The effects of monetary policy shocks on a panel of stock market volatilities: A factor augmented Bayesian VAR approach *

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Abstract

This paper investigates the response of stock market volatility to a monetary policy shock using a structural factor-augmented Bayesian vector autoregressive (FAVAR) model. We construct a monthly dataset of realized volatilities of the constituents of the S&P500 index and extract volatility factors from this dataset using a suitable dynamic factor model (DFM). The volatility factors are included in a structural FAVAR model where the dynamic response of stock market volatility to a monetary policy shock is analyzed. This approach does not only allow us to study the response of the aggregate market volatility but also the responses of all the volatilities of the single stocks and the different sectors included in the dataset. In general, the results show that the stock market returns decrease and the stock market volatility increases following a monetary policy tightening. Although the magnitude of the volatility response to monetary policy shocks varies between the different stocks and sectors, the dynamics of the response does not differ widely. Both the magnitude and dynamics of the volatility response depend on the sample period examined.

Keywords: dynamic factor model, Bayesian estimation, factor-augmented vector autoregression, monetary policy, stock market volatility, long memory

JEL Classification Code: C32, C38, C58, E52

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1 Introduction

Understanding the dynamic relationship between monetary policy and financial stock market is of large interest to both political decision makers and market participants. Although the main targets of monetary policy are related to macroeconomic variables such as employment, inflation, and output, monetary policy tools only have indirect effects on these variables. On the other hand, the effect of monetary policy on financial markets is direct and immediate. Policy makers use actions such as a change in the federal funds rate to affect financial markets in order to achieve their macroeconomic targets through different channels. In addition, from the investors' perspective, recognizing the reaction of stock markets to monetary policy shocks can lead to more profitable trading. Thus, it is crucial to understand the magnitude and dynamics of the stock market's reaction to monetary policy.

In this paper we model a large dataset of monthly volatilities and include them together with other macroeconomic variables and stock returns in a structural VAR to analyze the dynamic response of the stocks' volatilities to monetary policy shocks using impulse response functions. In contrast to the existing literature, the emphasis of this paper is not only limited to the response of the aggregate market volatility but also includes the response of all the stocks and the different sectors that are part of the volatilities dataset. We also compare the magnitude and dynamics of the response of the volatility to a monetary policy shock in different sample periods and assess whether the volatility response depends on the period examined or not. To sum up, we choose an appropriate measure of monthly volatility, model a large dataset of volatilities together with returns and other macroeconomic variables in a parsimonious way, and analyze the response of each volatility series to monetary policy shocks.

Following an expansionary monetary policy, interest rates decrease leading to a higher demand on stocks compared to bonds and hence, stock prices increase. There are, however, different channels through which monetary policy can affect the economy using asset prices[1]. According to Tobin (1969), movements in stock prices can affect the economy through the investment channel. An increase in stock prices makes it cheaper for firms to invest because each issued share produces more funds. This means that buying facilities and equipments is cheaper for the firm. Therefore, a rise in stock prices leads to a lower cost of capital and as a result investments and output increase. As highlighted in Bernanke and Gertler (1995), asymmetric information problems present in credit markets serve as another transmission mechanism for monetary policy through asset prices. In the literature such a mechanism is usually referred to as the balance sheet or credit view channel. When the net worth of business firms becomes lower, lending problems to these firms related to adverse selection and moral hazards become more severe. A rise in stock prices reduces both adverse selection and moral hazard problems leading to an increase in lending. Consequently, investment spending and aggregate spending increase. Alternatively, monetary policy transmission can also take place through the household's balance sheet, specifically through household wealth effect. In the life cycle model of Modigliani (1971), the lifetime resources of consumers determine their consumption. Stocks are a main component of financial wealth which is an important part of consumers' lifetime

[1] Mishkin (2007) surveys how monetary policy affects the economy through asset prices.

resources. An increase in stock prices raises household wealth; accordingly, the lifetime resources of consumers increase resulting in a rise in consumption. Using US data, Lettau et al. (2002) show empirically that the household wealth channel plays a minor role in influencing consumption.

The response of the stock market to monetary policy is not only limited to stock market returns, but also extends to stock market volatility through different channels. Since monetary policy tightening can be viewed as new information in the market, investors try to rebalance their portfolios between equities and bonds more actively following a monetary policy tightening. Such behavior spurs an increase in trading volume translating into an increase in volatility because of the well documented strong positive correlation between trading volume and volatility in the literature[2]. Declining stock prices are usually accompanied by rising volatility, and vice versa. Although a sizable literature has documented the negative correlation between stock returns and volatility, there is less agreement on the direction of the causality. The early work of Black (1976) and Christie (1982) attributes the asymmetric relation between stock returns and volatility to changes in debt-to-equity ratio. This asymmetric return-volatility relationship is known in the literature as the leverage effect. In the leverage effect hypothesis, when asset prices go down, the relative value of the companies' debt increases compared to their equity. Therefore, when stock prices decline, companies become riskier and more volatile. Another explanation advocated by French et al. (1987) and Campbell and Hentschel (1992) that illustrates the asymmetric relation between stock returns and volatility is referred to as the volatility feedback hypothesis. In the volatility feedback hypothesis monetary policy can exert direct influence on volatility through the risk premium. If volatility is priced, an expected increase in volatility requires a higher rate of return. As a result, immediate stock prices decline in order to allow for higher future returns. Thus, negative news can increase future volatility and expected returns while decreasing contemporaneous returns. In sum, the causality in the leverage effect runs from prices to volatility as opposed to the volatility feedback which depends on the reverse causal relationship. However, at lower frequencies, the relationship between returns and volatility may appear immediate and the two explanations become indistinguishable.

Since the effect of monetary policy on stock market variables is of large interest in both financial and monetary economics, there is a large literature in both fields. In finance, many papers focus on the effects of the announcements of federal open market committee (FOMC) related to the federal funds target rate on financial variables. Most of the literature related to the effect of monetary policy on asset prices follows the work of Cook and Hahn (1989). In this paper, the authors measure the impact of monetary policy on the bond market by regressing changes in returns on changes in the federal funds target rate. Using a similar line of research, Reinhart and Simin (1997), Bernanke and Kuttner (2005), Gürkaynak et al. (2005), Zebedee et al. (2008), among many others investigate the impact of monetary policy announcements on stock returns. In these studies both daily and high frequency data are used. Although an increase in federal funds rate lowers stock returns, the magnitude of the change depends on the data, the sample period, and the method used in each study. More recently, Chuliá et al. (2010), Andersson (2010), Gospodinov and Jamali (2012a), among others analyze the effects of monetary policy announcements on stock market volatility. Although the main focus of the literature is on

[2]See e.g. Karpoff (1987) for a survey of this literature.

the stock market as a whole, Chuliá et al. (2010) examine the response across the different stocks and sectors to monetary policy announcements. Adopting a different methodology, Flannery and Protopapadakis (2002) and Bomfim (2003) use generalized autoregressive conditional heteroskedasticity (GARCH) models to estimate the effects of monetary policy on the volatility of different assets.

Although the previously mentioned literature focuses intensively on the effects of monetary policy on the stock market, the univariate regression framework used does not, however, assess the dynamic relationship between the variables of interest. Since the pioneering work of Sims (1980), vector autoregressive (VAR) models have became very popular in modeling multivariate time series used in macroeconomics. In VARs, the dynamic response of the variables in the system to an impulse in another variable can be examined by means of impulse response analysis. Thorbecke (1997), Millard and Wells (2003), Bjørnland and Leitemo (2009), among others use structural VARs to analyze the effects of monetary policy shocks on stock market returns. They include different monthly macroeconomic variables along with federal fund rate and stock market returns index in a structural VAR to investigate the response of the stock market returns to an identified monetary policy shock using impulse response functions. Gospodinov and Jamali (2012b) expand this framework by including stock market volatility index in a structural VAR. They analyze the dynamic response of the stock market volatility to a monetary policy shock.

To summarize, in this paper we construct a large dimensional panel of financial stocks and we compute monthly realized volatilities for the whole dataset. We propose three approaches to analyze the response of the panel of volatilities to monetary policy shocks. In the first approach, to reduce the large dimension, we extract a volatility factor from the realized volatilities dataset using the DFM of Luciani and Veredas (2012). This DFM allows us to extract volatility factors while accounting for the stylized facts in the realized volatilities. Then we follow Bernanke et al. (2005) and augment the estimated factor in a structural factor-augmented vector autoregressive (FAVAR) model where we employ a recursive identification scheme. Impulse responses are used to investigate the response of the volatility factor to a monetary policy shock. In a similar fashion as Blaes (2009), we can use the DFM equation to obtain the impulse responses of all the series included in the dataset from which the volatility factor is extracted. Different tests and information criteria suggest the use of one volatility factor to summarize the variation in the whole dataset; this means that the responses of the different stocks will only vary in magnitude or direction but not in dynamics. In the second approach the dataset is divided into 9 different sectors. A volatility factor is estimated from each sector and then the 9 estimated volatility factors are included together in a structural FAVAR where impulse responses are used to analyze the response of the different sectors' volatilities. The responses of the stocks from each sector are obtained using the DFM equation. This approach allows the dynamics of the volatilities responses to vary across the different sectors, but within each sector the volatilities of the single stocks only vary in magnitude or direction and not in dynamics. Instead of using a DFM, in the third approach we include a number of stocks' volatilities directly in a structural VAR and examine their responses using impulse response functions. Due to the large dimensionality of this structural VAR, we estimate the model using the Bayesian method implemented by Banbura et al. (2010). This approach does not impose any restrictions on the dynamics or magnitude of the responses of the stocks' volatilities included in the structural VAR; however, in this approach, a limited number of stocks can be included in the structural VAR[3]. In order to allow for a fair comparison between all the three different approaches, in the first and the second approach we estimate the structural FAVAR model using the same Bayesian technique used in the third approach.

The results obtained from the impulse responses show that the stock market returns decrease and the volatility increases following a contractionary monetary policy shock. In general, the impulse responses suggest a strong negative correlation between the dynamic responses of the stock returns and the volatility. The magnitude of the volatility responses varies between the different sectors and stocks. For instance, a monetary policy shock has a stronger impact on the financial sector as opposed to other sectors. In addition, the magnitude of the responses of the companies which have large market capitalization (market cap) tends to be stronger. Both the magnitude and the dynamics of the responses of the variables in the system vary across the different policy regimes. In particular, starting from Greenspan's chairmanship of the Federal Reserve, the effect of monetary policy shocks on stock market variables is stronger compared to previous periods.

The rest of the paper is organized as follows. In section 2 we analyze the financial dataset, present the DFM, and extract volatility factors. Section 3 introduces the structural VAR model and summarizes its Bayesian estimation. The results are presented in section 4. Section 5 concludes.

2 Data description and factors extraction

The financial dataset[4] consists of 213 daily price series and covers the period from 02/01/ 1973 to 31/07/2012. It contains American companies that are part of the S&P500 index for the whole duration of the sample. The data represents 9 different sectors[5], namely, industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and consumer staples (CS). Daily returns for each of the 213 series are computed as:

$$R^i_{n,t} = \log(P^i_{n,t}) - \log(P^i_{n-1,t}), \tag{2.1}$$

where $P^i_{n,t}$ is the closing price on day n and month t for variable i. Although a lot of work has been done recently to compare different methods for estimating daily volatility, few papers focused on comparing monthly volatility measures (see e.g. Liu and Tse (2013)).

[3]For instance,Banbura et al. (2010) included up to 131 variables in a structural VAR. To do so, they used a high degree of shrinkage.

[4]All the series in the financial dataset are obtained from Datastream. A complete description of the dataset can be found in table 3 in the appendix.

[5]IND includes 34 series, FIN includes 28 series, HC includes 16 series, CD includes 32 series, ITTS includes 17 series, UT includes 28 series, MAT includes 16 series, EN includes 17 series, and CS includes 25 series. The S&P500 index includes one sector for information technology and another sector for telecommunication services. Since there are only 3 series from the telecommunications services that cover the whole sample, we include the telecommunications services along with information technology in one sector.

Using the GARCH model of Bollerslev (1986) and its extensions to estimate monthly volatility is not uncommon. The use of squared daily stock returns over a month as a measure for monthly volatility has become popular since French et al. (1987) and Schwert (1989). Later such measure was called realized volatility by Andersen et al. (2001) when applied to high frequency data to obtain daily measure for volatility[6]. In this paper we adopt the realized volatility as a measure of monthly volatility. Following French et al. (1987) and Schwert (1989), monthly realized volatility for each series is estimated as:

$$RV_t^i = \sqrt{\sum_{n=1}^{N} \left(R_{n,t}^i - \overline{R}_t^i\right)^2}, \tag{2.2}$$

where N is the number of trading days in month t and $\overline{R}_t^i$ is the average daily return of stock i in month t. From now on, we denote the log of realized volatility as realized volatility[7]. Accordingly, a monthly panel of realized volatility is constructed from January 1973 to July 2012. The monthly panel of realized volatilities is analyzed in table 1 in a similar way as Luciani and Veredas (2012) analyze their daily panel of realized volatilities[8]. The daily panel of realized volatilities used in Luciani and Veredas (2012), however, is constructed from 02/01/2001 to 31/12/2008 and consists of 90 US equity companies that are part of S&P100 index.

Many studies document the long memory behavior observed in daily realized volatility. In order to capture the long memory found in daily realized volatility, Andersen et al. (2003) propose the use of an ARFIMA (p, d, q) model[9]. The fractional integration parameter, denoted by d, measures the value of differencing required to render the long memory processes short memory. So the realized volatility, RV_t^i, is fractionally integrated of order d_i if $(1-L)^{d_i} RV_t^i$ is integrated of order zero, $I(0)$. Usually the values of d_i range between 0 and 1, and values closer to 1 refer to more persistent processes. Values of d_i between 0 and 0.5 refer to mean reverting and finite variance processes while values of d_i between 0.5 and 1 only entail variance stationarity. The first panel in table 1 reports values for d_i estimated from ARFIMA$(1, d, 0)$ models[10]. The median value for the estimated d parameter in the whole dataset is 0.48 suggesting the presence of long memory; however, the degree of long memory is smaller than a value of 0.55 obtained by Luciani and Veredas (2012) from their daily dataset[11]. Such result might cautiously suggest that daily realized volatility has a higher degree of long memory compared to monthly volatility. Observing the first panel in more depth, one can notice that the difference between the maximum and minimum values for d in the panel as well as within each sector is quite substantial. On the other hand, the median values across the sectors are very close to each other.

[6] It is also possible to use high frequency data to obtain monthly realized volatility; however, we do not use such method due to the unavailability of the data. In this paper we use daily observations to calculate monthly measure of realized volatility.

[7] Similar to the measure Luciani and Veredas (2012) have used.

[8] This dataset is originally used in Barigozzi et al. (2010).

[9] See e.g. Palma (2007) for surveying time series models with long memory.

[10] The ARFIMA$(1, d, 0)$ model is estimated using the nonlinear least square method in Ox by Doornik (2009). This method was preferred since it does not restrict the d parameter to be less than 0.5 like the maximum likelihood method. Other ARFIMA (p, d, q) model specifications are also examined; however the results do not vary largely.

[11] In general, one should note that different estimation methods for the ARFIMA(p, d, q) results in different estimates for the the d parameter.

Table 1: Descriptive statistics

		ALL	IND	FIN	HC	CD	ITTS	UT	MAT	EN	CS
					ARFIMA $(1, d, 0)$						
	max.	0.64	0.61	0.55	0.60	0.60	0.53	0.62	0.56	0.58	0.64
d	med.	0.48	0.51	0.47	0.47	0.50	0.47	0.49	0.46	0.44	0.48
	min.	0.32	0.41	0.39	0.41	0.32	0.40	0.39	0.42	0.37	0.33
					Autocorrelation						
	max.	0.81	0.75	0.69	0.79	0.76	0.64	0.71	0.73	0.70	0.81
Lag 1	med.	0.58	0.60	0.57	0.59	0.63	0.55	0.58	0.54	0.56	0.59
	min.	0.33	0.42	0.45	0.41	0.42	0.39	0.47	0.45	0.33	0.44
	max.	0.69	0.57	0.49	0.64	0.59	0.48	0.58	0.60	0.56	0.69
Lag 6	med.	0.38	0.38	0.38	0.36	0.41	0.37	0.38	0.34	0.37	0.39
	min.	0.17	0.24	0.23	0.24	0.23	0.24	0.26	0.17	0.20	0.19
	max.	0.59	0.48	0.39	0.56	0.49	0.37	0.48	0.47	0.46	0.59
Lag 12	med.	0.28	0.28	0.26	0.27	0.29	0.25	0.27	0.25	0.29	0.29
	min.	0.03	0.15	0.09	0.12	0.11	0.08	0.12	0.03	0.10	0.12
					Autocorrelation squares						
	max.	0.84	0.78	0.73	0.79	0.78	0.69	0.81	0.69	0.68	0.84
Lag 1	med.	0.51	0.53	0.48	0.56	0.58	0.54	0.46	0.50	0.48	0.48
	min.	0.13	0.13	0.31	0.33	0.19	0.22	0.22	0.40	0.26	0.33
	max.	0.70	0.61	0.44	0.59	0.54	0.52	0.53	0.47	0.54	0.70
Lag 6	med.	0.27	0.25	0.26	0.28	0.29	0.28	0.24	0.27	0.29	0.26
	min.	0.00	0.00	0.06	0.09	0.00	0.07	0.00	0.14	0.00	0.13
					Autocorrelation absolute values						
	max.	0.82	0.75	0.67	0.79	0.73	0.64	0.71	0.64	0.65	0.82
Lag 1	med.	0.54	0.51	0.49	0.56	0.56	0.54	0.50	0.51	0.53	0.52
	min.	0.24	0.29	0.31	0.36	0.37	0.29	0.24	0.43	0.29	0.31
	max.	0.69	0.58	0.47	0.64	0.57	0.48	0.54	0.48	0.54	0.69
Lag 6	med.	0.34	0.32	0.31	0.33	0.35	0.34	0.29	0.31	0.36	0.31
	min.	0.00	0.03	0.14	0.15	0.04	0.12	0.02	0.14	0.00	0.14
					Skewness						
	max.	1.43	1.43	1.07	0.82	1.33	0.80	1.32	0.74	1.11	1.04
	med.	0.42	0.52	0.30	0.50	0.41	0.40	0.49	0.37	0.28	0.34
	min.	-2.52	-1.67	-0.19	-0.24	-0.88	-0.33	-2.37	-0.01	-1.43	-2.52
					Kurtosis						
	max.	17.37	10.07	6.19	4.53	6.46	7.48	17.37	5.17	9.99	11.58
	med.	3.72	4.06	3.59	3.60	3.72	3.87	3.93	3.58	3.64	3.64
	min.	2.56	2.81	2.64	2.56	2.86	3.05	3.01	2.96	2.92	2.69

Descriptive statistics for the monthly realized volatility for (ALL) 213 companies from S&P 500 in the period between January 1973 and July 2012 representing 9 sectors: industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and Consumer staples (CS). the first panel shows the fractional integration parameter d estimated from ARFIMA$(1, d, 0)$, the second panel presents autocorrelations for lags 1, 6, and 12, the third and fourth panels show the autocorrelations for squared and absolute realized volatilities respectively for lags 1 and 6, and the fifth and sixth panels show skewness and kurtosis respectively. All panels present maximum (max.), median (med.), and minimum (min.) values.

While the degree of long memory is heterogeneous among all the assets, it is quite similar across the different sectors indicating that long memory can be a market feature.

Long memory processes are usually characterized by a slow decay in the sample autocorrelation functions. The second panel in table 1 reports the sample autocorrelation functions for all the sectors for lags 1, 6, and 12. Similar to the fractional integration parameter, we observe large differences between maximum and minimum values within the sectors, but median values across the different sectors are very similar. One observes that the median for lag 1 is 0.58 , for lag 6 is 0.38, and for lag 12 is 0.28. This persistence in autocorrelations is a feature of long memory processes. Again, although the autocorrelations of the monthly realized volatilities are persistent, they are not as persistent as daily realized volatility.

The third and fourth panels in table 1 show the autocorrelations for both the squares and absolute values of the monthly realized volatilities; both are measures of the volatility of realized volatility. The dependence observed in both these two measures is an evidence of conditional dynamics in realized volatility. The last two panels in table 1 report both skewness and kurtosis. The results suggest that although both skewness and kurtosis are different among assets and across sectors, both are present in the monthly realized volatility. So, in general, monthly realized volatilities are skewed and show heavy tails.

Since the previous analysis show that the monthly realized volatilities share the same stylized facts observed in the daily realized volatilities as shown in Luciani and Veredas (2012), we follow their proposed dynamic factor model to extract factors from the monthly panel of realized volatilities. Following the notation of Luciani and Veredas (2012), the dynamic factor model can be written as:

$$\mathbf{RV_t} = \mathbf{\Lambda F_t} + \xi_\mathbf{t}, \tag{2.3}$$

$$\mathbf{D}(L)\mathbf{F_t} = \mathbf{C}(L)\mathbf{H_t^{1/2}}\mu_\mathbf{t} \quad \mu_\mathbf{t} \sim \mathcal{D}(\mathbf{0}, \mathbf{1}, \gamma_\mu, \nu_\mu), \tag{2.4}$$

$$(1 - L)^{\delta_i}\xi_{it} = G_i(L)\epsilon_{it} \quad \epsilon_{it} \sim \mathcal{D}(0, \sigma_{\epsilon_i}, \gamma_{\epsilon_i}, \nu_{\epsilon_i}). \tag{2.5}$$

$\mathbf{RV_t}$ is the $N\times 1$ vector of realized volatilities, $\mathbf{\Lambda}$ is the $N\times r$ loading matrix, $\mathbf{F_t}$ are the $r \ll N$ common factors, and $\xi_\mathbf{t}$ is the $N \times 1$ vector of idiosyncratic components which captures the firm's specific dynamics. The common factors evolve according to a VARFIMA model with conditional heteroskedasticity as shown in equation (2.4) where $\mathbf{D(L)}$ is a diagonal matrix of polynomials of fractional integration, $C(L)$ is the pure MA representation of a VARMA model for $\mathbf{D(L)F_t}$, and the variance covariance of realized volatilities is captured by $\mathbf{H_t^{1/2}}$. The orthogonal common shocks, $\mu_\mathbf{t}$, follow a standardized skewed and heavy tailed distribution where the parameter γ_μ controls the skewness and ν_μ controls the tails. In equation (2.5), ARFIMA processes are used to model the idiosyncratic components, where δ_i measures the degree of fractional integration of the i^{th} idiosyncratic component and $G_i(L)$ is the pure MA representation of an ARMA model for $(1 - L)^{\delta_i}\xi_{it}$. The idiosyncratic shock, ϵ_{it}, follows a zero-location distribution with dispersion parameter σ_{ϵ_i}, skewness parameter γ_{ϵ_i}, and tail parameter ν_{ϵ_i}.

The model of Luciani and Veredas (2012) relates to fractional cointegration in a similar way as the model of Bai and Ng (2004) is related to cointegration. Luciani and

Veredas (2012) document the usefulness of their model in estimating factors from a large dataset where long memory is present using both a Monte Carlo study and an empirical application. Using a theoretical proof, Bai and Ng (2004)[12] show that the factors can be estimated consistently using the principal components method on the first differenced data. In general, the method of principal components only provides consistent estimates of the factors when the error terms are stationary. When the variables of interest are cointegrated or fractionally cointegrated, the estimates of the factors obtained using principal components are not consistent since the error terms are not guaranteed to be stationary. Applying the principle components method to the first differenced data allows for consistent estimation of the factors and the error terms regardless to their dynamic properties. More formally, define $\mathbf{rv_t} = \Delta\mathbf{RV_t}$, $\mathbf{f_t} = \Delta\mathbf{F_t}$, and $\mathbf{z_t} = \Delta\xi_\mathbf{t}$ for $t = 2, \dots, T$. By first differencing equation (2.3), we get $\mathbf{rv_t} = \mathbf{\Lambda f_t} + \mathbf{z_t}$. The principal components method can be used to obtain the estimates $\widehat{\mathbf{f}}_t$, $\widehat{\mathbf{\Lambda}}$, and $\widehat{\mathbf{z}}_t$. Consistent estimates $\widehat{\mathbf{F}}_t$ and $\widehat{\xi}_t$ are obtained by cumulating $\widehat{\mathbf{f}}_t$ and $\widehat{\mathbf{z}}_t$ i.e. $\widehat{\mathbf{F}}_t = \sum_{t=2}^{t} \widehat{\mathbf{f}}_\mathbf{t}$ and $\widehat{\xi}_t = \sum_{t=2}^{t} \widehat{\mathbf{z}}_t$.

Without any further restrictions, the method of principal components estimates the space spanned by the latent factors. Thus, principal components estimate the factors and the factor loadings up to a rotation. When the interest is in forecasting, for instance, the identification of the factors and the factor loadings is not an issue. On the other hand, in this paper we are interested in the factor loadings in order to relate the response of the estimated factor to the response of the variables. Therefore, it is important to estimate the identified factors and factor loadings. To clarify the issue related to identification, the DFM in matrix form:

$$RV = F\Lambda' + \xi, \tag{2.6}$$

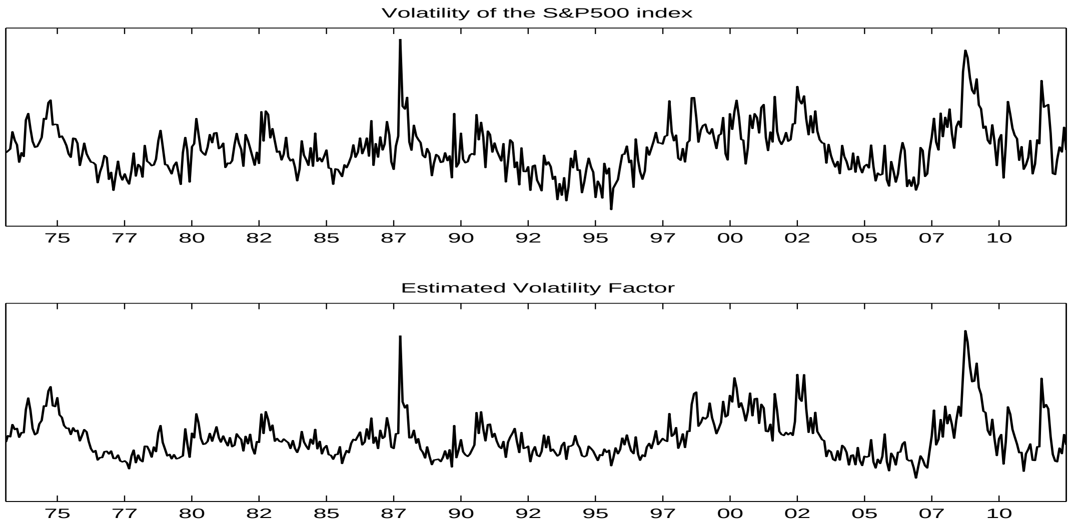
where $RV = (RV_1, \dots, RV_T)'$ is the $T \times N$ matrix of realized volatilities, $F = (F_1, \dots, F_T)'$ is the $T \times r$ matrix of common factors, and $\xi = (\xi_1, \dots, \xi_T)'$ is the $T \times N$ matrix of idiosyncratic components. The principal components method estimates $\tilde{F} = FH$ and $\tilde{\Lambda} = \Lambda H'^{-1}$ where H is an $r \times r$ invertible matrix. The product $\tilde{F}\tilde{\Lambda}'$ estimates $F\Lambda'$, and for any $r \times r$ invertible matrix R, the product of $F\Lambda'$ is equivalent to $FRR^{-1}\Lambda'$. Therefore, r^2 restrictions are required to identify the factors and the factor loadings. Bai and Ng (2013) show using a theoretical proof that, under different restrictions, the principal components method can estimate the identified factors and factor loadings. Following Bai and Ng (2013), we impose the following restrictions: 1) $\frac{1}{T}F'F = I_r$ and 2) $\Lambda'\Lambda$ to be a diagonal matrix with distinct elements. Imposing the previous restrictions allows us to estimate the identified factors and factor loadings.

In order to estimate the model in (2.3)-(2.5), one should first determine the number of factors to be used. Since the number of factors is unknown in practice, we use the Bai and Ng (2002) information criteria to determine it. The information criteria point to only one factor. As a robustness check, we also look at the percentage of variation explained by each factor; it turns out that the first factor explains 22% of the variation in the data, the second factor explains 2.77% and each of the other factors explains less than 2% of the variation in the data. Such result also suggests the suitability of using one factor in the analysis. This is in line with both Luciani and Veredas (2012) and Barigozzi et al. (2010) and also supports the hypothesis of the co-movement of the monthly realized volatilities.

[12]This result is also valid for the model of Luciani and Veredas (2012) since none of their assumptions violate the assumptions of Bai and Ng (2004) and so a proof is not needed.

The estimated first factor shows a high degree of long memory. The fractional integration parameter of the estimated first factor is 0.64; higher than any single series in the panel of monthly realized volatilities from which the factor was extracted. This is due to the fact that the estimated factor is a linear combination which smoothes out the temporary volatility shocks in the single firms. Such result holds for all aggregates in general. The estimated factor, $\hat{F}_t$, also correlates highly with the monthly realized volatility of the S&P500 index with a correlation coefficient of 0.9[13]. It can be observed from the plots of the monthly volatility of the S&P500 index and the estiamated volatility factor in figure 1 that they are highly correlated; this is important to ensure that the response of the volatility factor to monetary policy shocks behaves in a similar way as the volatility of the S&P500 index.

Figure 1: Volatility plots



Plots of the monthly volatility of the S&P 500 index and the estimated volatility factor from the whole dataset in the period between February 1973 and July 2012.

In addition, we also divide the dataset into 9 different sectors. Following the above procedure, we estimate volatility factors from each sector. Table 2 shows the percentage of variation explained by the first 5 factors extracted from each sector. With the exception of the first factor estimated from each sector, all the other factors summarize a small percentage of the variation within each sector. This result suggests that the first factor largely summarizes the variation in each sector. The correlation coefficients between the estimated volatility factors are shown in table 4 in the appendix. Figure 4 in the appendix shows the plots of the first factors estimated from each sector. From the plots, one can

[13] Although the dataset used here only contains the 213 assets that are part of S&P500 index for the whole duration used in this paper, the estimated factor from this panel still correlates highly with the realized volatility of the S&P500 index. I also tried to divide the sample into two periods, and compare the estimated factor from each period with the corresponding realized volatility of the S&P500 index. It turns out that the correlation coefficient for the first period is 0.93 while the coefficient for the more recent period is 0.88. This might be because the dataset does not include many of the American companies in both the Information technology and telecommunication services sectors that only became part of the S&P500 index more recently.

observe high correlations between the different sectors. All the sectors' estimated volatility factor capture the high volatility during the Black Monday, the dot-com bubble, and the recent financial crises. However, the magnitude of the spikes during crises periods differs between the different sectors.

Table 2: Percentage of variation

	1	2	3	4	5
ALL	22.04	2.77	1.55	1.46	1.33
IND	29.30	3.74	3.40	3.35	3.22
FIN	28.22	4.98	4.31	4.19	4.03
HC	28.75	7.03	6.46	6.04	5.79
CD	22.30	4.50	4.04	3.85	3.61
ITTS	29.15	7.24	6.41	6.15	5.20
UT	35.56	6.05	4.30	3.52	3.45
MAT	33.92	6.43	5.97	5.75	5.56
EN	34.10	6.54	6.23	5.50	5.22
CS	25.24	5.24	4.81	4.47	4.25

The percentage of the overall variation explained by the first 5 factors from each sector and the whole dataset.

Within each sector, the estimated factor loading for each company is shown in table 3 in the appendix. This shows how the estimated first volatility factor for each sector loads on the monthly realized volatility of each company that belong to the sector. Although the differences between the factor loadings of the companies in each sector is small, companies with large market cap tend to have larger factor loadings compared to other companies within their sectors. For example, the sectors' estimated volatility factor load highly on companies such as Bank of America, Chevron Corp., Dow Chemical, Exxon Mobil Corp., General Electric, IBM, Johnson & Johnson, and Procter & Gamble.

To sum up, in this section we construct a monthly dataset of realized volatilities of the constituents of the S&P500 index and its different sectors. The analysis of the dataset shows that the monthly realized volatilities have features, such as long memory, co-movement, conditional volatility, skewness, and heavy tails. To account for the stylized facts in the monthly realized volatilities, we use the DFM of Luciani and Veredas (2012) to consistently estimate the identified factors and their correspondent identified factor loadings from the different datasets. In the following sections, we include the estimated volatility factor(s) in a structural FAVAR model and analyze the response of the estimated volatility factor(s) to monetary policy shocks. From the response of the estimated volatility factor, we obtain the response of the different series from which the factor is extracted through equation (2.3). This is, however, not possible if we use the volatility of the S&P500 index instead of the volatility factor.

3 Structural VAR model

Since the seminal work of Sims (1980), VAR models have been the workhorse of empirical macroeconomics in both forecasting and structural analysis. In contrast to dynamic simultaneous equation models, VARs do not impose restrictions on the parameters; as a result, they allow for more general representation of the relationships in the data. Structural VARs are very useful in empirical analysis because they have different applications, such as impulse responses, forecast error variance decompositions, and historical decompositions. Impulse responses, which are of main interest in this paper, can be used to examine the expected response of the variables in the model to a structural shock. As a starting point, following the standard VAR literature, we define a VAR with an intercept in the reduced form as:

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{3.1}$$

where v is a $k \times 1$ vector of intercepts, y_t is a $k \times 1$ vector of endogenous variables, u_t is a $k \times 1$ vector of innovations with $E(u_t) = 0$ and $E(u_t u_t') = \Psi$, $A_1, \ldots, A_p$ are the $k \times k$ coefficient matrices, and p is the lag order.

3.1 Bayesian estimation

Due to the large dimensionality used in some approaches[14] in this paper, we use a Bayesian VAR (BVAR). The estimation of the BVAR follows the approach of Banbura et al. (2010) which is based on the earlier work of Litterman (1986), Kadiyala and Karlsson (1997), and Sims and Zha (1998). Following the idea of the Minnesota prior suggested by Litterman (1986) and the notation used by Banbura et al. (2010), we set the following moments for the coefficients' prior distribution:

$$E[(A_l)_{ij}] = \begin{cases} \Delta_i, & i = j\ ,\ l = 1 \\ 0, & \text{otherwise} \end{cases}\ , \tag{3.2}$$

$$V[(A_l)_{ij}] = \begin{cases} \dfrac{\lambda^2}{l^2}, & i = j \\ \dfrac{\lambda^2}{l^2}\dfrac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise} \end{cases}\ , \tag{3.3}$$

where $(A_l)_{ij}$ is the ij-th coefficient of A_l. Δ_i reflects the researcher's belief about the persistence of variable i. For stationary variables, Δ_i should be close to 0, while for variables in levels, Δ_i is usually set to 1. The overall tightness of the prior distribution is controlled be the hyperparameter λ; for $\lambda = \infty$ the posterior expectations and the ordinary least squares estimates coincide, but if $\lambda = 0$, the posterior is equal to the prior. As has been shown in De Mol et al. (2008), when the number of variables in the system increases, the shrinkage should also increase in order to avoid over-fitting. In practice, σ_i^2 is usually replaced by the OLS estimate of the error variance from a univariate autoregressive model of order p in the i^{th} equation.

The Minnesota prior is an automatic way of choosing the coefficients' expectations and variances in which a distinction is made between own lags and lags of other dependent

[14] Although the relatively parsimonious first approach can be estimated using classical methods, the second and the third approaches are of larger dimensions. In order to allow for fair comparison between all the three different approaches used in this paper, we use the same Bayesian estimation method for all the three approaches. In addition, the use of Bayesian techniques allows us to study the model using shorter sample periods.

variables. In the Minnesota prior, with the exception of the coefficients of the dependent variable's first own lag, the prior's expectation of all the coefficients is zero. Since closer lags are expected to be more relevant, the factor $1/l^2$ allows the coefficients to be shrunk more as the lag length increases. The term σ_i^2/σ_j^2 addresses the difference in scaling and variability in the data. In the original Minnesota prior the coefficients are assumed to be normally and independently distributed, while the variance covariance matrix, Ψ, is assumed to be diagonal, fixed, and equal to Σ, where $\Sigma = \text{diag}(\sigma_1^2, \cdots, \sigma_k^2)$. Since the focus of this paper is in structural analysis, it is important to take into account the possible correlations between the residuals of the different variables. Therefore, the assumption of a diagonal covariance matrix is not reasonable. In order to avoid this implausible assumption, we follow Kadiyala and Karlsson (1997) and use a Normal inverted Wishart prior while maintaining the properties of the Minnesota prior. For clarity, we use a VAR in matrix form:

$$Y = XA + U, \tag{3.4}$$

where $Y = (y_1, \cdots, y_T)'$ is a $T \times k$ matrix of endogenous variables, $X = (x_1, \cdots, x_T)'$ and $x_t = (1, y'_{t-1}, \cdots, y'_{t-p})'$ is a $T \times m$ matrix of ones and lagged endogenous variables, and $U = (u_1, \cdots, u_T)'$ is a $T \times k$ matrix of innovations. $A = (v, A_1, \cdots, A_p)'$ is a $m \times k$ matrix of coefficients, where $m = kp + 1$. The normal inverted Wishart prior can be written as:

$$\text{vec}(A)|\Psi \sim N(\text{vec}(A_0), \Psi \otimes \Omega_0) \quad \text{and} \quad \Psi \sim iW(S_0, a_0). \tag{3.5}$$

We choose the prior parameters A_0, Ω_0, S_0, and a_0 to allow the prior expectations and variances to match those implied by equations (3.2) and (3.3), and the expectation of Ψ to coincide with Σ of the Minnesota prior. The prior is implemented by adding dummy observations Y_d and X_d to the VAR in equation (3.4). The following T_d observations are added to the system:

$$Y_d = \begin{pmatrix} \text{diag}(\delta_1\sigma_1, \cdots, \delta_k\sigma_k)/\lambda \\ 0_{k(p-1)\times k} \\ \cdots\cdots\cdots\cdots \\ \text{diag}(\sigma_1, \cdots, \sigma_k) \\ \cdots\cdots\cdots\cdots \\ 0_{1\times k} \end{pmatrix} \qquad X_d = \begin{pmatrix} 0_{kp\times 1} & J_p \otimes (\sigma_1, \cdots, \sigma_k)/\lambda \\ & \cdots\cdots\cdots\cdots \\ 0_{k\times 1} & 0_{k\times kp} \\ & \cdots\cdots\cdots\cdots \\ \kappa & 0_{1\times kp} \end{pmatrix},$$

where κ is a very small number reflecting the uninformative prior for the intercept and $J_p = \text{diag}(1, \cdots, p)$. Including the above set of dummy observations is similar to setting the normal inverted Wishart prior using $A_0 = (X'_d X_d)^{-1} X'_d Y_d$, $\Omega_0 = (X'_d X_d)^{-1}$, $S_0 = (Y_d - X_d A_0)'(Y_d - X_d A_0)$, and $a_0 = T_d - m$. The VAR in matrix form after augmenting the dummy observations to the VAR in equation (3.4):

$$Y_* = X_* A + U_*, \tag{3.6}$$

where $Y_* = (Y', Y'_d)'$, $X_* = (X', X'_d)'$, and $U_* = (U', U'_d)'$. Defining $\tilde{A} = (X'_* X_*)^{-1} X'_* Y_*$ and $\tilde{\Sigma} = (Y_* - X_*\tilde{A})'(Y_* - X_*\tilde{A})$, the normal inverted Wishart posterior has the form:

$$\text{vec}(A)|\Psi, Y \sim N(\text{vec}(\tilde{A}), \Psi \otimes (X'_* X_*)^{-1}) \quad \text{and} \quad \Psi|Y \sim iW(\tilde{\Sigma}, T + k + 2). \tag{3.7}$$

Using the above formulation, the posterior expectation of the coefficients obtained from both the normal inverted Wishart and the Minnesota setups coincides with the OLS estimates obtained from the regression in equation (3.6).

3.2 Structural analysis

In the previous subsection we introduced the reduced form VAR model in order to allow for estimation; however, the main interest is in the structural shocks and not just the reduced form shocks. To identify a monetary policy shock, we include in the monthly structural VAR the log of personal consumption expenditure (PCE)[15] as a measure of inflation, the log of industrial production (IP) as a measure of aggregate economic activity, and federal funds rate (FFR) as a monetary policy instrument. IP, PCE, and FFR are the minimum set of variables required to identify a monetary policy shock (see e.g. Christiano et al. (1999)). We also include the log of intermediate materials (COM)[16] as a forward looking variable in order to mitigate a possible price puzzle. To analyze the effects of a monetary policy shock on the stock market, we also include S&P500 returns (RET) in addition to measure(s) of volatility (VOL) in the structural VAR.

The variance covariance matrix of the reduced form VAR in equation (3.1) can be decomposed into $\Psi = W\Sigma_e W'$, where W is a lower triangular matrix with unit diagonal and Σ_e is a diagonal variance covariance matrix of the structural shocks. Using the Cholesky decomposition $\Psi = CC'$, we define $W = CD^{-1}$ where D is a diagonal matrix with the same elements as the main diagonal of C. Premultiplying the reduced form VAR by $B = W^{-1}$ gives the structural VAR:

$$By_t = \nu + B_1 y_{t-1} + \ldots + B_p y_{t-p} + e_t, \tag{3.8}$$

where $\nu = Bv$, $B_i = BA_i$ for $i = 1, \ldots, p$, and $e_t = Bu_t$ is a $K \times 1$ vector of structural shocks. In the literature different identifying assumptions could be imposed on the contemporaneous matrix B. Here we opt for the commonly used recursive ordering assumption which implies that B is a lower triangular matrix and hence provides enough restrictions to recover the structural shocks from the reduced form innovations. The variables in the structural VAR are ordered as follows:

$$y_t = (\mathrm{COM}_t{}', \quad \mathrm{PCE}_t{}', \quad \mathrm{IP}_t{}', \quad \mathrm{FFR}_t{}', \quad \mathrm{RET}_t{}', \quad \mathrm{VOL}_t{}')'. \tag{3.9}$$

This ordering scheme suggests that macroeconomic variables respond with a time lag to monetary policy shocks while stock market variables respond contemporaneously to all the variables in the system. FFR responds contemporaneously to all macroeconomic variables but responds with a time lag to financial stock market variables. This ordering scheme is suggested in many papers in the literature such as Christiano et al. (1999), Bernanke et al. (2005), among many others. The structural shock, e_t^{FFR}, from the FFR equation in equation (3.8) is identified as a monetary policy shock. The impulse responses to a structural monetary policy shock can be obtained from the infinite order moving average (MA) representation of equation (3.8). Since the model is exactly identified, we compute the impulse responses and their error bands following Canova (1991) and Gordon and Leeper (1994). In this procedure, draws are first made from the posterior of the reduced form parameters and then structure parameters are computed for each draw.

[15] We also tried to use consumer price index (CPI) as a measure of inflation: however, PCE provides a less pronounced price puzzle.

[16] COM was the best forward looking variable in mitigating the price puzzle among many variables that we tried.

4 Results

In this section we present the results for the three approaches used to analyze the effects of a monetary policy shock on the stock market volatility. In order to capture the long memory in the realized volatility we estimate all the structural VAR models using 6 lags. The results obtained from the Bayesian estimation are based on 20,000 draws. As suggested by Sims and Zha (1999), we use probability bands corresponding to 68%. To avoid misleading cancellation of the long run relationship between the variables, all the variables are included in levels with the exception of returns[17]. COM, PCE, IP, Ret and VOL are included in logs multiplied by 100; therefore, the impulse responses are percentage changes compared to the initial level. In all the studys we increase the federal funds rate by 100 basis points. To avoid overfitting, parameters are shrunk more when the number of variables in the system increases or when the sample period is shorter. For the variables COM, PCE, IP,and FFR we set $\delta_i = 1$, for RET we set $\Delta_i = 0$, while for VOL we use $\Delta_i = 0.3$[18].

4.1 One factor structural FAVAR

In this approach we augment the estimated volatility factor from the whole panel of realized volatilities in a structural FAVAR model, i.e., in equation (3.9), $\mathrm{VOL}_t \equiv \hat{F}_t$. This parsimonious approach allows us to analyze the response of the aggregate market volatility to a monetary policy shock[19]. In addition, using equation (2.3), impulse responses of each single stock to a monetary policy shock can be obtained by multiplying the impulse responses of the volatility factor by the corresponding factor loading. Since the whole variation of the panel of volatilities is summarized by only one factor, the responses of the single stocks only vary in magnitude[20] but not in dynamics.

The impulse responses of the variables in the system estimated using the sample between February 1973 and July 2012 are shown in figure 2. The results show that industrial production significantly goes down 4 months following a monetary policy shock; this is in line with theory. The response of the personal consumption expenditure is, however, not significant. Although, according to theory, inflation should go down following a contractionary monetary policy shock, a large literature documents a price puzzle in structural VARs (see e.g. Hanson (2004)). Stock market returns decrease by more than 1% while the volatility factor increases by more than 0.4% after the shock. The stock market returns reach their lowest level one month after the shock and then start to increase reaching a positive value after 7 periods and then return to their initial value. Similarly, the esti-

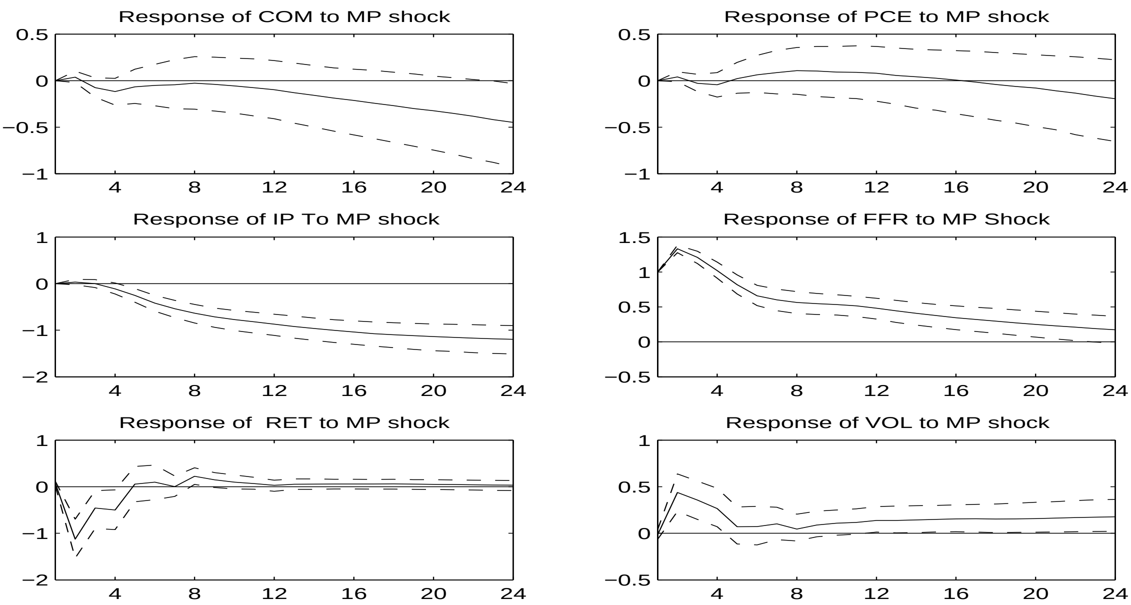
[17] As a robustness check, we also included the macroeconomic variables in growth rates; the results, however, do not vary.

[18] We also used different sets of sensible values of Δ_i; However, the results are robust to the different choices.

[19] For robustness, a similar exercise is conducted while substituting the volatility factor with the volatility of the S&P500 index. The results obtained are quite similar; this validates our usage of a volatility factor in the analysis instead of including a volatility of an index.

[20] Although in this approach the responses of the stocks are allowed to vary in magnitude and direction, the factor loadings are positive in 211 out of 213 stocks included in the panel of volatilities.

Figure 2: Impulse responses



Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between February 1973 and July 2012.

mated volatility factor attains its highest level after one month and tapers back to its original state after 4 months. In accordance with the theory, the results show that the stock markets returns decrease while the volatility increases following a tightening monetary policy. In addition, a strong negative correlation between stock market returns and volatility is quite obvious from the impulse responses.

Assuming that the parameters of the model remain constant in a long sample period might not be appropriate. Therefore, in order to have a better understanding of the dynamic response of the stock market variables to a monetary policy shock, we estimate the model over shorter sample periods[21]. In the first sample we estimate the model in the period between February 1973 and January 1978. This sample represents the period when the Federal Reserve was under the chairmanship of Arthur F. Burns. Although Arthur F. Burns was the chairman from February 1970 to January 1978, the starting date of our sample is determined by the availability of the data. The results of the impulse responses for this sample periods are shown in figure 6 in the appendix. Following a monetary policy shock, industrial production significantly goes down while personal consumption expenditure moves slightly up. It is worth noting here that according to Taylor (1999), the Federal Reserve accommodated inflation to a larger degree before the 1980s. The

[21] Alternatively one can estimate the model in a long sample period using either a structural time-varying parameter VAR (TVP-VAR) or Markov-switching VAR (MS-VAR). In the TVP-VAR, the underlying assumption is that the parameters of the model vary smoothly between consecutive periods. On the other hand, the MS-VAR assumes that all growth periods as well as all recession periods are similar in different times. However, since we have 6 variables in the system, the estimation of both models is exhaustive and a lot of shrinkage should be applied to allow for estimation. Therefore, we prefer to estimate the model at meaningful shorter sample periods.

stock returns fall down by less than 3% after one period and returns back to their original position after 2 periods. In the long run, we can also observe positivie slight changes in stock returns which only last for short periods. In this sample period the monetary policy has a strong effect on the stock returns in terms of magnitude, but these effects only last for short durations. On the other hand, the response of the volatility during this period is insignificant.

The second sample period used is August 1979 to July 1987. Paul Volcker, who is accredited of ending the high inflation during the early 1980s, was the chairman of the Federal Reserve during this period. Figure 7 in the appendix shows the impulse responses of the system under the chairmanship of Paul Volcker. The industrial production starts to decrease 4 months after the monetary policy shock. Eight months after the monetary policy shock, the personal consumption expenditure falls significantly. The stock market returns decrease by more than 0.6% two months after the shock, while the volatility increases by less than 0.2% immediately after the shock and then starts to return back to its original state after two months. According to these results, a monetary policy shock of a similar size has a stronger impact on inflation during Volcker's period compared to Burn's period. On the other hand, the response of the stock market returns to a monetary policy shock is stronger and faster during Burn's period. In both periods, the responses of the stock market volatility are minimal.

In the third experiment, we examine the period between August 1987 and January 2006 when Alan Greenspan was the chairman of the Federal Reserve. During Greenspan's chairmanship of the Federal Reserve, the financial markets experienced both the Black Monday and the dot-com bubble. Since the financial market has strong effects on the economy, one should expect the Federal Reserve to use its own tools to influence the financial market in order to achieve its macroeconomic targets. The results of the impulse responses are shown in figure 8 in the appendix. Industrial production initially increases for three periods following a contractionary monetary policy shock and then begins to decrease. Although this contradicts the theory, this result is not uncommon in the literature (see e.g. Brissimis and Magginas (2006)). In this sample period, we can also observe a strong price puzzle which lasts for more than 6 months. The responses of stock market variables are quite pronounced during Greenspan's period. Stock returns decrease by around 5% one period after the shock and then start to increase again reaching their original state after 5 months. The volatility factor increases by around 0.8% following the shock and then starts decreasing immediately. These results might suggest that the decisions made by the Federal Reserve during this period had a strong influence on the financial market, specially during financial crises periods.

The last sample covers the period between February 2006 and July 2012. This represents the period under the chairmanship of Ben Bernanke. Analyzing this period is quite difficult because it is mainly covered by the recent financial crises. In addition, in a large part of the sample the federal funds rate is close to zero and the Federal Reserve is using quantitative easing. Although it might be inappropriate to use our methodology to identify a monetary policy shock in this sample period, we include the results for completeness[22]. The impulse responses are shown in figure 9 in the appendix. Both

[22] We also estimate the model in the period between February 2006 and November 2008 to avoid the period where the federal funds rate is close to zero; the results are similar to the ones reported.

industrial production and personal consumption expenditure decrease following the shock. The stock market returns decrease by around 6% one period after the shock and remain at this level for three periods and then start to increase again afterwards. After one period, the volatility factor starts increasing for three periods by 5% and then decreases to its initial value. In general, the responses of the variables to a monetary policy shock are stronger in magnitude and more persistent in this sample period compared to previous periods.

4.2 Sectors structural FAVAR

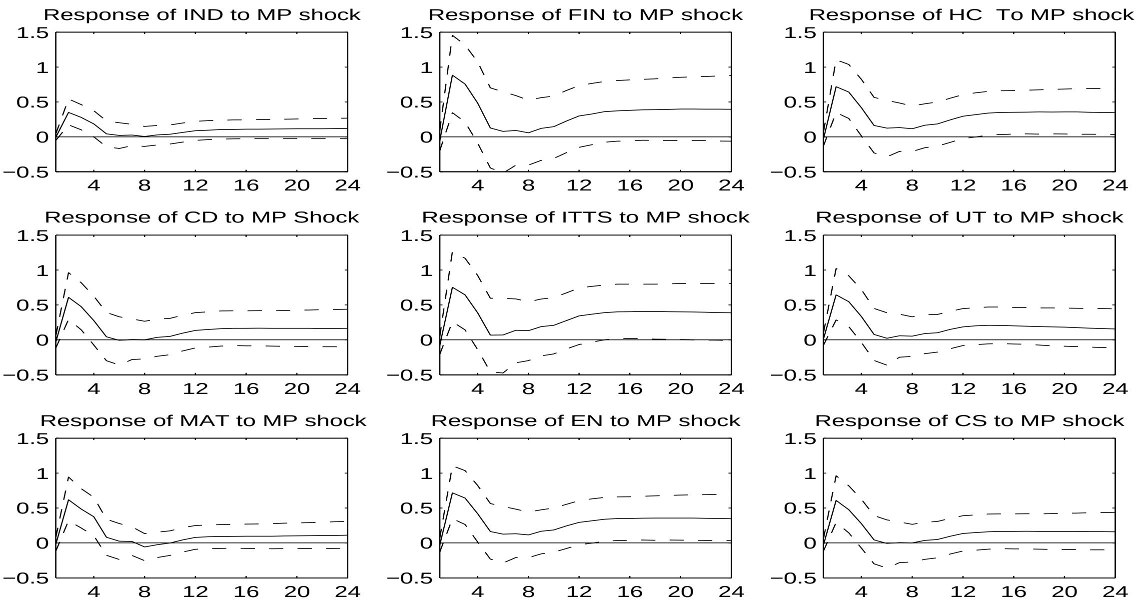
The assumption implied by the first approach is that the dynamics of the impulse responses of the single stocks' volatilities do not vary. This might be too restrictive. In order to relax this assumption, we include the volatility factors estimated from each sector in the FAVAR instead of including only one factor representing all stocks. Therefore, in this approach, we use $\text{VOL}_t \equiv \hat{F}_{t,sectors}$ in equation (3.9), where $\hat{F}_{t,sectors}$ is a 9×1 vector of the estimated volatility factors from each of the 9 different sectors. This approach allows us to investigate the responses of the different sectors to a monetary policy shock; both the magnitude and the dynamics of the sectors' responses are allowed to vary. Within each sector, the impulse response of each stock's volatility to a monetary policy shock can be obtained by multiplying the impulse response of the sector's volatility by the corresponding factor loading of the stock. Since only one factor summarizes the variation within each sector, the impulse responses of the different stocks in each sector only vary in magnitude. Given that companies which have large market cap tend to have larger factor loadings compared to other companies within the same sector as shown in table 3 in the appendix, the magnitude of the volatility responses of the large market cap companies is in general stronger.

The impulse responses of the different sectors to a monetary policy shock using the sample period between February 1973 and July 2012 are shown in figure 3. The magnitude of the responses vary between the sectors. The results show that the response of the financials sector to a monetary policy shock is stronger than other sectors; this result confirms the findings of Chuliá et al. (2010). On the other hand, the response of the industrials sector is less sensitive to monetary policy shocks compared to other sectors. The dynamics of the responses of the different sectors look very similar; the volatility increases one period after the shock and then starts tapering to its original value. The responses of some sectors, however, are more persistent compared to other sectors. For instance, from the responses of the health care sector and the energy sector, we can notice that after one year there is still a significant increase in volatility relative to its initial value.

4.3 Structural VAR for volatilities

Instead of using a structural FAVAR model, in this approach we include realized volatilities of different stocks directly in a structural VAR. This approach allows us to analyze the response of the volatilities of the different stocks to monetary policy shocks without any restrictions on their magnitude or dynamics. However, due to the large dimensionality

Figure 3: Impulse responses



Responses of the volatilities of the different sectors included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between February 1973 and July 2012.

of this structural VAR, the number of realized volatilities that can be included in the structural VAR is restricted.

Figures 10 and 11 in the appendix show the responses of the realized volatilities of the stocks in both the energy and materials sectors to a monetary policy shock in the period between February 1973 and July 2012. For the energy sector in figure 10, we include $\text{VOL}_t \equiv RV_{t,energy}$ in equation (3.9), where $RV_{t,energy}$ is a 17×1 vector of the realized volatilities of the stocks in the energy sector. And for the materials sector in figure 11, we include $\text{VOL}_t \equiv RV_{t,materials}$ in equation (3.9), where $RV_{t,materials}$ is a 16×1 vector of the realized volatilities of the stocks in the materials sector. In both figures the dynamics of the responses of the different realized volatilities look very similar; however, the magnitude and the significance of the responses vary between the different stocks. In figure 10, we observe that the responses of both Chevron Corp. and Exxon Mobil Corp. have strong magnitude compared to other companies in the energy sector; both companies have large factor loadings as shown in table 3 in the appendix and have large market cap. In figure 11, we notice that Dow Chemical, which has a large factor loading and large market cap, shows a response with strong magnitude.

Although this approach allows the dynamics of the responses to be different, the variation between the dynamics of the responses of the realized volatilities is minimal. The results of the impulse responses obtained from this totally unrestricted approach justify our results from the first and the second approach. In addition, we highlight that companies with large market cap are more likely to have larger factor loadings and stronger responses to monetary policy shocks in terms of magnitude.

5 Conclusion

In this paper we construct a monthly dataset of realized volatilities which consists of the components of the S&P500 index. The monthly dataset is analyzed and the presence of long memory, conditional heteroskedasticity, skewness, and heavy tails is evident in the monthly realized volatilities. In order to account for the aforementioned stylized facts present in the data, we follow Luciani and Veredas (2012) and estimate the volatility factors by applying the principle components method on the differenced data. It is shown that only one volatility factor is enough to appropriately summarize the variation in the data suggesting that there is a common dynamic factor leading the co-movement of the different stocks in the market.

In the second estimation step, we augment a VAR with macroeconomic variables with the estimated volatility factor to form a structural FAVAR model. The FAVAR is used to analyze the response of the stock market volatility to a contractionary monetary policy shock. In this paper we use three approaches that allow us to study the response of the aggregate market volatility, the sectors' volatilities, and the stocks' volatilities. The results of the impulse responses suggest that the stock market returns decrease while the volatility increases following a monetary policy tightening; a strong negative correlation between returns and volatility can be observed from their dynamic responses. Although the dynamics do not vary widely between the responses of the different stocks and sectors, the magnitude of the responses differs. For instance, the response of the financials sector to a monetary policy shock is stronger in magnitude than other sectors. Moreover, companies with large market cap are more likely to exhibit responses with stronger magnitude. In addition, we analyze the responses of the variables in the system at different policy regimes. According to the results, starting from Greenspan's chairmanship of the Federal Reserve, the responses of stock market variables to monetary policy shocks become more pronounced compared to earlier periods.

The results are important for both investors and policy makers. From investors' perspective, an investor can make profitable trades if he successfully anticipates policy actions. From the policy point of view, understanding the magnitude and dynamics of the response of the stock market variables to policy actions is very important because this response can influence the real economy through different channels.

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Appendix

Table 3: Dataset for financial stocks

	Name	Code	Sector	Λ
1	3M	902172(P)	IND	0.17
2	ABBOTT LABORATORIES	916328(P)	HC	0.29
3	ADVANCED MICRO DEVC.	936365(P)	ITTS	0.27
4	AGL RESOURCES	906820(P)	UT	0.23
5	AIR PRDS.& CHEMS.	905271(P)	MAT	0.30
6	ALCOA	905113(P)	MAT	0.26
7	ALTRIA GROUP	904853(P)	CS	0.18
8	AMER.ELEC.PWR.	905425(P)	UT	0.15
9	AMERICAN EXPRESS	906156(P)	FIN	0.20
10	AMERICAN INTL.GP.	916305(P)	FIN	0.25
11	ANALOG DEVICES	905276(P)	ITTS	0.24
12	APACHE	921983(P)	EN	0.26
13	APPLIED MATS.	905296(P)	ITTS	0.21
14	ARCHER-DANLS.-MIDL.	921093(P)	CS	0.18
15	AUTOMATIC DATA PROC.	912669(P)	ITTS	0.24
16	AVERY DENNISON	921161(P)	IND	0.21
17	AVON PRODUCTS	905793(P)	CS	0.21
18	BALL	932060(P)	MAT	0.26
19	BANK OF AMERICA	923937(P)	FIN	0.22
20	BANK OF NEW YORK MELLON	905840(P)	FIN	0.22
21	C R BARD	905592(P)	HC	0.22
22	BAXTER INTL.	916365(P)	HC	0.28
23	BB&T	992305(P)	FIN	0.12
24	BEAM	904259(P)	CD	0.19
25	BECTON DICKINSON	905876(P)	HC	0.26
26	BEMIS	912125(P)	MAT	0.24
27	H&R BLOCK	905596(P)	CD	0.15
28	BOEING	904818(P)	IND	0.18
29	BRISTOL MYERS SQUIBB	905080(P)	HC	0.30
30	BROWN-FORMAN 'B'	912216(P)	CS	0.16
31	CAMPBELL SOUP	905075(P)	CS	0.21
32	CATERPILLAR	902224(P)	IND	0.19
33	CENTERPOINT EN.	904842(P)	UT	0.20
34	CENTURYLINK	906838(P)	ITTS	0.16
35	CHEVRON	905024(P)	EN	0.29
36	CHUBB	916790(P)	FIN	0.21
37	CINCINNATI FINL.	951545(P)	FIN	0.16
38	CLIFFS NATURAL RESOURCES	912420(P)	MAT	0.19
39	CLOROX	916125(P)	CS	0.17
40	CMS ENERGY	901686(P)	UT	0.15
41	COCA COLA	904282(P)	CS	0.24
42	COLGATE-PALM.	906148(P)	CS	0.23

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Table 3 – *Continued from previous page*

	Name	Code	Sector	Λ
43	COMCAST 'A'	981550(P)	CD	0.11
44	COMERICA	922964(P)	FIN	0.19
45	COMPUTER SCIS.	916091(P)	ITTS	0.17
46	CONAGRA FOODS	929814(P)	CS	0.21
47	CONOCOPHILLIPS	901666(P)	EN	0.25
48	CONSOLIDATED EDISON	902288(P)	UT	0.21
49	COOPER INDUSTRIES	912568(P)	IND	0.16
50	CORNING	912273(P)	IND	0.16
51	CUMMINS	905966(P)	IND	0.16
52	CVS CAREMARK	912635(P)	CS	0.19
53	DEERE	906189(P)	IND	0.15
54	R R DONNELLEY & SONS	905047(P)	IND	0.17
55	DOVER	904830(P)	IND	0.20
56	DOW CHEMICAL	905114(P)	MAT	0.29
57	DTE ENERGY	905214(P)	UT	0.18
58	E I DU PONT DE NEMOURS	902199(P)	MAT	0.31
59	DUKE ENERGY	904383(P)	UT	0.21
60	EATON	903749(P)	IND	0.21
61	ECOLAB	921268(P)	MAT	0.20
62	EDISON INTL.	902324(P)	UT	0.19
63	EMERSON ELECTRIC	905115(P)	IND	0.16
64	ENTERGY	902306(P)	UT	0.18
65	EQT	904390(P)	UT	0.13
66	EQUIFAX	906194(P)	FIN	0.15
67	EXELON	902317(P)	UT	0.18
68	EXXON MOBIL	905039(P)	EN	0.31
69	FAMILY DOLLAR STORES	923755(P)	CD	0.14
70	FIRST HORIZON NATIONAL	905780(P)	FIN	0.15
71	FIRSTENERGY	905159(P)	UT	0.17
72	FLOWSERVE	905755(P)	IND	0.13
73	FMC	905082(P)	MAT	0.22
74	FORD MOTOR	902230(P)	CD	0.21
75	FOREST LABS.	921276(P)	HC	0.22
76	FRONTIER COMMUNICATIONS	922301(P)	ITTS	0.08
77	GANNETT	923449(P)	CD	0.23
78	GENERAL DYNAMICS	907652(P)	IND	0.17
79	GENERAL ELECTRIC	906150(P)	IND	0.21
80	GENERAL MILLS	905801(P)	CS	0.23
81	GENUINE PARTS	906511(P)	CD	0.20
82	GOODYEAR TIRE & RUB.	904837(P)	CD	0.19
83	WW GRAINGER	905898(P)	IND	0.18
84	HALLIBURTON	904678(P)	EN	0.28
85	HARRIS	905409(P)	ITTS	0.26
86	HASBRO	912030(P)	CD	0.17
87	HJ HEINZ	902262(P)	CS	0.23

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Table 3 – *Continued from previous page*

	Name	**Code**	**Sector**	Λ
88	HELMERICH & PAYNE	921049(P)	EN	0.26
89	HESS	905802(P)	EN	0.26
90	HEWLETT-PACKARD	905277(P)	ITTS	0.21
91	HORMEL FOODS	921051(P)	CS	0.13
92	HOST HOTELS & RESORTS	912588(P)	FIN	0.18
93	HUMANA	916860(P)	HC	0.22
94	INTERNATIONAL BUS.MCHS.	906187(P)	ITTS	0.31
95	HUNTINGTON BCSH.	951068(P)	FIN	0.17
96	ILLINOIS TOOL WORKS	905052(P)	IND	0.20
97	INGERSOLL-RAND	905446(P)	IND	0.20
98	INTEGRYS ENERGY GROUP	902336(P)	UT	0.21
99	INTEL	922726(P)	ITTS	0.30
100	INTL.PAPER	904069(P)	MAT	0.30
101	INTERPUBLIC GP.	923465(P)	CD	0.16
102	JACOBS ENGR.	912142(P)	IND	0.14
103	JOHNSON & JOHNSON	912212(P)	HC	0.33
104	JOHNSON CONTROLS	907677(P)	CD	0.20
105	JP MORGAN CHASE & CO.	902242(P)	FIN	0.23
106	KELLOGG	905922(P)	CS	0.25
107	KIMBERLY-CLARK	902354(P)	CS	0.18
108	KROGER	912134(P)	CS	0.16
109	LEGGETT&PLATT	906487(P)	CD	0.15
110	LENNAR 'A'	912219(P)	CD	0.14
111	LEUCADIA NATIONAL	921925(P)	FIN	0.15
112	ELI LILLY	921290(P)	HC	0.28
113	LIMITED BRANDS	937343(P)	CD	-0.03
114	LINCOLN NAT.	912402(P)	FIN	0.21
115	LOEWS	922418(P)	FIN	0.19
116	LOWE'S COMPANIES	905620(P)	CD	0.16
117	M&T BK.	951503(P)	FIN	0.17
118	MARSH & MCLENNAN	904780(P)	FIN	0.21
119	MASCO	905624(P)	IND	0.16
120	MATTEL	912811(P)	CD	0.17
121	MCCORMICK & CO NV.	510493(P)	CS	0.14
122	MCDONALDS	921910(P)	CD	0.19
123	MCGRAW-HILL	905414(P)	CD	0.19
124	MEADWESTVACO	905806(P)	MAT	0.27
125	MEDTRONIC	906496(P)	HC	0.21
126	MOLEX	929635(P)	ITTS	0.24
127	MOTOROLA SOLUTIONS	904878(P)	ITTS	0.30
128	MURPHY OIL	906404(P)	EN	0.25
129	MYLAN	906931(P)	HC	0.00
130	NABORS INDS.	916532(P)	EN	-0.05
131	NEWELL RUBBERMAID	906933(P)	CD	0.16
132	NEWMONT MINING	912160(P)	MAT	0.18

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Table 3 – *Continued from previous page*

	Name	Code	Sector	Λ
133	NEXTERA ENERGY	905016(P)	UT	0.20
134	NISOURCE	906176(P)	UT	0.17
135	NOBLE ENERGY	906557(P)	EN	0.25
136	NORDSTROM	906560(P)	CD	0.17
137	NORTHEAST UTILITIES	921999(P)	UT	0.20
138	NORTHERN TRUST	905861(P)	FIN	0.17
139	NORTHROP GRUMMAN	905809(P)	IND	0.15
140	NUCOR	921482(P)	MAT	0.24
141	OCCIDENTAL PTL.	905102(P)	EN	0.26
142	OMNICOM GP.	932913(P)	CD	0.17
143	ONEOK	904480(P)	UT	0.14
144	PACCAR	921757(P)	IND	0.15
145	PALL	921484(P)	IND	0.12
146	PARKER-HANNIFIN	905150(P)	IND	0.20
147	PENNEY JC	912781(P)	CD	0.18
148	PEPCO HOLDINGS	904509(P)	UT	0.20
149	PEPSICO	905677(P)	CS	0.24
150	PERKINELMER	912157(P)	HC	0.26
151	PFIZER	904030(P)	HC	0.29
152	PG&E	902314(P)	UT	0.20
153	PINNACLE WEST CAP.	902607(P)	UT	0.17
154	PITNEY-BOWES	905118(P)	IND	0.16
155	PNC FINL.SVS.GP.	944175(P)	FIN	0.22
156	PPG INDUSTRIES	901897(P)	MAT	0.29
157	PPL	902107(P)	UT	0.17
158	PREC.CASTPARTS	997350(P)	IND	0.06
159	PROCTER & GAMBLE	912228(P)	CS	0.28
160	PROGRESSIVE OHIO	936324(P)	FIN	0.18
161	PUB.SER.ENTER.GP.	902321(P)	UT	0.21
162	RAYTHEON 'B'	912633(P)	IND	0.19
163	REGIONS FINL.NEW	951051(P)	FIN	0.12
164	ROBERT HALF INTL.	923649(P)	IND	0.13
165	ROCKWELL AUTOMATION	902233(P)	IND	0.18
166	ROWAN COMPANIES CL.A	907620(P)	EN	0.27
167	RYDER SYSTEM	906284(P)	IND	0.19
168	SCANA	904539(P)	UT	0.20
169	SCHLUMBERGER	912090(P)	EN	0.30
170	SEALED AIR	923036(P)	MAT	0.18
171	SEMPRA EN.	902103(P)	UT	0.19
172	SHERWIN-WILLIAMS	905361(P)	CD	0.18
173	J M SMUCKER	912441(P)	CS	0.16
174	SNAP-ON	906400(P)	CD	0.20
175	SOUTHERN	902325(P)	UT	0.20
176	SOUTHWEST AIRLINES	905647(P)	IND	0.15
177	SOUTHWESTERN ENERGY	930551(P)	EN	0.11

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Table 3 – *Continued from previous page*

	Name	Code	Sector	Λ
178	SPRINT NEXTEL	904864(P)	ITTS	0.18
179	STANLEY BLACK & DECKER	921503(P)	CD	0.20
180	STARWOOD HTLS.& RSTS.	514950(P)	CD	0.17
181	STATE STREET	951052(P)	FIN	0.21
182	SUNOCO	905255(P)	EN	0.22
183	SYSCO	916079(P)	CS	0.21
184	TARGET	923425(P)	CD	0.20
185	TECO ENERGY	905454(P)	UT	0.19
186	TENET HLTHCR.	912969(P)	HC	0.16
187	TERADYNE	912744(P)	ITTS	0.29
188	TESORO	912052(P)	EN	0.15
189	TEXAS INSTS.	905061(P)	ITTS	0.26
190	TEXTRON	921649(P)	IND	0.19
191	THE HERSHEY COMPANY	905077(P)	CS	0.19
192	TRAVELERS COS.	933974(P)	FIN	0.21
193	THERMO FISHER SCIENTIFIC	906394(P)	HC	0.24
194	TJX COS.	921855(P)	CD	0.17
195	TORCHMARK	993394(P)	FIN	0.20
196	TYSON FOODS 'A'	906643(P)	CS	0.13
197	UNION PACIFIC	905105(P)	IND	0.19
198	UNITED TECHNOLOGIES	905122(P)	IND	0.19
199	V F	901892(P)	CD	0.19
200	VARIAN MED.SYS.	906220(P)	HC	0.26
201	VORNADO REALTY TST.	912146(P)	FIN	0.12
202	VULCAN MATERIALS	905816(P)	MAT	0.20
203	WAL MART STORES	916548(P)	CS	0.22
204	WALGREEN	904866(P)	CS	0.18
205	WALT DISNEY	921964(P)	CD	0.20
206	WASHINGTON PST.'B'	922079(P)	CD	0.15
207	WEYERHAEUSER	905818(P)	FIN	0.19
208	WHIRLPOOL	904869(P)	CD	0.21
209	WILLIAMS COS.	922407(P)	EN	0.21
210	WISCONSIN ENERGY	902335(P)	UT	0.21
211	XCEL ENERGY	905010(P)	UT	0.21
212	XEROX	905284(P)	ITTS	0.28
213	ZIONS BANCORP.	951584(P)	FIN	0.18

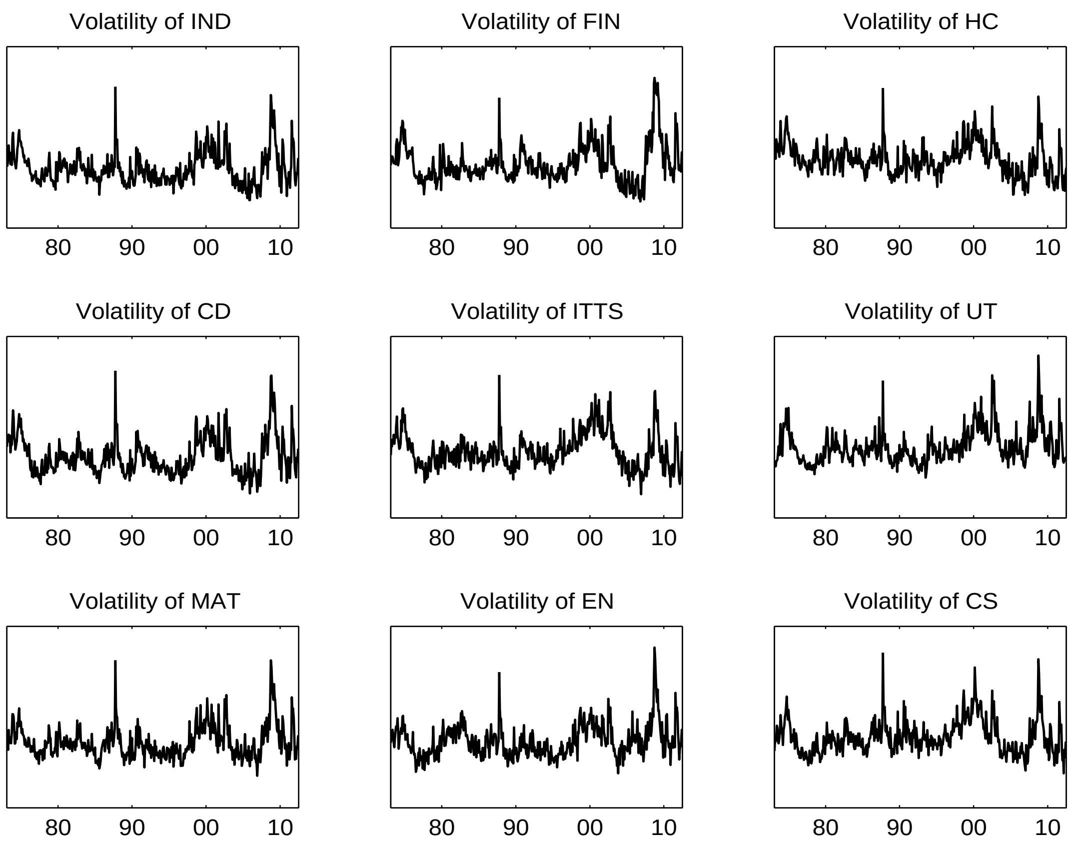
The table contains a list of the companies that are part of the S&P500 index and cover the period from 02/01/1973 to 31/07/2012. The data, obtained from Datastream, represents 9 different sectors, namely, industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and consumer staples (CS). The names and codes are similar to the ones used by Datastream. The factor loading, Λ, obtained from the dynamic factor model, shows how the estimated first volatility factor for each sector loads on the monthly realized volatility of each company within the sector.

Table 4: Correlations

	S&P	ALL	IND	FIN	HC	CD	ITTS	UT	MAT	EN	CS
S&P500	1	0.90	0.89	0.84	0.72	0.87	0.77	0.77	0.88	0.81	0.80
ALL		1	0.97	0.93	0.85	0.96	0.89	0.85	0.95	0.86	0.91
IND			1	0.90	0.84	0.95	0.86	0.75	0.94	0.82	0.85
FIN				1	0.72	0.91	0.76	0.75	0.88	0.77	0.81
HC					1	0.80	0.86	0.64	0.76	0.66	0.84
CD						1	0.83	0.75	0.93	0.82	0.84
ITTS							1	0.72	0.79	0.68	0.86
UT								1	0.77	0.75	0.74
MAT									1	0.85	0.82
EN										1	0.74
CS											1

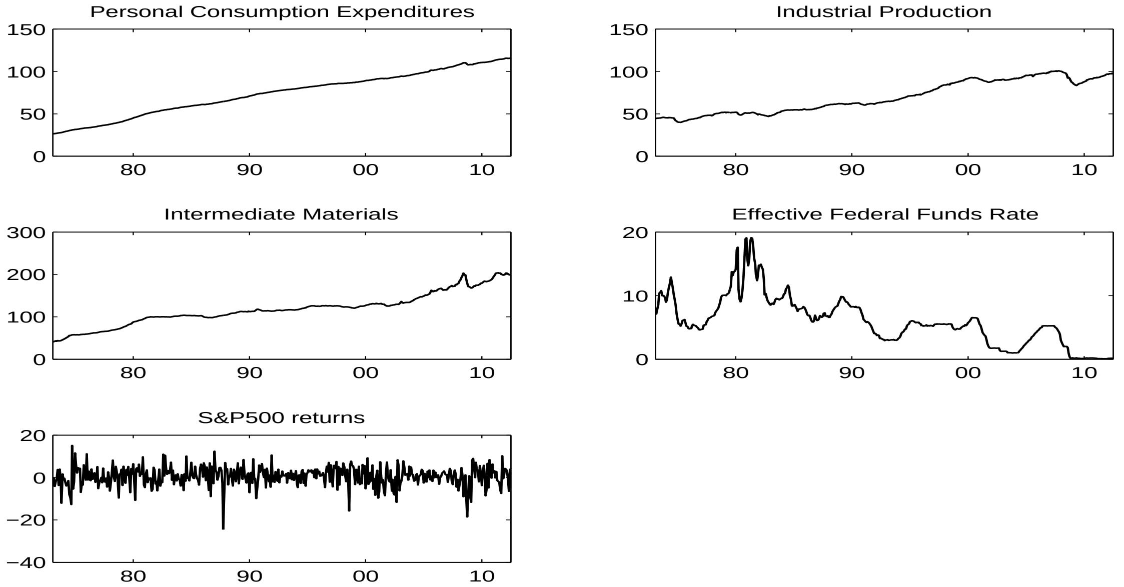
Correlation coefficients between the monthly volatility of the S&P500 index and the estimated volatility factors from the different sectors and the whole dataset.

Figure 4: Volatility plots



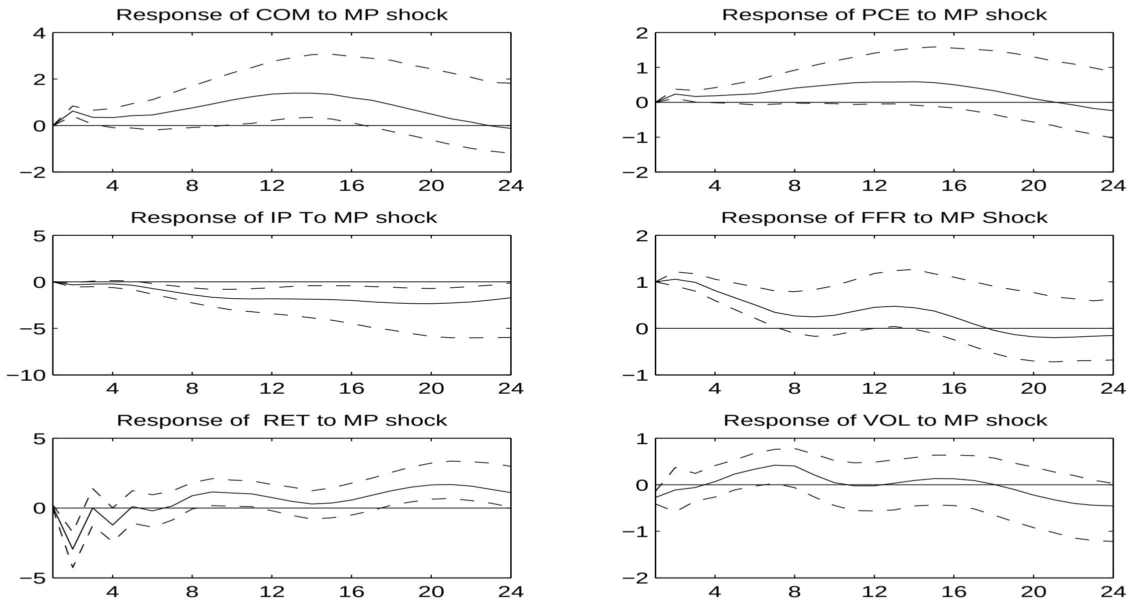
The estimated monthly volatility factor for each sector in the period between February 1973 and July 2012.

Figure 5: Monthly variables plots



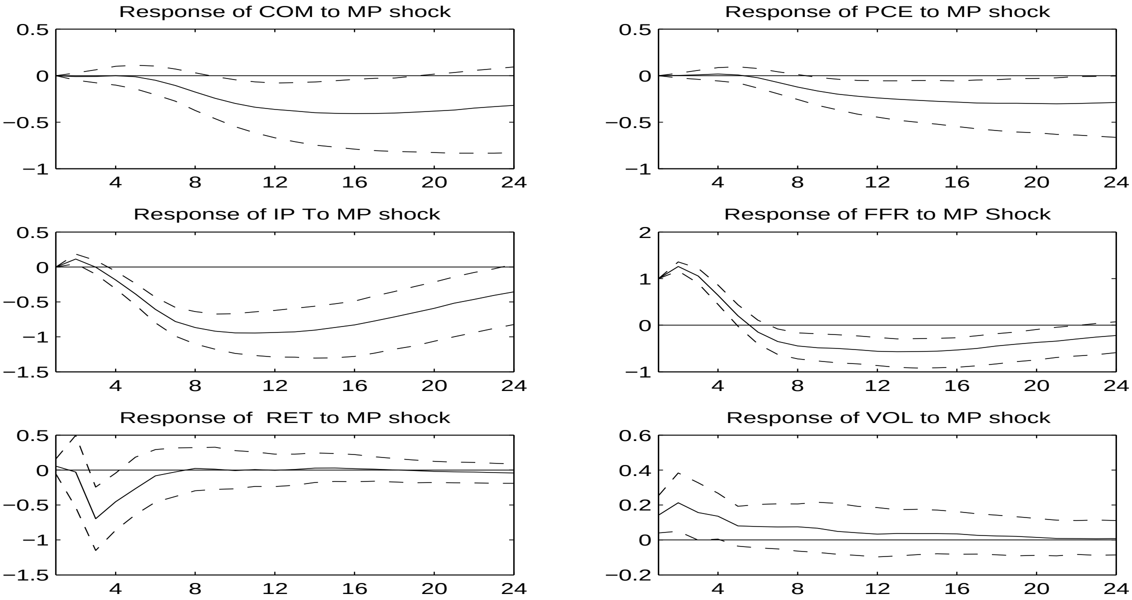
The monthly time series plots of the macroeconomic variables and the returns of the S&P500 index in the period between February 1973 and July 2012.

Figure 6: Impulse responses



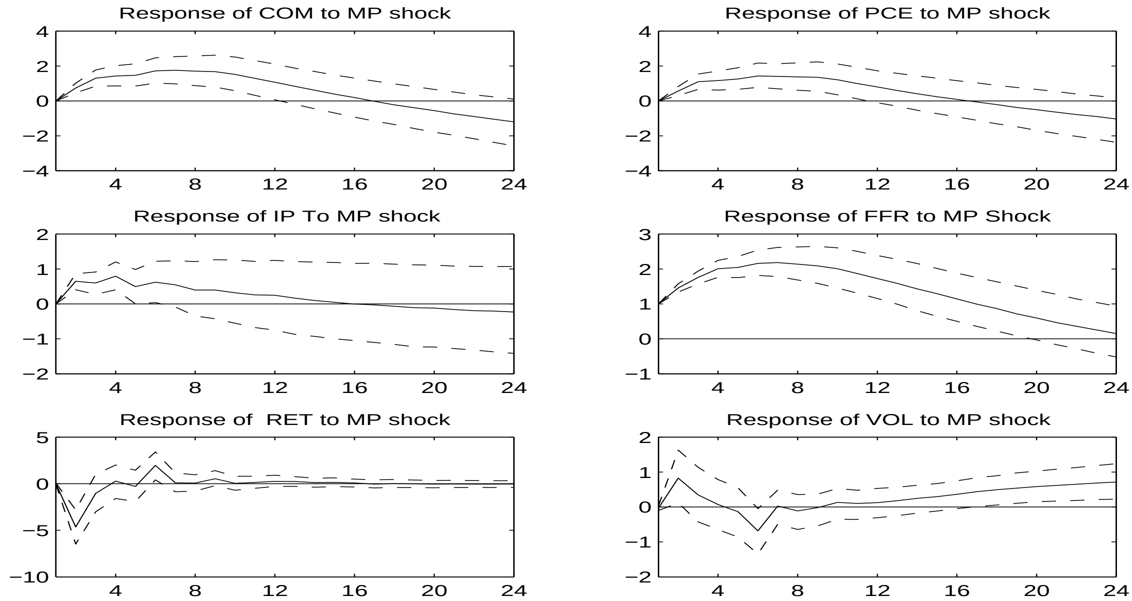
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between February 1973 and January 1978.

Figure 7: Impulse responses



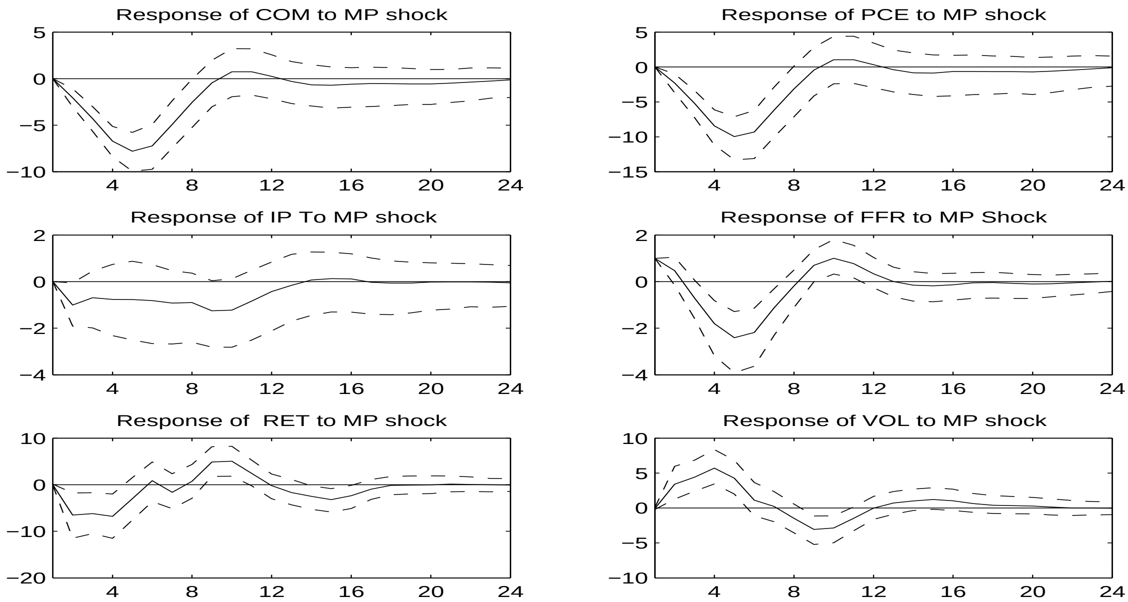
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between August 1979 and July 1987.

Figure 8: Impulse responses



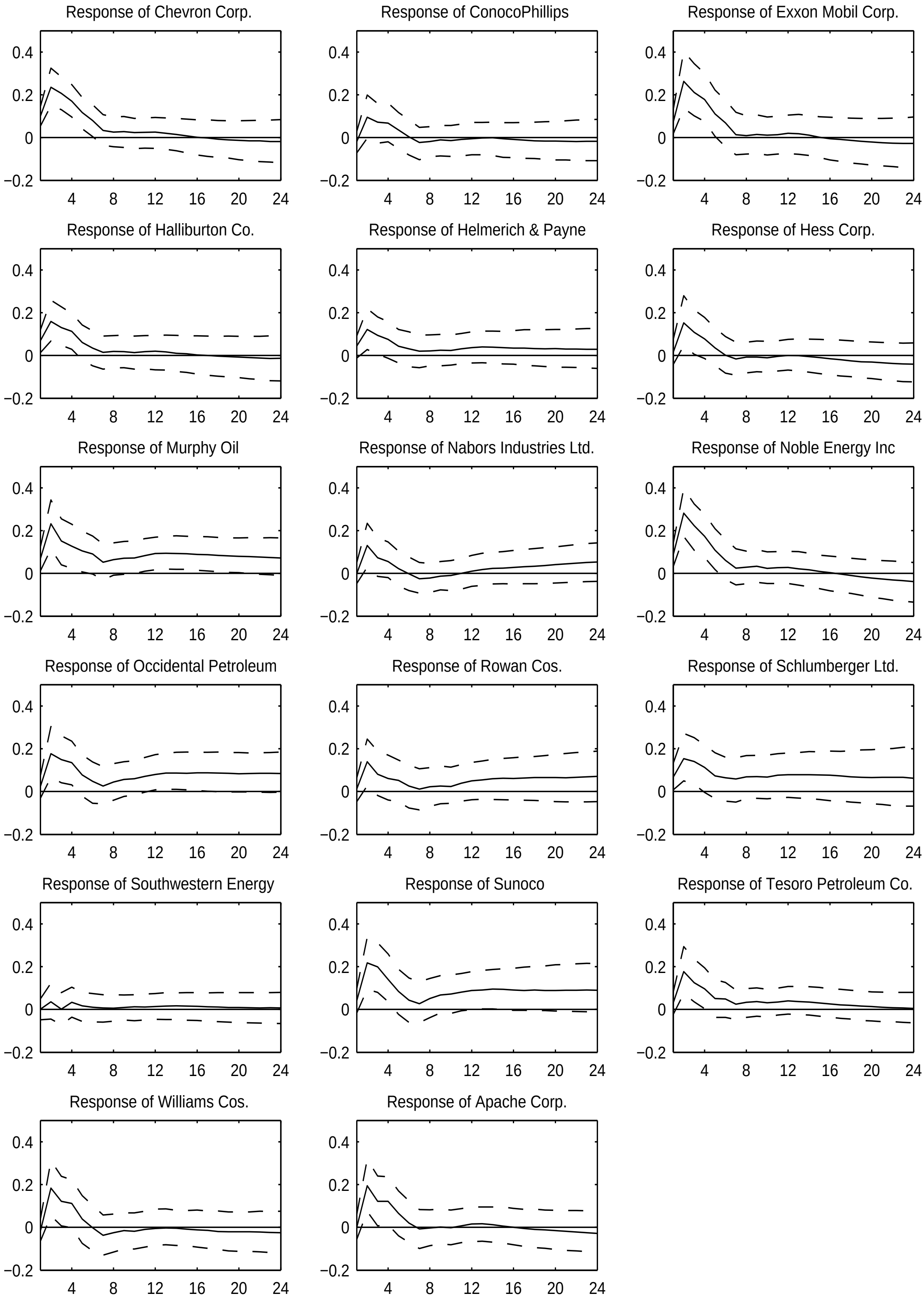
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between August 1987 and January 2006.

Figure 9: Impulse responses



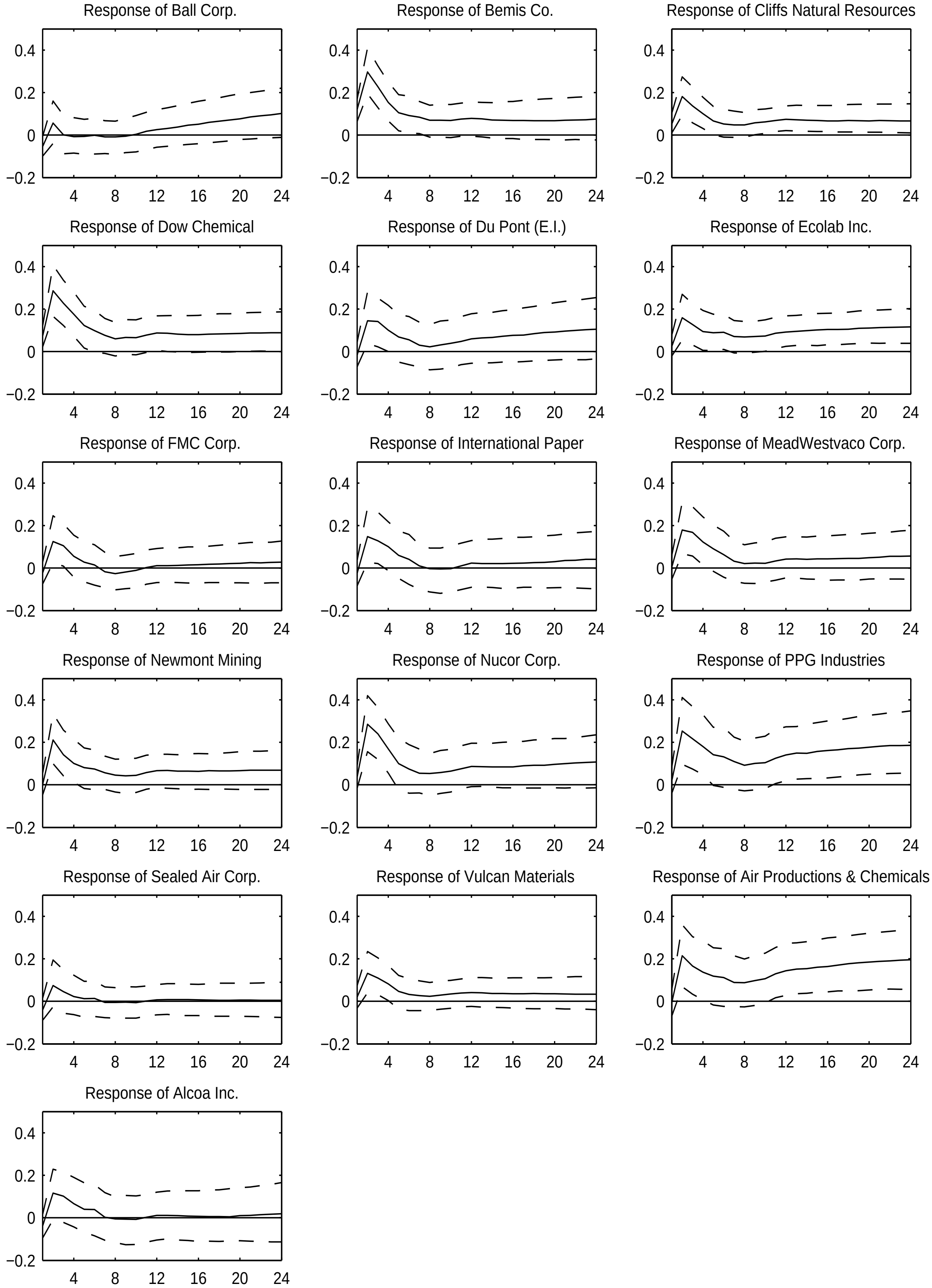
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between February 2006 and July 2012.

Figure 10: Impulse responses



Responses of the realized volatilities of the companies in the energy sector included in the structural VAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between February 1973 and July 2012.

Figure 11: Impulse responses



Responses of the realized volatilities of the companies in the materials sector included in the structural VAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation confidence interval under normality. The model is estimated using the sample between February 1973 and July 2012.