility model of Harris et al. (2011) to decompose total volatility into a long run persistent component and short run cyclical component and use these to explore the relationship between volatility and the real economy.

We show that adverse shocks to the long run persistent component of volatility have a measurable and economically significant impact on the real economy and that the impact is stronger for stock market volatility than for bond market volatility. We also show that the link between volatility and the real economy is, as expected, stronger for the long run persistent component of volatility than it is for total volatility. In contrast, the short run cyclical component of volatility has a much weaker relationship with the real economy, but is instead more closely associated with investor sentiment. This is consistent with the idea that volatility reflects both the market's expectations of future cash flows and discount rates, but also short term, behavioural effects that are not directly linked to the economic activity.

Our paper has direct policy implications. First, policy makers and practitioners may wish to choose a measure of volatility most suitable for their needs. For example, if they are more concerned with how volatility interacts with the macroeconomy, our results suggest that they should consider persistent volatility because it is less noisy and more closely linked to macroeconomic fundamentals. Conversely, if they are more interested in studying the relationships between sentiment and volatility, they may wish to focus on transitory volatility. Second, our results carry the potential to improve the forecasting performance of the two-factor volatility model. In particular, conditional on macroeconomic shocks, our paper provides endogenous responses of persistent volatility, which has been shown by the literature to be important in forecasting volatility over longer horizons.

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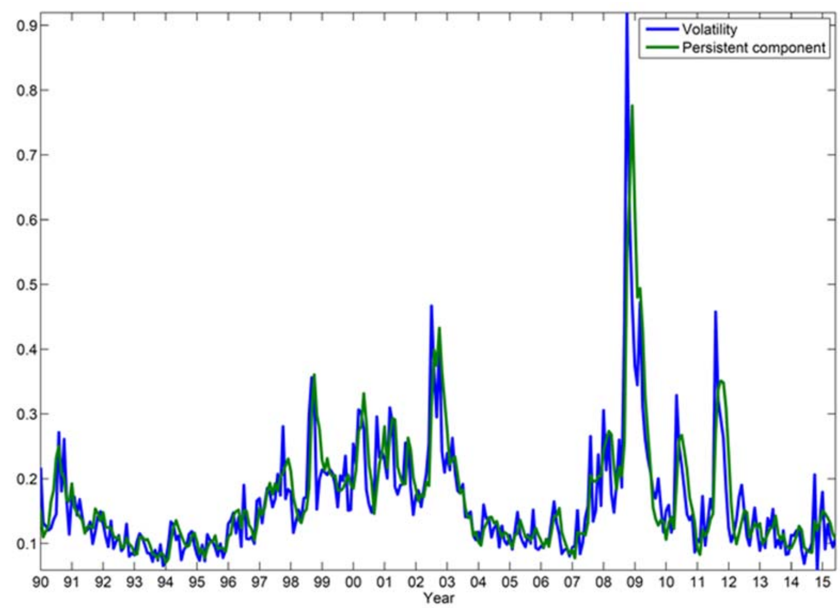
Table 1: The *contemporaneous* sign restrictions imposed on the SVAR model (8) for structural shocks identification

	Variables				
	Volatility	Investor Sentiment	Industrial Production	Inflation	Short-term interest rate
Volatility shock	+	0	0	0	?
Sentiment Shock	?	-	0	0	?
Aggregate Demand shock	?	?	-	-	-
Aggregate Supply Shock	?	?	-	+	+
Monetary policy shock	?	?	-	-	+

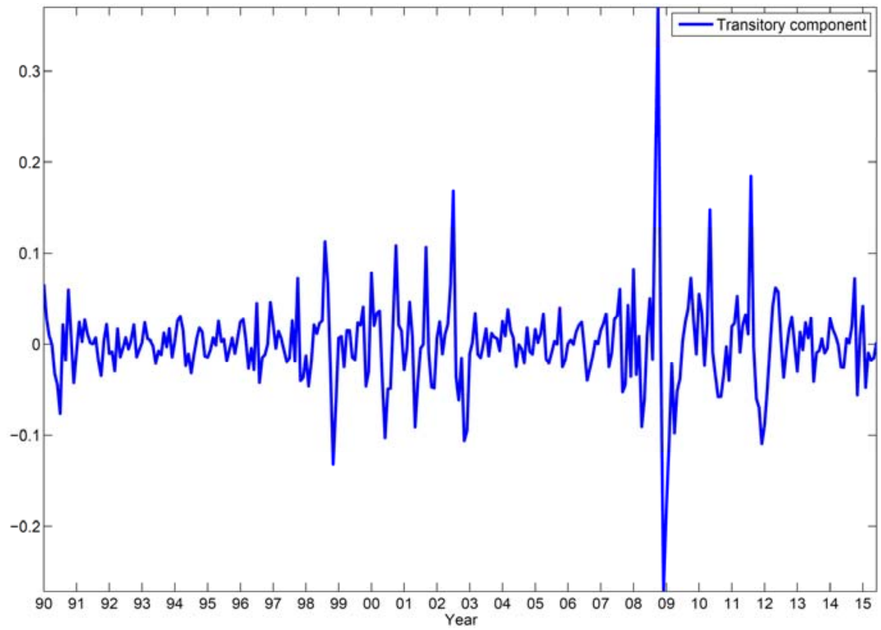
Note: This table displays the imposed sign restrictions which are used to identify structural shocks (listed row-wise) in the SVAR model (8). '+' refers to a contemporaneous increase in a variable when a structural shock hits, whereas '-' refers to a contemporaneous decrease and '0' means that the certain variable is unchanged. '?' means that the researcher is agnostic about the response of the variables. Note that the five structural shocks are orthogonal to each other by construction. See main text for details.

Figure 1 The Persistent and Transitory Components of Realized Volatility

Panel A: Volatility and Long Run Trend



Panel B: The Cyclical Component of Volatility



Notes: Panel A shows the standard deviation of log returns for the US stock market estimated using equation (5) and the long run trend estimated using the Hodrick-Prescott filter with a smoothing parameter of 5,760,000. Panel B shows the cyclical component of volatility defined as the difference between the original series and the trend (equation (6)). The sample period is 02/01/1990 to 30/6/2015.

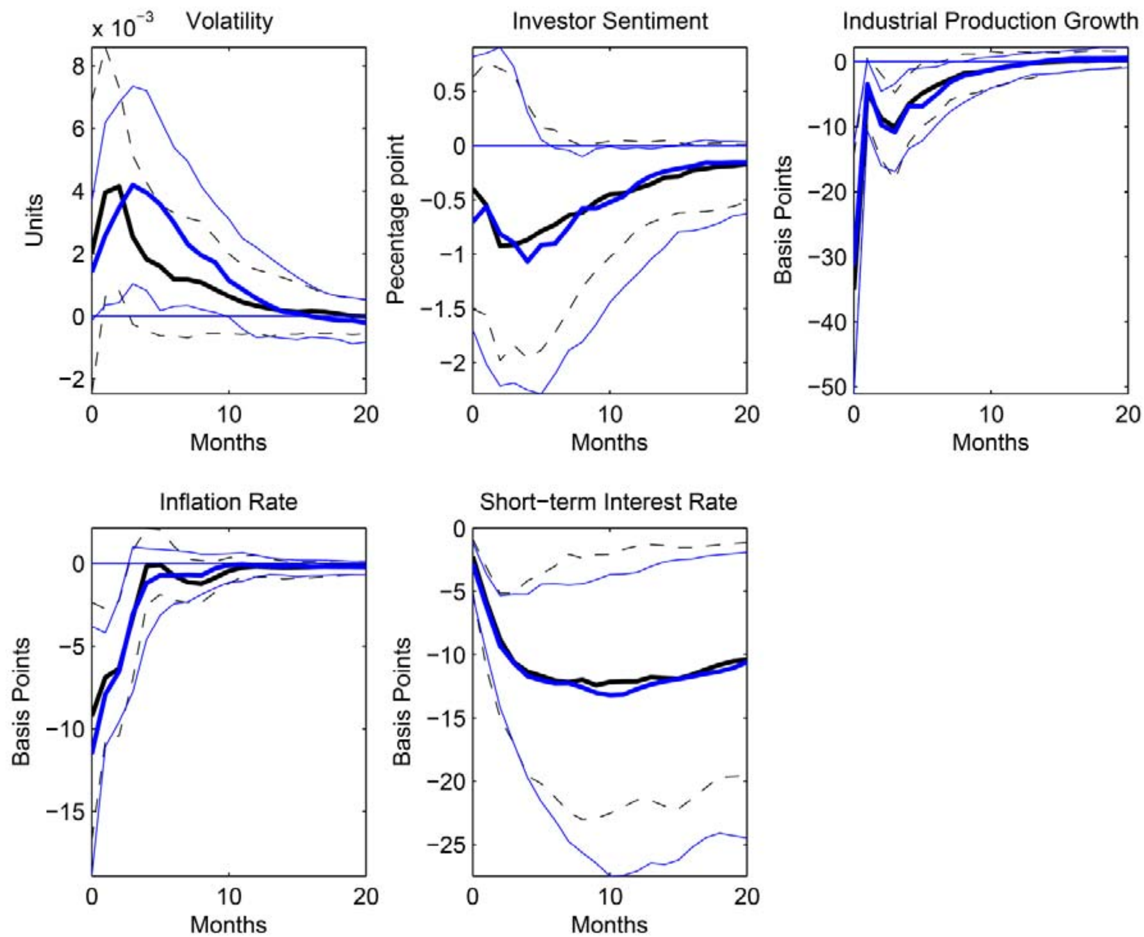


Figure 2: Impulse responses for adverse Aggregate Demand shock computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas blue lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

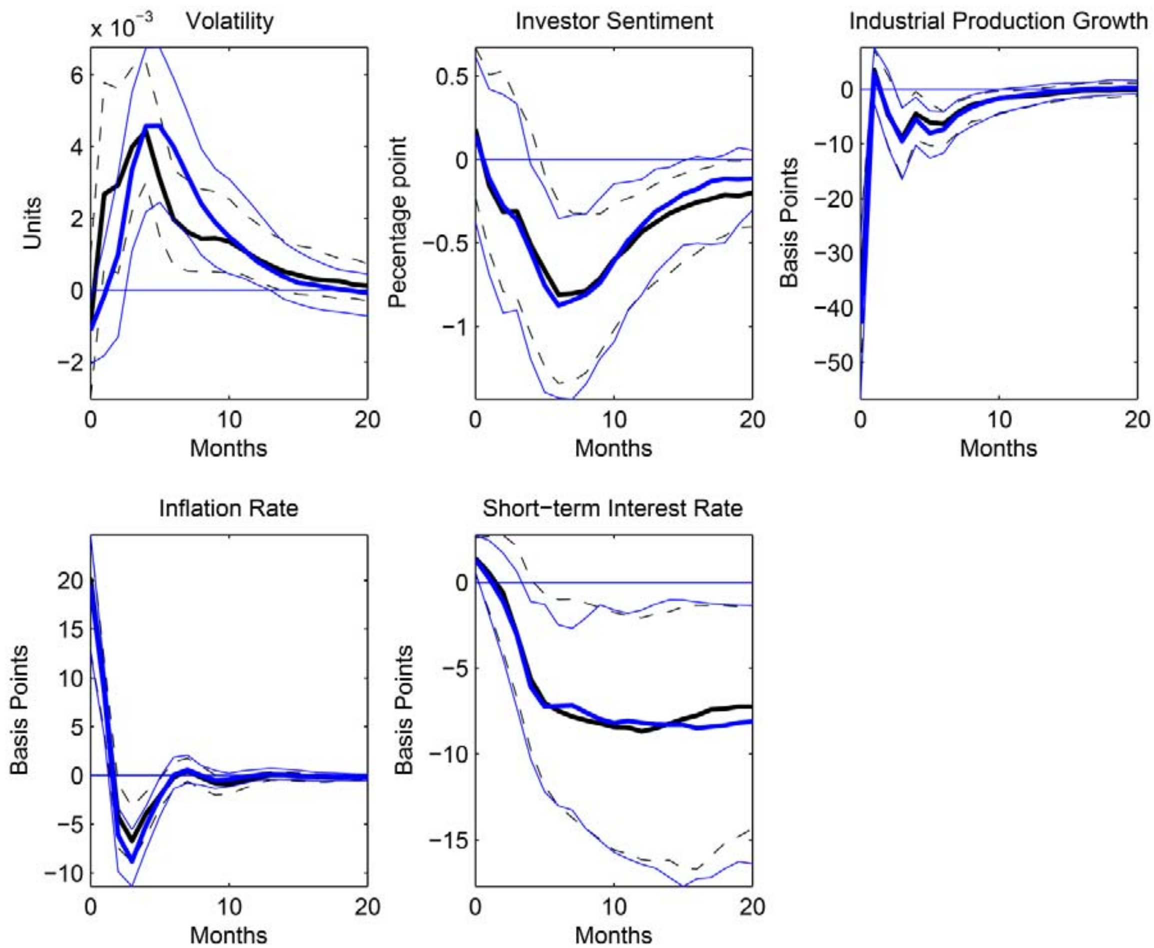


Figure 3: Impulse responses for adverse Aggregate Supply shock computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas blue lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

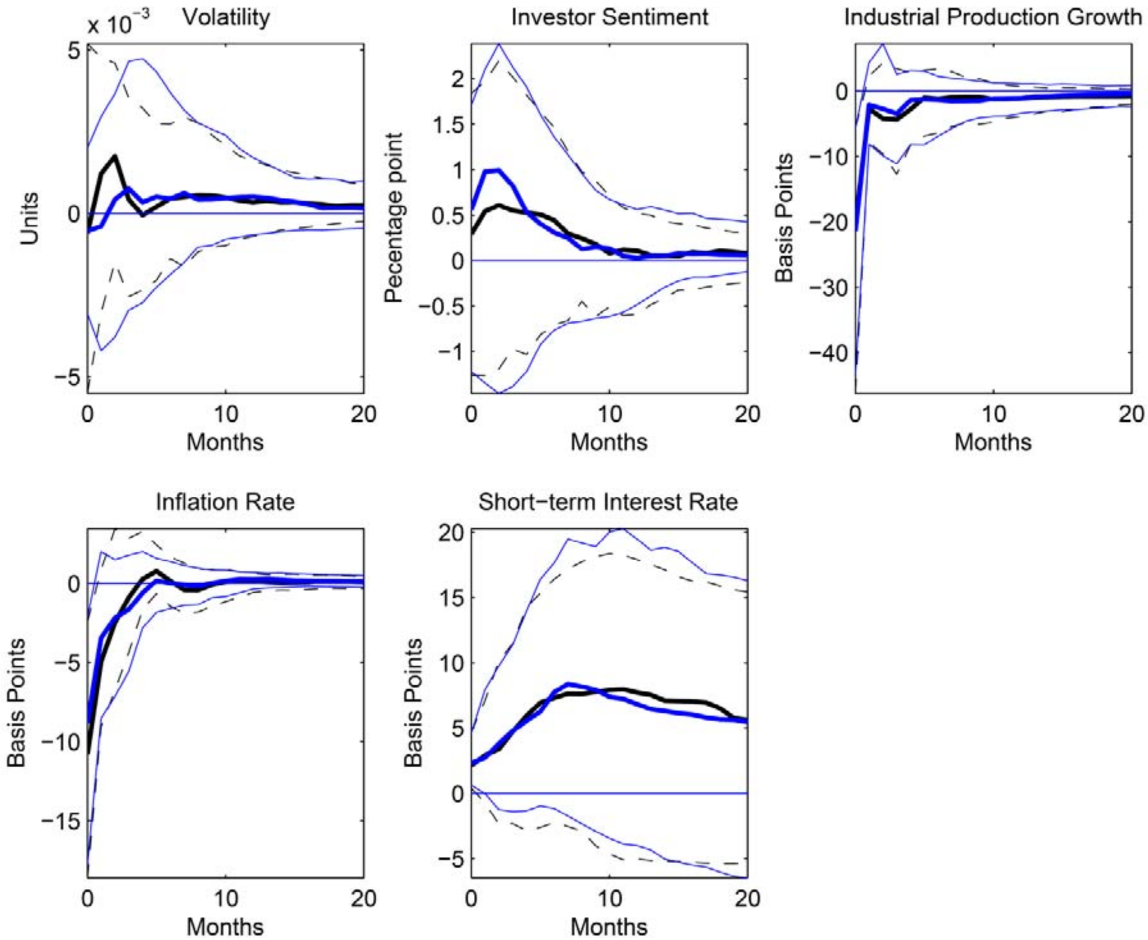


Figure 4: Impulse responses for contractionary monetary policy shock computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas blue lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

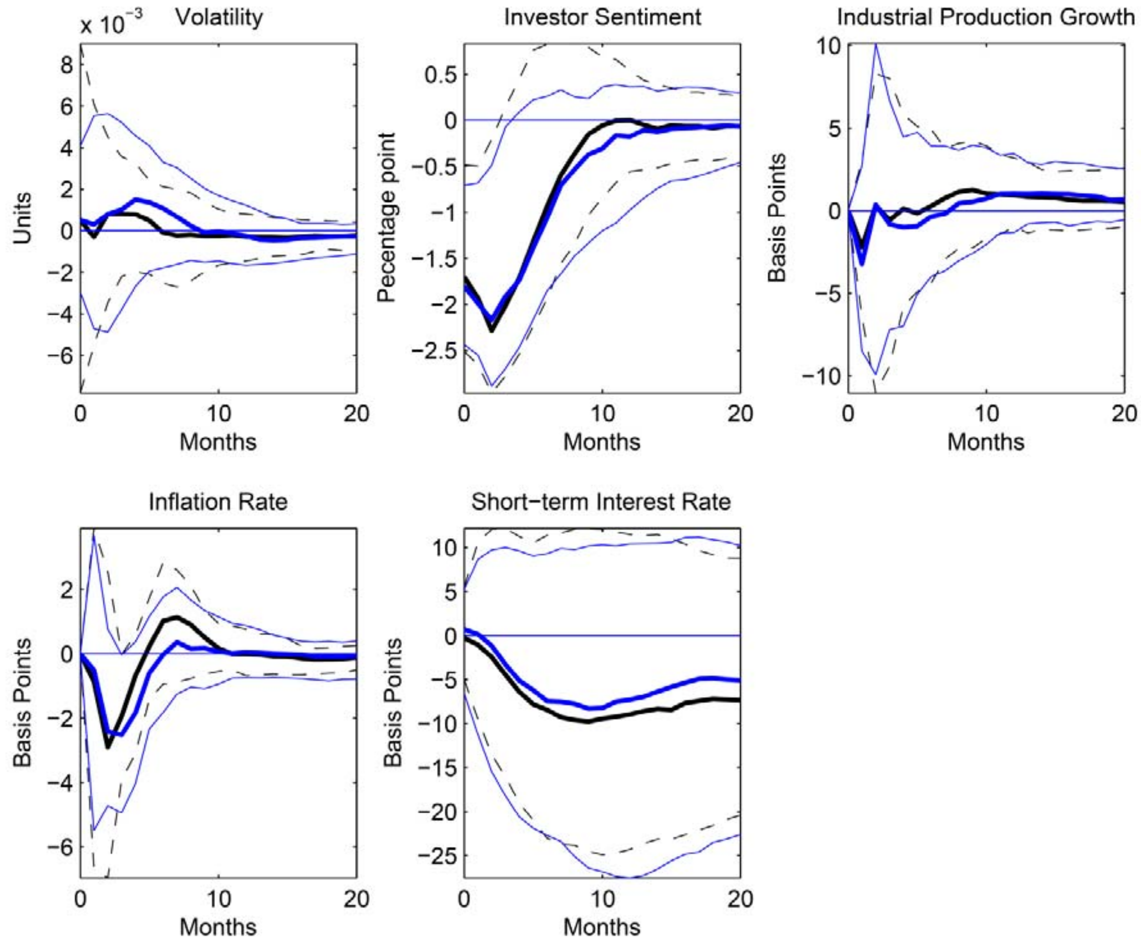


Figure 5: Impulse responses for adverse investor sentiment shock computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas blue lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

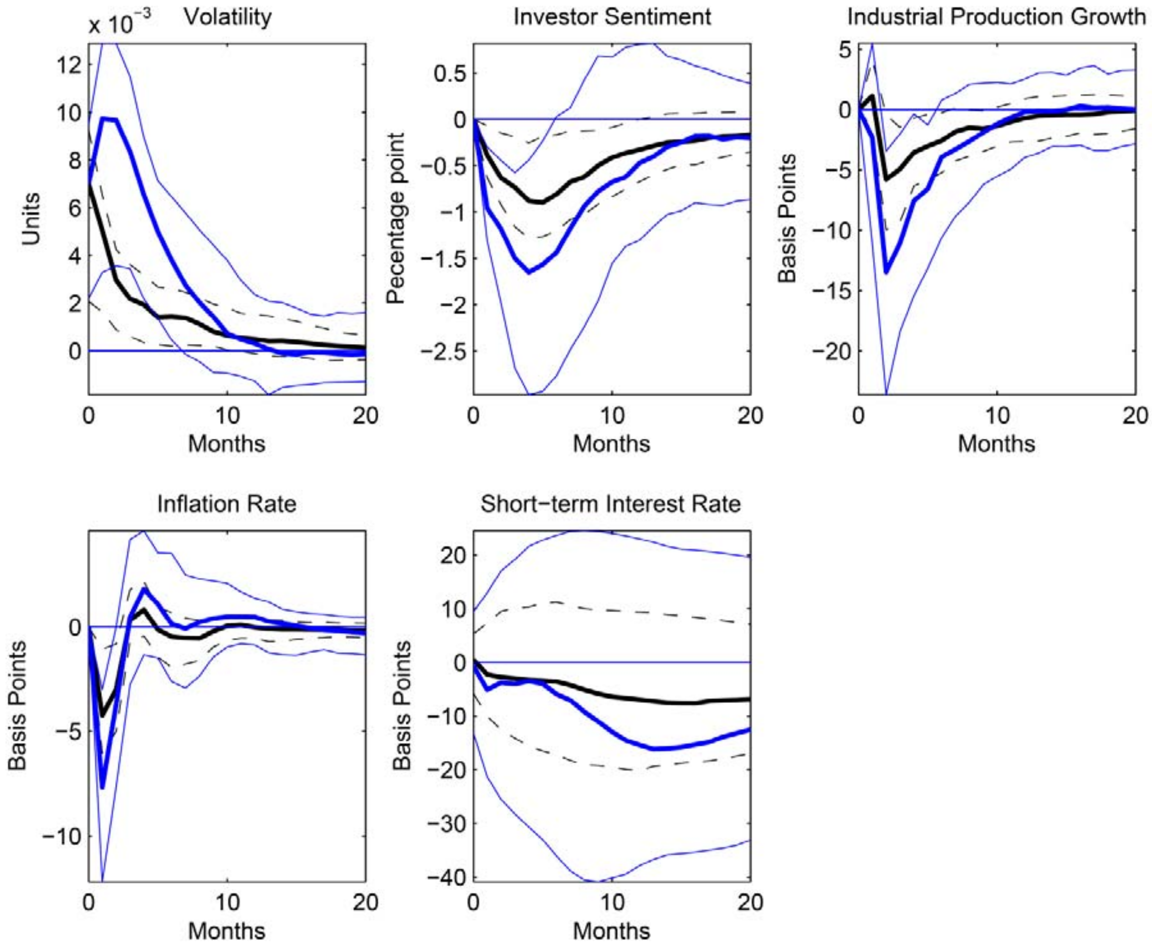


Figure 6: Impulse responses for adverse volatility shocks computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas blue lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

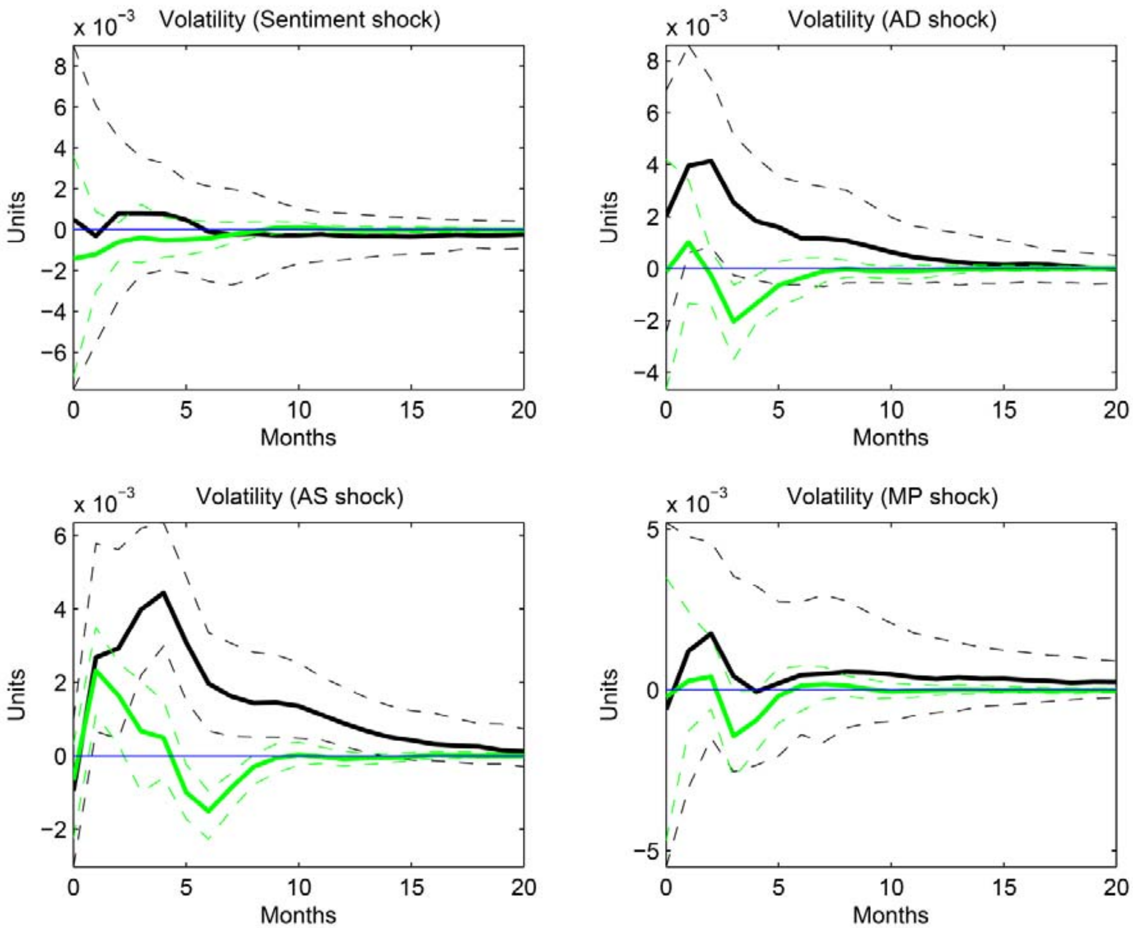


Figure 7: Impulse responses for volatility conditional on (i) adverse sentiment shocks; (ii) adverse Aggregate demand (AD) shocks; (iii) adverse Aggreate supply (AS) shocks; (iv) contractionary monetary policy shocks as computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas green lines correspond to the system using the transitory component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

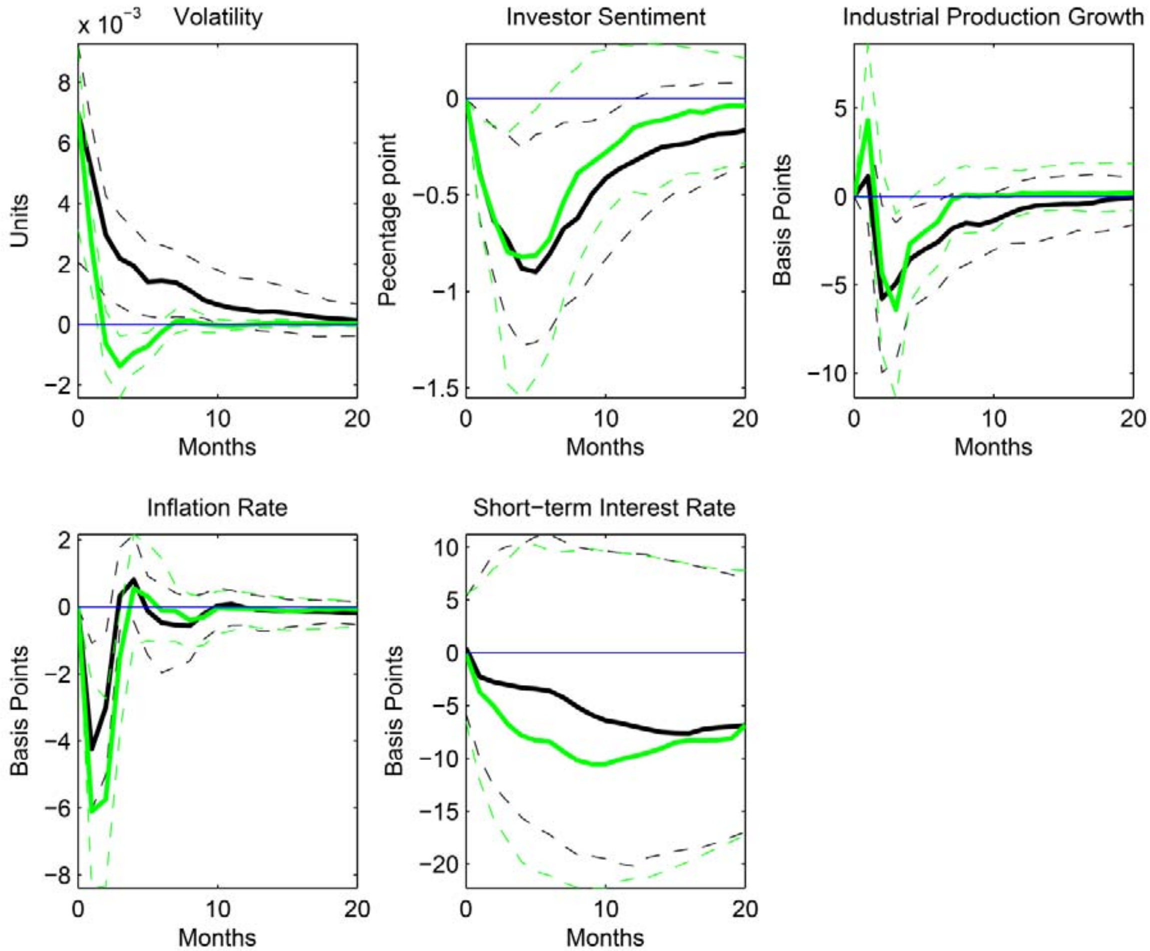


Figure 8: Impulse responses for adverse volatility shocks computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas green lines correspond to the system using the transitory component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

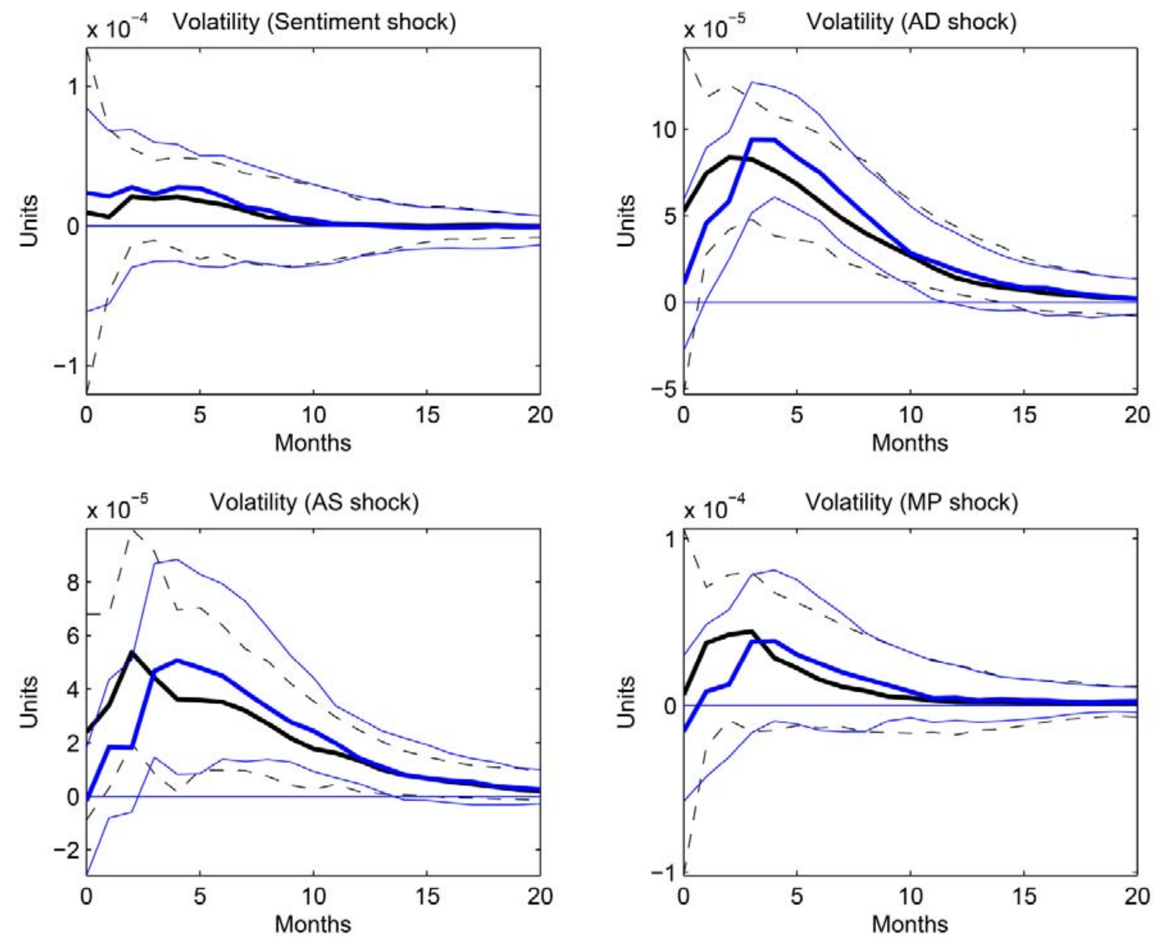


Figure 9: Impulse responses of volatility conditional on (i) adverse sentiment shocks; (ii) adverse Aggregate demand (AD) shocks; (iii) adverse Aggreate supply (AS) shocks; (iv) contractionary monetary policy shocks as computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US bond volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas green lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

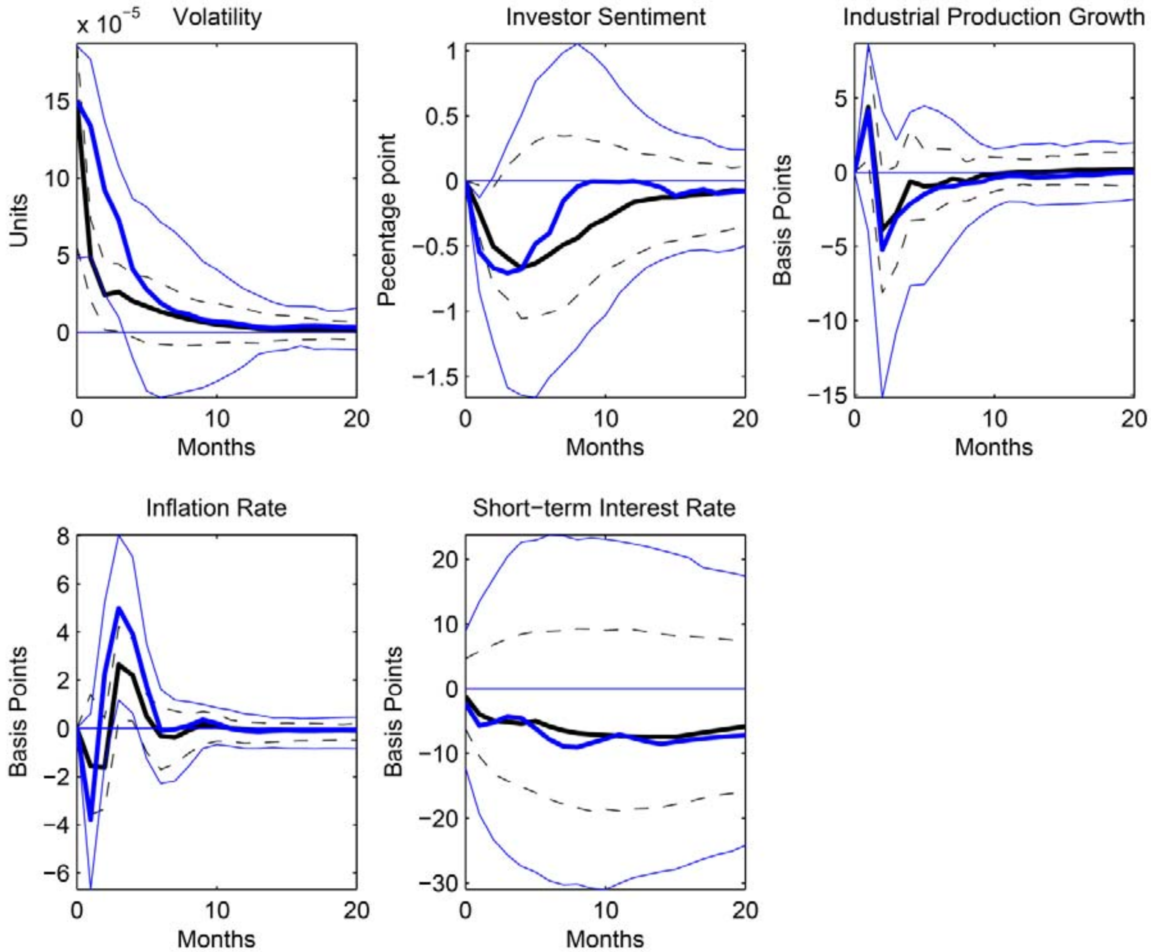
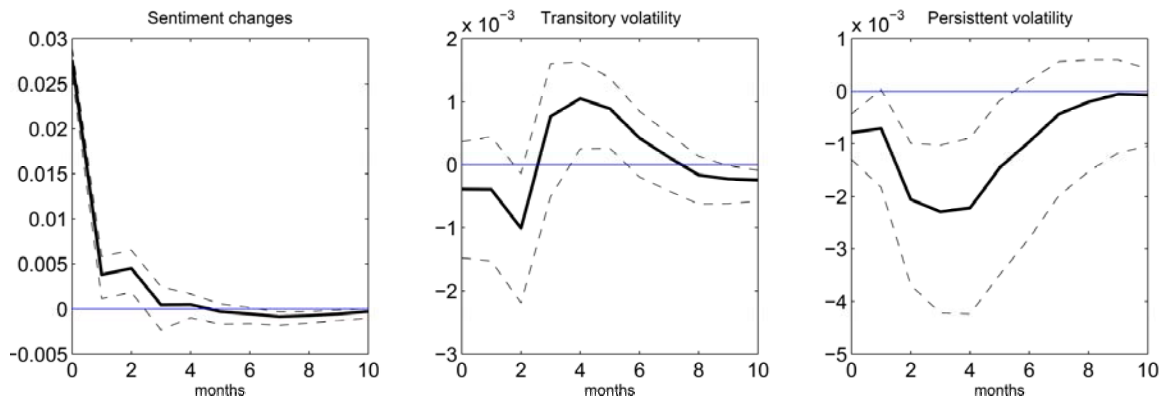


Figure 10: Impulse responses for adverse volatility shocks computed by the SVAR model (8) and by the structural shock identification scheme described in Table 1 using US bond volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Black lines correspond to the system using total volatility, whereas green lines correspond to the system using the persistent component of volatility. Sample period: 2001M7-2015M6. See the main text for details.

Panel A: Unanticiapted benign shocks to changes in sentiment



Panel B: Responses of sentiment changes to negative transitory and persistent volatilities

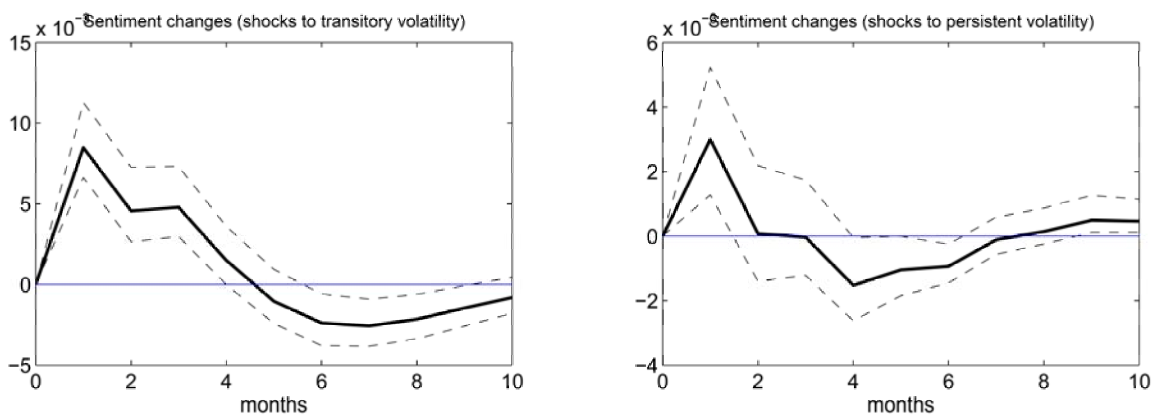


Figure 11: Impulse Responses for benign shocks to changes in investment sentiment (Panel A) and to negative volatility shocks using (i) a three-variable SVAR system described in section 5 (ii) the recursiveness assumption and (iii) the data on US stock volatility. Error bands are constructed at the 68 percent interval following Sims and Zha (1999). Sample period: 2001M7-2015M6. See the main text for details.