The Effects of Monetary Policy on Industry-level Stock Returns in a Changing World *

Pierre Guérin† Danilo Leiva-Leon‡

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Abstract

This paper provides a comprehensive analysis of the time-varying effects of monetary policy shocks on stock returns across economic sectors. In doing so, we perform our analysis from different perspectives to obtain a detailed picture of the timing, magnitude and duration of monetary policy effects using event studies and a time-varying parameter factor-augmented vector autoregressive model. We find that a surprise monetary policy tightening leads to a decline in stock returns in most industries, and uncover evidence in favor of substantial time variation. Moreover, we show that there is a substantial heterogeneity in the magnitude of the responses across industries. Finally, we show that the cross-sectional and time variations in the responses to monetary policy shocks are well explained by network measures of industry-level stock returns. We find that higher connectedness is associated with a more adverse response to monetary policy shocks.

Keywords: Stock market, Monetary policy, Time-varying parameter factor model, Network analysis.

JEL Classification Code: E44, C32, G12.

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†Bank of Canada, e-mail: pguerin@bank-banque-canada.ca

‡Central Bank of Chile, e-mail: dleiva@bcentral.cl

1 Introduction

The Great Recession and the unwinding of unconventional monetary policies in a number of advanced economies have rekindled an interest in evaluating the effects of monetary policy on asset prices. In particular, while the conventional view is that unexpected monetary policy tightening episodes are associated with a negative response of share prices, Galí (2014) challenged this view developing a general equilibrium model where increases in interest rates lead to an increase in the bubble component of stock prices. As a result, if the bubble component of stock prices is predominant relative to their fundamental component, it could well be that observed stock prices react positively to surprise increases in the policy rate. In an empirical evaluation of this model, Galí and Gambetti (2015) find evidence in favor of protracted episodes in which stock prices respond positively to a surprise tightening in monetary policy, most notably since the 1980's. However, the vast majority of the literature finds that surprise monetary policy tightening episodes lead to declines in equity returns. For example, Bernanke and Kuttner (2005) estimate that a 100 basis point increase in the policy rate is associated with a roughly 4 per cent decline in stock returns.

In this paper, we study in a dynamic fashion the linkages between monetary policy and the stock market. A key aspect of our analysis is that we study the response of stock returns to monetary policy shocks at the industry level and evaluate the degree of time variation in the responses. The rationale for doing so is that industries with different expected dividends and perceived riskiness (i.e., risk premium) on stocks may well react differently to unanticipated changes in monetary policy. Hence, it is important to study at a detailed industry-level the effects of monetary policy surprises on the stock market, since it permits us to obtain a better understanding of the drivers of monetary policy changes on the stock market. Likewise, it is important to account for possible structural breaks by explicitly modeling time variation, since omitting to do so could lead to an erroneous impulse response analysis if the relation between monetary policy and the stock market has changed over time.

The literature on the effects of monetary policy on the stock market has expanded in a number of ways. First, one strand of the literature uses vector autoregression (VAR) to study the dynamic interactions between central bank actions and asset prices. A key issue relates to the identification of the model in that recursive assumptions about the timing of the contemporaneous relation between interest rate and asset prices may be considered too restrictive. In this respect, D'Amico and Farka (2011) and Faust et al. (2004) suggest the use of high-frequency data to allow for a simultaneous response of monetary policy to asset prices. This approach typically entails to proceed in two steps in that a high-frequency relation between interest rate and asset prices is initially estimated, and in a second step, this coefficient estimate previously estimated is used to help achieve identification in the VAR system. Alternatively, one can also use the heteroskedastic feature of financial data to provide additional insight for the statistical identification of the model (see Rigobon and Sack (2004), and also Furlanetto (2011) for an international perspective). Second, the literature often estimates monetary policy shocks from Federal fund futures data and measures the effects of monetary policy surprises on the stock market based on an event-study approach. Events typically correspond to days in which the Federal fund rates was changed. For example, in Bernanke and Kuttner (2005), (daily) monetary policy surprises are inferred from the change in the futures contract's price relative to the day prior the policy action. Alternatively, using intraday data in a tight window surrounding the FOMC announcements can help to obtain estimates of the effects of monetary policy on stock prices as free as possible of endogeneity and simultaneous responses issues (see, e.g., Gurkaynak et al. (2005)).

A closely related work to this paper is Galí and Gambetti (2015), who empirically test the framework of Galí (2014) in which a tightening of the monetary policy stance is not necessarily associated with a decline in stock prices. Using a time-varying parameter VAR model, they find that stock prices have increasingly responded in a positive way to a tightening in monetary policy in the recent period, suggesting that the bubble component of stock prices has been prevalent in recent times. A related contribution to this paper, yet very different from a methodological point of view is Ehrmann and Fratzscher (2004), who investigate the industry-specific effects of monetary policy. In particular, they find that cyclical sectors, such as technology, communications and cyclical consumer goods react two to three times more to monetary policy shocks than less cyclical sectors (e.g., utilities and non-cyclical consumer goods sectors).

The key contribution of this paper is to use industry-specific returns to document the time-varying effects of monetary policy on the stock market. In doing so, we perform three different types of analyses, which allows us to check the robustness of our results to different empirical approaches. First, we use event study regressions to evaluate the instantaneous effects of monetary policy on stock returns. For the period extending to December 2008, in line with Bernanke and Kuttner (2005), we use the unexpected change in the Federal funds rate target as derived from the changes in the Federal funds rate in the days of monetary policy announcement. For the most recent period characterized by unconventional monetary policy measures, we follow Rogers et al. (2014) and measure monetary policy surprises from the daily changes in the first principal component of the Treasury futures yields. Second, we use a factor-augmented VAR (FAVAR) model to assess the reaction of industry-specific returns to monetary policy shocks in a unified framework and to trace out the dynamic effects of monetary policy surprises at a lower frequency. Third, we estimate a time-varying parameters factor-augmented VAR model to explicitly account for time-variation in the relation between monetary policy and stock returns. Moreover, unlike most of the literature that concentrates on the (aggregate) effects of monetary policy shocks on the stock market (e.g., the S&P 500 index), our empirical framework based on factor analysis allows us to provide a comprehensive assessment of the industry-specific effects of monetary policy shocks on the stock market as well as evaluating the extent of time variation in the responses.

Our key results are as follows. First, our event-study designed at evaluating the effects of monetary policy shocks allows us to obtain a first pass evidence on the effects of monetary policy on asset prices. We find that an unexpected tightening of monetary policy is associated with a decline in the aggregate stock market and across most industries. Note, however, that the magnitude of the responses varies substantially across industries. Second, we run a lower frequency analysis based on both a (linear) and time-varying parameter factor-augmented VAR model. We show that there is variation both over time and across industries in the responses to monetary policy shocks. Interestingly, we find similar results across the event-study and the factor-augmented VAR model in that the industries that react the most to monetary policy shocks typically line up well with each other regardless of the empirical strategy chosen (event-study or multivariate VAR analysis). Third, we find that more procyclical industries (i.e., industries whose returns covary the most with GDP growth) tend to react more to monetary policy shocks. Conversely, industries with returns little related to the business cycle tend to be more insensitive to monetary policy shocks. Finally, a network analysis of stock returns indicates that highly responsive industries to monetary policy shocks tend to exhibit also high levels of interconnectedness with the rest of industries. The results indicate that Fabricated products and Machinery, Personal and Business Services, Business Equipment, Apparels, and Others are the industries that may play the most important role in the propagation of monetary policy shocks since they are the most responsive to monetary policy shocks and also the most interconnected with the rest of industries in the US economy.

The paper is organized as follows. Section 2 presents empirical evidence based on high-frequency (daily data). Section 3 introduces the econometric models used in the structural VAR analysis, and presents the baseline impulse response analysis along with a number of robustness checks. Section 4 investigates the determinants of the cross-sectional and temporal variations of the responses of stock returns to monetary policy shocks. Section 5 concludes.

2 A Preliminary Look at the Relationship Between the Stock Market and Monetary Policy

In this section, we present first-pass evidence on the effects of monetary policy shocks on stock returns based on an event study. Event studies are widely used in empirical macroeconomics and empirical finance to measure the impact of news on asset prices (see, e.g., the literature review in Gurkaynak and Wright (2013)). Event studies are akin to controlled experiments, whose success rests on two premises: a clear measure of the news component (the monetary policy shock in our study), and a neat estimate of the news on the relevant asset prices, which is achieved by concentrating our analysis on the days of U.S. monetary policy announcements.

2.1 Before the Zero Lower Bound

The event study used to assess the impact of monetary policy shocks on industry-specific stock returns is conducted at the daily frequency. A key advantage of operating at the daily frequency is to mitigate concerns related to the identification of monetary policy shocks and simultaneous responses between monetary policy and stock returns. The empirical strategy is based on regressions of daily returns on a measure of monetary policy shocks, which are initially calculated along the lines of Kuttner (2001). Note that such monetary policy shocks are also denoted as monetary policy "surprises" or "news." In detail, monetary policy surprises are derived from the change in the "30 Day Federal Funds Futures" relative to the day prior to the policy action, which is appropriately scaled to reflect the fact that the futures contract is based on a monthly average of the Federal funds rate. Therefore, the monetary policy surprise Δi^u is calculated as follows

$$\Delta i^u = \frac{D}{D-d}\left(f^0_{m,d} - f^0_{m,d-1}\right), \tag{1}$$

where D is the number of days in the month, and $f^0_{m,d}$ is the current-month futures rate. The expected component of the rate change is thereby defined as

$$\Delta i^e = \Delta i - \Delta i^u. \tag{2}$$

The effects of monetary policy surprises on industry-specific stock returns are then evaluated from the following regression

$$y_{i,t} = \alpha_i + \beta^e_i \Delta i^e_t + \beta^u_i \Delta i^u_t + \epsilon_{i,t}, \tag{3}$$

where $y_{i,t}$ corresponds to the stock return for industry i belonging to one of the 30-industry of the Fama French portfolio and $\epsilon_{i,t}$ is the error regression term.[1] The sample size extends from February 1994 to December 2008, and gathers 126 observations corresponding to days in which the Federal Open Market Committee (FOMC) issued statements. We also include intermeeting changes in our sample (that is, April 18, 1994; October 15, 1998; January 3, 2001; April 18, 2001; January 22, 2008; and October 8, 2008), but exclude the announcement made on September 17, 2001 in the wake of the September 11 attacks as it is commonly done in the literature. Note that excluding these intermeeting FOMC moves would lead to smaller responses of equity returns to monetary policy shocks, but we do include unscheduled meetings so as to follow the majority of the literature. Finally, note that our baseline results are very much robust to ending the sample in June 2007 (i.e., before the start of the turmoil on financial markets). Our estimation sample starts in 1994, since prior to 1994, the FOMC did not issue monetary policy statements and changes in the target rate had to be inferred from the size and type of open market operations.

A few additional comments are required. First, recall that a positive surprise means that the monetary policy rate was increased more or reduced less than the market anticipated, thus representing bad news, that is, an unexpected tightening in the stance of monetary policy. Similarly, a negative surprise means that the monetary policy rate ended up lower than expected, thus representing good news. Second, note that in line with Rogers et al. (2014), the empirical results are based on robust regressions (using a bisquare weighting function) to mitigate the impact of outliers, which is relevant in our case of study, see Figure 1 and Figure 2 of Appendix C.[2]

Table 3 reports the results of the daily regression analysis. Panel A shows the results for the sample extending from February 1994 to December 2008, reporting that a surprise 100 basis point increase in the policy rate leads to a roughly 4 per cent decline in a broad stock index (the S&P 500 index). This result is in line with the existing literature (see, e.g., Bernanke and Kuttner (2005)). However, the estimated coefficients vary substantially across industries. For example, "Autos," "Buseq," "Fabpr" react the most to monetary policy shocks. In particular, a one per cent (100 basis point) surprise increase in the policy rate is estimated to lead to a 4.26 per cent decline in the aggregate S&P500 index

[1] The 30-industry Fama French portfolio data are available online at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[2] Figure 1 is a scatterplot of the S&P 500 returns against monetary policy surprises as defined from equation (1) for the sample extending from February 1994 to December 2008. This figure shows a visible negative relationship between S&P 500 returns and federal funds rate surprises. Figure 2 is the corresponding figure for the sample extending from October 2008 to December 2014, that is, when using principal component analysis of the Treasury yields futures as a measure of monetary policy surprises. There is also an apparent negative relation, albeit there are noticeable outliers.

compared with a 8.29 per cent decline in the fabricated products and machinery "FabPr" industry stock returns. In contrast, industries that do not react significantly to monetary policy shocks are energy-related industries (e.g., "Oil," "Coal" and "Steel"), alimentary industries ("Food" and "Beer") and utilities ("Util"). Alimentary and energy industries have typically low market "betas", which suggests that industries that are the less sensitive to monetary policy shocks tend to have returns less correlated with the aggregate market return. Moreover, it is interesting to note that energy-related stock indices react positively (albeit insignificantly) to monetary policy surprises in that this runs somewhat against the perception that low real interest rates leads to high real commodity prices (Barsky and Kilian (2002)) to the extent that commodity-sensitive stock indices have predictive power for commodity prices.[3] This suggests that the empirical relevance of models relating oil price fluctuations to changes in U.S. interest rates remains rather elusive.[4]

2.2 At the Zero Lower Bound

One caveat of this approach is that as the Federal funds rate reached the zero lower bound, and the Federal Reserve started large scale asset purchases, the short-term interest rate no longer conveyed comprehensive information about the stance of the U.S. monetary policy. As a result, to identify monetary policy surprises over the recent period, we follow Rogers et al. (2014) and calculate monetary policy surprises from the first principal component of the daily changes in Treasury futures for selected maturities (2 years, 5 years, 10 years, and 30 years) in the days of U.S. monetary policy announcement. In this case, the industry-specific effects of (unconventional) monetary policy surprises are obtained from the following regression

$$y_{i,t} = \alpha_i + \beta_i MPS_t + u_{i,t}, \tag{4}$$

where MPS_t denotes the daily monetary policy surprise obtained from the principal component analysis of Treasure futures and $u_{i,t}$ is the error regression term. In this case, the sample size extends from October 2008 to December 2014, and includes 58 observations.

Panel B of Table 3 shows the results for the sample ranging from October 2008 to December 2014, which thereby includes the unconventional monetary policy episodes in the U.S. While the responses are mostly negative across industries, the responses are somewhat mitigated compared with Panel A. In particular, the responses of "BusEq" and "FabPr"

[3]Chen (2014) finds evidence that oil-sensitive stocks have predictive power for crude oil price fluctuations at a short horizon.

[4]In Figure 1, we show that responses of monetary policy shocks at the industry-level are not fully consistent with the five-factor asset pricing model from Fama and French (2015). In section 4 of the paper, we investigate in more details the determinants of the responses to monetary policy shocks.

to monetary policy surprises are no longer significant. A notable exception, however, is the finance industry ("Fin"), which now exhibits the most negative response to a surprise monetary policy tightening among all industries. This is not too surprising given that the financial sector was one of the focal points in the Great Recession and the ensuing economic recovery. Moreover, note that the imprecision of the estimates is much larger in Panel B compared with Panel A (only 13 industries respond statistically significantly to monetary policy shocks in Panel B compared with 22 industries in Panel A).

However, the analysis presented in Panels A and B are not directly comparable in that the underlying policy surprises are not directly equivalent. This is in part due to the different sample sizes across both panels, but more importantly because Panel A defines monetary policy surprises from federal funds rate unexpected changes, whereas Panel B uses comovements in Treasury yields futures in the days of monetary policy announcements as a measure of monetary policy shocks. Since both definitions of shocks are not directly comparable, the statistical significance of the results across panels should be interpreted cautiously. Hence, to provide a fairer comparison across both panels, Figure 1 provides an overall perspective of industry-specific relative responsiveness to monetary policy surprises, which is calculated as the share of the monetary effect in a given industry with respect to the total effect across all industries. The figure shows that some industries, such as Autos and Clothes, have been highly affected before and during the ZLB. Instead, other industries were highly affected before the ZLB, but currently they experience much lower effects, this is the case of Fabricated products, Business Equipment and Textiles. Conversely, some industries are being more affected at the ZLB than before that period, such as Finance, Steel, Meals. These results provide preliminary insights about a significant heterogeneity in the responsiveness of stock markets to monetary policy shocks not only across time but also across different sectors of the economy. The next section of this paper focuses on providing a deeper exploration of such heterogeneity in a unified framework.

Finally, to put our results in perspective with the literature, we compare our results with those presented in Rogers et al. (2014). In detail, Rogers et al. (2014) estimate that a 25 basis points reduction in the ten-year Treasury yields leads to a 0.72 per cent or 0.86 percent increase in the S&P stock futures depending on the size of the window surrounding the monetary policy announcements. This is somewhat stronger than our estimates, which imply that a 25 basis point decrease in the ten-year Treasury yields leads to a 0.45 per cent decline in the S&P500 index. However, our estimation sample in Panel B extends from October 2008 to December 2014, which is longer than the estimation sample used by Rogers et al. (2014) (October 2008 to June 2013). In fact, Rogers et al. (2014) find that the U.S. monetary policy announcements have essentially no effect on S&P futures when excluding the 2008-2009 Great Recession episode. As such, this suggests that using longer estimation samples will most likely lead to lower estimates for the effects of unconventional monetary policies on stock returns, which thereby helps to explain the differences with our results. Moreover, additional differences between our work and the study by Rogers et al. (2014) is that we use daily data as opposed to intradaily data and we use actual S&P500 returns rather than S&P stock futures data.

3 The Dynamic Effects of Monetary Policy Shocks On Industry-Specific Stock Returns

The analysis presented in the previous section presents two important caveats. First, it does not allow us to trace out the dynamic effects of monetary policy surprises on asset prices. Vector autoregressive models are instead explicitly designed to do so, and are typically estimated at a monthly or quarterly frequency. Second, industry-specific stock returns experience a significant degree of comovement that should be taken into account when comparing the degree of responsiveness to monetary policy shocks associated to each industry. To tackle the high-dimensionality of this problem in a unified econometric model (stock returns from thirty industries and a set of macroeconomic variables), we use a FAVAR model that permits us to elegantly summarize the information from the industry-specific stock returns in a few factors at most. Note that it is important to include macroeconomic variables in the VAR system, since at a lower frequency, monetary policy explicitly reacts to fluctuations in the macroeconomic environment. Moreover, as shown in section 2, the effects of monetary policy may change over time, therefore, we also account for potential instabilities in the relationship between stock market returns and the other variables in the VAR system (macroeconomic and financial variables), using a time-varying parameter FAVAR model. As such, this allows us to check the extent of time variation in the responses of industry-specific stock returns to monetary policy surprises.

3.1 Factor-Augmented Time-Varying Parameter Model

We rely on an econometric model closely related to the one from Korobilis (2013) in that we use a factor-augmented time-varying parameter VAR model with stochastic volatility, and estimated with Bayesian methods. It is also related to Del Negro and Otrok (2008) given that we model time-variation in the dynamics of the factor loadings. Modeling time variation in the factor loadings is likely to be an empirically relevant feature, since we deal with financial data which exhibit a substantial amount of volatility. The literature on this front has been relatively limited. For example, Korobilis (2013) concentrated his analysis on the effects of monetary policy shocks on real economic activity, whereas Del Negro and Otrok (2008) studied international business cycle dynamics.[5] The Bayesian Time-varying Parameters FAVAR model (TVP-FAVAR) we introduce is described by the following set of equations

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} I & \mathbf{0} \\ \Lambda_t^Y & \Lambda_t^F \end{bmatrix} \begin{bmatrix} Y_t \\ F_t \end{bmatrix} + \begin{bmatrix} 0 \\ e_t^F \end{bmatrix}, \; e_t^F \sim N(0, \Omega) \tag{5}$$

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \Phi_t(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \begin{bmatrix} u_t^Y \\ u_t^F \end{bmatrix}, \; u_t = \begin{bmatrix} u_t^Y \\ u_t^F \end{bmatrix}, \; u_t \sim N(0, \Sigma_t) \tag{6}$$

where Y_t collects n observed fundamentals, F_t is a vector of q unobserved components driving a large set of variables X_t. Equation (5) is the measurement equation of the state-space system (or Factor equation) and equation (6) its transition equation.

Let $\Lambda_t = vec([\Lambda_t^Y, \Lambda_t^F])$, where $vec(\cdot)$ is the column stacking operator. The law of motion of Λ_t, is given by

$$\Lambda_t = \Lambda_{t-1} + \epsilon_t, \;\; \epsilon_t \sim N(0, \Xi). \tag{7}$$

The autoregressive coefficients can be collected in $\phi_t = vec(\Phi_t)$, with $\Phi_t = [\Phi_{0,t}, \Phi_{1,t}, ..., \Phi_{p,t}]$, and follow the law of motion given by

$$\phi_t = \phi_{t-1} + \xi_t, \;\; \xi_t \sim N(0, \Theta_\phi). \tag{8}$$

The innovations of the VAR system u_t are normally distributed and their variances evolve over time such that

$$\Sigma_t = A_t^{-1} H_t (A_t^{-1})', \tag{9}$$

where the matrix A_t summarizes the contemporaneous relations between the M variables in the system (where $M = n + q$). A_t is a lower triangular matrix with ones on its diagonal, and the matrix H_t is a diagonal matrix. Let h_t be the vector containing the diagonal elements of $H_t^{1/2}$, and $a_{i,t}$ a column vector with nonzero elements of the $(i+1)$-th row of A_t^{-1} with $i = 1, ..., n$. The dynamics of h_t and a_t are given by

$$log(h_t) = log(h_{t-1}) + \eta_t, \;\; \eta_t \sim N(0, \Theta_h), \tag{10}$$

[5] See also Eickmeier et al. (2015) and Mikkelsen et al. (2015) for frequentist approaches to the estimation of dynamic factor models with time-varying factor loadings.

$$a_{i,t} = a_{i,t-1} + \zeta_{i,t}, \;\; \zeta_{i,t} \sim N(0, \Theta_{a,i}). \tag{11}$$

Note that in line with the existing literature, we assume random walk dynamics for all time-varying parameters of the model (i.e., the Λ_t's, ϕ_t's, h_t's and $a_{i,t}$'s). However, the h_t's are assumed to follow a geometric random walk. Moreover, following the literature, we assume that all innovations of the model are distributed as multivariate normal distributions with zero mean and a block diagonal variance-covariance matrix.[6]

Further details on the estimation method are reported in Appendix A, including full details on the priors distributions used and the algorithm used to simulate the posterior distributions of the model parameters and latent variables. Notice that the constant coefficients FAVAR model from Bernanke et al. (2005) can be seen as a limiting case of the TVP-FAVAR model when $\Xi = 0$, $\Theta_\phi = 0$, $\Theta_h = 0$, and $\Theta_h = 0$.

3.2 Empirical Issues

Data

The vector Y_t includes the following variables: GDP growth (first difference of the log-level), GDP deflator (first difference of the log-level), dividend series (first difference of the log-level), the World Bank (non-energy) Commodity price index (first difference of the log-level), the short-term interest rate (in level). The short-term interest rate is the Federal Funds rate until 2008Q4, but we use the Wu and Xia (2015) shadow interest rate from 2009Q1 onwards to circumvent the zero lower bound problem. Unlike the observed short-term interest rate, the shadow rate is not bounded below by 0 percent. The shadow rate is assumed to be a linear function of three latent variables called factors of a Nelson-Siegel-Svensson yield curve. The latent factors and the shadow rate are estimated with an extended Kalman filter. The variables in X_t include (quarterly) industry-level stock returns for each of the 30-industry of the Fama French portfolio (and we standardize the industry-level stock returns prior the estimation of the model). The full sample size extends from 1960Q2 to 2014Q4.

Number of Factors

We rely on Bai and Ng (2007) to determine the number of factors that are more suitable to explain the co-movement among the 30 industry-specific returns. This approach allows us to estimate the number of dynamic factors without having to actually estimate them.

[6] Allowing for off-diagonal elements would complicate the estimation on a computational point of view, but would also prevent one from obtaining a structural interpretation of the shocks.

The results indicate that one dynamic factor summarizes best the co-movements in the 30 industries. Also, the use of a single factor is useful for ease of interpretation, since the factor estimate closely mimics the fluctuations in a broad stock market index (the S&P500 index). We estimate the factor by extracting the first principal component from the 30 industry-specific returns. Unlike the estimation of the factor jointly with the other elements of the model, principal components analysis permits us to mitigate the estimation uncertainty in the econometric model. Moreover, it is not problematic in our application, since principal components factor estimator remains consistent if faced with moderate structural instability in the factor loadings (see Stock and Watson (2002)).

Model selection

Calculating the marginal likelihood is a standard way to perform model selection in the context of Bayesian estimation. However, it is not straightforward to calculate the marginal likelihood of time-varying parameters models and substantial uncertainty can be associated with the marginal likelihood estimates. As a result, we refrained from using such an approach for model selection. Instead, we estimated a model with four autoregressive lags for both the linear and time-varying parameter FAVAR. The reason for doing so is that we can perform a straightforward comparison with Galí and Gambetti (2015) in that they estimate a time-varying parameter VAR model with 4 autoregressive lags.[7]

Normalization

It is important to specify the restrictions necessary to uniquely identify the factors and factor loadings so as to identify the factors against any rotations. In practise, this is done by restricting the upper $K \times K$ block of Λ^f to an identity matrix and the upper $K \times M$ block of Λ^y to zero. As such, these identification restrictions imply that the Y_t's do not affect contemporaneously the K variables in X_t, hence, they do not react contemporaneously to innovations in Y_t. These restrictions are akin to those imposed by Bernanke et al. (2005).

Identification

Finally, the model is identified with a recursive (Cholesky) structure. We adopt the following ordering for the variables: GDP, GDP deflator, dividend series for the S&P 500 deflated by the GDP deflator, the World Bank commodity price index, the short-term interest rate and the factor extracted from industry-specific stock returns. This is consistent with an ordering from slow-moving to fast-moving (i.e., financial) variables,

[7] As a robustness check, we also estimated models with fewer autoregressive lags and a larger number of factors. The results were qualitatively unchanged in that there was a substantial degree of heterogeneity in the responses to monetary policy shocks across industries in a similar way to the model with four lags and one factor.

which is common in this type of application. As such, this identification structure rules out the possibility of a contemporaneous response of the monetary policy authorities to stock market fluctuations, a feature that is not necessarily undesirable from an empirical point of view (see, e.g., Furlanetto (2011) or Galí and Gambetti (2015)).[8] Note also that, starting from Rigobon and Sack (2003), part of the literature uses heteroskedastic features in the residuals as an identification device for the shocks of interest. While this approach is appealing from a statistical point of view, it is problematic in that assuming known dates for changes in variance is somewhat unrealistic. Moreover, using flexible models such as Markov-switching or smooth transition models for modelling variance changes is computationally challenging for large VAR systems such as ours. Hence, we refrain from using such tools. However, we also perform a robustness check in which we estimate a model that allows for a (calibrated) simultaneous response of the monetary policy authorities to stock market shocks.

3.3 Monetary Policy Effects across Industries

There is a substantial literature on the effects of monetary policy surprises on the stock market based on VAR analysis (early references include Thorbecke (1997), Rigobon and Sack (2003) and Bjørnland and Leitemo (2009)). Our analysis contributes to this literature along two key dimensions. First, we use industry-specific returns to provide a detailed picture of the monetary policy effects on the stock market. In doing so, we use a factor-augmented VAR model to deal with parameter proliferation given that our analysis would be intractable in a standard VAR setting. Second, we use a time-varying parameter model, which allows us to account for possible time variation in the dynamic relations between the variables in our VAR system. This is important, since, for example, this allows us to investigate whether stock prices have responded differently to monetary policy surprises in the recent period, which is characterized by unconventional monetary policy measures in the U.S.

3.3.1 Time-invariant Effects

Figure 2 shows the responses of macroeconomic and financial fundamentals along with industry-specific stock returns to a surprise 100 basis point increase in the policy rate

[8]Interestingly, based on a formal statistical analysis that allows for a contemporaneous response of monetary authorities to stock prices, Lütkepohl and Netsunajev (2014) find that the short-term interest rate does not respond significantly to stock returns shocks. As such, this supports our baseline (recursive) identification scheme in which the contemporaneous relation between short-term interest rate and stock prices is set to zero.

obtained with the linear version of the FAVAR model.[9] Following Galí and Gambetti (2015), we show cumulative responses (except for the response of the short-term interest rate). Note that the (cumulative) responses for industry-level stock returns are presented in standard deviation units. First, the monetary policy shock temporarily increases the level of interest rates, which documents the persistence of the shock. Moreover, as expected, GDP shows a prolonged negative response to a surprise monetary policy tightening. Inflation, as defined from the GDP deflator, does not react significantly to a monetary policy shock except for horizons between one and two years where the response is marginally (and significantly) positive. Note that it is not unusual in this type of VAR system where inflation often exhibits a positive hump-shaped response to a surprise monetary policy tightening (a phenomenon referred to as a "price puzzle"). Dividends decline following a monetary policy shock, but the response is significantly negative only at long horizons (i.e., for $h > 12$). This is consistent with the responses of output and interest rate in that a fall in output and higher cost of borrowing are expected to be associated with lower future dividends. Moreover, commodity prices do not react significantly to a monetary policy shock, which lines up well with the results from the event study presented in section 2. Overall, these responses are very similar to those obtained from the linear model in Galí and Gambetti (2015).

We now turn our attention to the responses of industry-level stock returns to monetary policy shocks. There are three important aspects regarding the responses of industrial stock returns. First, for all industries, the impact response is negative (except for the "Food", "Beer" and "Smoke" industries, which exhibit a positive response (albeit insignificant). Second, for most industries, the maximum impact occurs at a one- or two-quarter horizon with the peak negative impact roughly amounting to a quarter of a standard deviation. Third, for most industries, responses are no longer significant at a 2-year horizon, suggesting that the effects of monetary policy on stock returns are rather temporary. However, there are few noticeable exceptions. In particular, "Food", "Beer" and "Smoke" industries show a positive and significant response at a distant projection horizon (10-quarter-ahead). Finally, while our results line up well with the conventional view related to the monetary policy effects on asset prices, the results from the linear FAVAR differ from Rigobon and Sack (2004) and Bjørnland and Leitemo (2009) in that we find a somewhat smaller response to monetary policy shocks than these studies.[10] However, our results are roughly comparable

[9] For brevity, we do not report the equations underlying the linear version of the FAVAR, since these equations can be found in Bernanke et al. (2005). Note also that we retain the same modelling choices in the linear model as in the time-varying parameter FAVAR model in that we estimate a model with a single factor and six autoregressive lags. We also use the same normalization and identification restrictions in the linear FAVAR as in the time-varying parameter FAVAR.

[10] In detail, Bjørnland and Leitemo (2009) estimate that a surprise 100 basis points increase in the federal

to the findings on aggregate equity returns from Lütkepohl and Netsunajev (2014), who document a maximum of a three per cent decline in (real) stock prices (S&P 500 index) following a 100 basis points increase in the short-term interest rate.

One important caveat of the linear FAVAR model is that it does not account for potential time instabilities in the parameters of the model (in the autoregressive matrices, the innovation variance of the VAR and the factor loadings), which is problematic since we deal with financial data that are prone to exhibit this type of instabilities. In the next subsection, we present the responses obtained from the time-varying parameter model, which can be seen as a general approximation of the linear model.

3.3.2 Time-varying Effects

Figure 3 shows the time-varying impulse responses of the first five variables in the VAR system to a surprise 100 basis point increase in the policy rate. Interestingly, there is a substantial degree of variation over time. For example, the medium-term response of GDP (i.e., at an 8-quarter horizon) is much stronger in the early part of the sample than at the very end, albeit the long-term response (i.e., at a 20-quarter horizon) is relatively unchanged over time. This suggests that the effects of monetary policy on the real economy have rather softened over time. Moreover, the response of the GDP deflator is typically negative, albeit there is evidence in favor of a "price puzzle" as the policy rate hits the zero lower bound. As such, this can explain the non-significant response of the GDP deflator to a monetary policy shock obtained from the linear model. Also, the responses of dividends and commodity prices experience substantial variation over time. In particular, the short-term response of the commodities index is stronger in the 1970's and to a lesser extent since the turn of the millennium compared with the 1980's and 1990's (but the medium-run response is unanimously negative regardless of the time period).

Figures 4 shows the response of stock returns for selected industries. To conserve space, we concentrate on describing salient features associated to the most responsive industries to monetary policy shocks based on our preliminary analysis in Section 2. The monetary policy effects on all the 30 industries are shown in Figures 3 and 4 of Appendix C. A number of salient facts emerge from the time-varying impulse response analysis. First, the very short-term responses are negative for all industries. These results are in line with the ones obtained with the event study in Section 2. In particuar, Figure 4 shows that the industry of fabricated products ("Fabpr") experienced more pronounced and persistent responsiveness

funds rate leads to a decline of about 12 per cent in the S&P500 index, whereas Rigobon and Sack (2004) find that a 25 basis points increase in the three-month interest rate leads to a 1.7 per cent decline in the S&P500 index.

before the mid-2000s than after that period. This agrees with our event study results in Figure 2, where the same industry is the most responsive one before the ZLB, while it becomes much less sensitive at the ZLB. A similar situation occurs in the industry of business equipments ("Buseq"), which experienced high responsiveness during the early 2000s, while it became relatively less responsive after that. Conversely, Figure 4 shows that the steel industry ("Steel") experiences a relatively constant and low responsiveness until the late 90s, for short horizons, while it significantly increases since the early 2000s. This agrees with Figure 2, where this industry presents a high (7%) relative instantaneous responsiveness during the ZLB, in comparison to what this industry experienced previous such period (0%). A similar case occurs in the financial industry ("Fin"), which, at short horizons, is more responsive the 2000s that after that period, agreeing with the results in the event study, where it experiences the highest relative responsiveness at the ZLB period.

Second, there is a substantial degree of variation in the shape of the responses across industries. For example, some industries ("Food", "Clths", "Auto" and "Meals") exhibit a relatively small degree of time variation in the shape of the responses, while other industries show substantial time variation in the responses to monetary policy shocks (e.g., "Mines", "Coal", "Util" "Telcm", "Buseq" and "Fin"). In particular, "Util" and "Fin" industries have a strong positive long-run response to monetary policy shocks in the late 1990's and early 2000's, which is not apparent in the rest of the sample. Likewise, the long-run response of "Telcm" industry to monetary policy shock is positive in the late 1990's, which is not apparent in other time periods. As such, our results suggest that there is a substantial degree of variation in the responses of industry-stock returns to monetary policy shocks (both over time and across industries).

Third, although the three-dimension charts are informative about the persistence of the monetary policy effects over time, they do not allow to trace in a precisely way all the negative responses at longer horizons, as in the case of the financial industry during the last part of the sample. Therefore, to get an overall assessment of the stock markets responsiveness across time and industries, the top chart of Figure 5 plots a heat map that contains this information for an horizon of 2 quarters. The figure shows that the negative effect of unexpected monetary policy decisions on stock markets has significantly increased over time. In particular, the responsiveness significantly increased during the early 2000's in industries such as "Steel", "Fabpr", "ElcEq", "Telcm", "Servs", "BusEq", among others. Also, since the beginning of the Great Recession (2008) onwards, other industries also became highly responsive, such as "Fin", "Cnstr", "Trans", and "Txtls". The bottom chart of Figure 5 plots the responsiveness across time periods and sectors for an horizon of 10 quarters, showing a higher heterogeneity across industries and less negative responsiveness. Instead, some industries indicate a positive reaction to monetary policy shocks, as is the case of ‘Beer”, ‘Coal”, ‘Util”, and ‘Telcm”.

One caveat of the three-dimension charts and the heat maps is that they do not permit us to statistically evaluate how significantly different from zero the responses are. This is important given that Figures 4 to 5 plot cumulative responses and could thereby lead to a misleading visual impression on the importance of the monetary policy shocks for equity returns. As a result, Figures 6 and 7 plot the median responses at selected horizons (two- and ten-quarter ahead) along with confidence bands (16-th and 84-th percentiles of the posterior distribution of the parameters of interest used to derive the impulse response estimates). At an horizon of two quarters, the response of industrial stock returns is negative across all industries, as can be seen in Figure 6, albeit the responses are not significantly different from zero for some specific industries for most of the sample (e.g., “Beer” and “Smoke” industries). Moreover, notice in Figure 7 that for an horizon of 10 quarters, most of the responses are not significantly different from zero, suggesting that the effects of monetary policy on equity returns are rather transitory. As such, this corroborates the results from the linear analysis.

It is important to notice that, while the magnitude of the responses to monetary policy shocks of the economic fundamentals (first five variables in the system) are very similar to those obtained in Galí and Gambetti (2015), the responses of stock returns differ substantially in that we do not find a uniformly strong positive response to monetary policy shocks starting from the early 1980s. There is a number of reasons to explain this discrepancy between our results and those of Galí and Gambetti (2015). First, we use industry-level stock returns rather than aggregate stock returns in the VAR system. Second, unlike Galí and Gambetti (2015), we do not disentangle the bubble component from the fundamental component of stock prices since it would not be straightforward to implement the Galí and Gambetti (2015) analysis with industry-level returns.

3.4 Robustness Checks

Our identification scheme has so far ruled out the possibility of a contemporaneous response of monetary policy to stock market shocks. As a first robustness check, we now investigate the possibility of a contemporaneous response of the monetary policy authorities to a stock market shock. In doing so, we follow Galí and Gambetti (2015) and calibrate the contemporaneous stock price coefficient entering in the interest rate equation. In detail, we calibrate this coefficient such that an unexpected one standard deviation increase in the factor extracted from the industry-specific stock returns leads to a 20 basis points increase in the policy rate (a one deviation rise in stock returns corresponds to a roughly 10 per cent increase in aggregate stock returns). This is consistent with the findings from D'Amico and Farka (2011), who estimate that a "5 per cent rise in the stock market tends to increase the federal funds rate by 9.1 basis points."

In Appendix C, Figure 5, and figures 6 and 7 show the responses of economic fundamentals and industry-level returns to a 100 basis point surprise increase in the policy rate, respectively. The results show that the shapes and magnitudes of the responses are similar across these two identification schemes. There is only a small difference in the shape associated to the "Fin" industry, and in terms of magnitude in "Whlsl" industry. To provide a more precise comparison between the monetary policy effects across these two identification schemes, in Figure 8 of Appendix C we plot the heat map of the industry-specific responsiveness across time and sectors based on the simultaneous responses identification scheme. The figure shows a similar map to the one obtained with a Cholesky identification scheme, plotted in Figure 5, indicating an increasing responsiveness over time. However, the magnitudes of the negative monetary policy effects across industries are slightly larger and more significant for an horizon of 2 quarters, as can be seen in Figure 9 of Appendix C, and basically unchanged for an horizon of 10 quarters, as shown in Figure 10 of Appendix C.

As an additional robustness check, we also conduct our analysis at the monthly rather than quarterly frequency. The rationale for doing so is that it can alleviate some of the concerns related to the simultaneous response of monetary policy to asset prices. Indeed, the higher the frequency, the less likely it is for monetary policy authorities to contemporaneously react to (high-frequency) fluctuations in asset prices. Moreover, as U.S. monetary policy decisions are made at a higher frequency than the quarterly frequency, estimating the VAR model at a quarterly frequency could potentially result in an improper statistical inference given that monetary policy decisions are made at a higher frequency than the data sampling interval (quarterly frequency).[11] In the literature, this is referred to as a temporal aggregation bias, which can lead to an erroneous impulse response analysis (see, e.g., Christiano and Eichenbaum (1987) or Foroni and Marcellino (2014) in the context of DSGE models).[12]

As a result, we now estimate a VAR at a monthly frequency with the following variables in the Y_t vector: headline industrial production index, headline consumer prices index

[11]In practice, starting from 1981, U.S. monetary policy decisions are taken eight times a year (decisions were made on a monthly basis before then).

[12]Note that it is not a trivial robustness check in that identifying assumptions at the monthly frequency may not necessarily carry over at the quarterly frequency (or conversely), see for example Kilian and Vigfusson (2015) for a related reference on this in the context of structural oil market models.

(CPI), dividend series, the World Bank commodity price index, and the short-term interest rate. All the Y_t variables are taken in first difference of their log-level except for the short-term interest rate, which is in level. The X_t variables in the monthly frequency VAR are the monthly 30-industry portfolio returns from the Fama-French database. For ease of inference, we retain the same modelling choices for the monthly VAR model as in the quarterly VAR model, that is, we estimate a model with one factor and four autoregressive lags.[13]

Figures 11 and 12 of Appendix C show the results to a 100 basis point tightening in U.S. monetary policy based on the monthly TVP-FAVAR. First, responses on impact are negative across all industries. In line with the results of the quarterly VAR, the effects of U.S. monetary policy shocks are usually stronger in the last part of the sample compared with the rest of the sample (e.g., “Games”, “Cnstr”, “Autos”, “Telcm”, and “Fin”). Second, for a number of industries, there is a substantial degree of time-variation in the long-run responses (e.g. “Mines”, “Coal”, “Trans” and “Books”). Third, some industries show little variation over time in their responses to monetary policy shocks (e.g., “Elceq”, “Whlsl” and “Meals”). Overall, the impulse responses from the monthly VAR are very similar to the responses from the quarterly VAR model, suggesting that the dynamic relationship between U.S. monetary policy and the stock market is very similar at the monthly and quarterly frequency.

4 Why Do Industries Respond Differently?

Our analyses presented so far have shown that there are substantial differences in the responses of stock returns to monetary policy shocks across industries (in terms of both magnitude and shape of the responses). We also uncovered evidence in favor of an elevated degree of variation over time. In this section, we evaluate the determinants of the responses to monetary policy shocks. We find that the structure of the network of industry-specific stock returns has a strong explanatory power for the responses to monetary policy shocks.

[13] Admittedly, this implies that the information set is not directly comparable across the monthly and quarterly VAR models in that the autoregressive dynamics in the quarterly VAR model includes 12 months of information compared with 4 months of information in the monthly VAR model. However, estimating a time-varying parameter VAR model with 12 lags is computationally challenging. As such, the monthly VAR impulse response analysis can be seen as a robustness check along two dimensions: a different data sampling frequency and a different lag order in the VAR.

4.1 Measuring Industrial Interdependence

Network-based measures have become increasingly popular to study interactions between economic agents, especially in financial markets following the 2008-2009 financial crisis. From a theoretical standpoint, Elliott et al. (2014) study which network structure is the most sensitive to financial contagions, concentrating their analysis on the diversification and dependence of a network. Acemoglu et al. (2012) find that sectoral interconnections play an important role as a source of macroeconomic fluctuations. Also, Camacho and Leiva-Leon (2015) study the linkages that propagate industry-specific business cycle shocks throughout the economy, finding a sequential transmission of the industrial shocks to the macroeconomic environment. Ahern (2014) investigates to what extent the degree of centrality matters for the cross section of stock returns. He finds that industries that are at the center of the network are characterized by higher industries' market "betas" (i.e., they covary more closely with market returns). He also estimates that the more central industries comove more closely with future consumption growth compared with less central industries.

A number of approaches can be used to measure interdependence among economic sectors. First, connectedness measures can be directly derived from Input-Output tables. One drawback of this approach is that Input-Output tables are only available at an annual frequency over relatively short samples, which is problematic from an empirical point of view. Alternatively, Diebold and Yilmaz (2014) suggest to estimate connectedness based on forecast error variance decomposition of VAR model. In particular, they estimate VAR models over rolling windows so as to obtain dynamic measures of connectedness. This approach is well suited to financial data in that this permits to estimate connectedness at high frequency as opposed to network measures derived from Input-Output tables. However, Diebold and Yilmaz (2014) use standard (frequentist) VAR models, which thereby limits the dimension of the system.[14] We therefore follow Korobilis and Yilmaz (2015) and estimate a large (Bayesian) time-varying parameter VAR model to obtain dynamic connectedness measures. A key advantage of modelling time variation in the parameters of the model (as opposed to the use of constant parameter VAR estimated over rolling windows) is to overcome the issue of selecting the choice of the optimal window size. The large TVP-VAR can be described by the following set of equations:

$$z_t = \beta_t x_t + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_t), \tag{12}$$

$$\beta_t = \beta_{t-1} + v_t, \quad v_t \sim N(0, Q), \tag{13}$$

[14]For example, Diebold and Yilmaz (2012) consider a system of four variables to study the connectedness of four asset classes, and Diebold and Yilmaz (2014) evaluate the network structure of thirteen major U.S. financial institutions.

where z_t is a vector including the 30 industry-specific daily returns and $x_t = [\mathbf{1}, z'_{t-1}, ..., z'_{t-p}]'$. Given the large dimension of the model (a 30-equation VAR model) and the time variation in the parameters of the model, Markov Chain Monte Carlo (MCMC) methods are not suitable for the estimation of such a model. We thereby follow Korobilis and Yilmaz (2015) and approximate time variation in the autoregressive parameters of the model β_t with forgetting factors. Time variation in the innovation Σ_t is obtained via an exponential weighted moving average for computational simplicity. As such, estimating the large TVP-VAR model described by equations (12) and (13) is straightforward since no extensive simulations are required. However, a few parameters have to be calibrated: the degree of shrinkage for the autoregressive VAR coefficients and the forgetting factor that governs the amount of persistence in the data.[15] We refer the reader to the online appendix and Korobilis and Yilmaz (2015) for additional details on this model.

Following Diebold and Yilmaz (2014), Table 1 shows the connectedness table summarizing pairwise directional connectedness. From this table, one can define different concepts of connectedness. First, the last column of Table 1 gives the share of the H step ahead forecast error variance of variable i at time t coming from shocks arising in other variables, which corresponds to "from connectedness." Second, the last row of Table 1 shows the "to connectedness", that is the fraction of the H step ahead forecast variance transmitted to other variables from variable j at time t. The higher the to connectedness of a given industry is, the more shocks it propagates to the rest of the network. Third, net connectedness is calculated as the difference between the to and from connectedness measures. A positive reading for the net connectedness measure indicates that an industry transmits more shocks than it receives. Fourth, total connectedness, which measures the system-wide connectedness amounts to the sum of the off-diagonal entries of Table 1. This measure conveniently summarizes how connected the entire network of industry-specific stock returns is (the higher total connectedness is, the more connected the network is).

[15] In detail, we set the forgetting factor to 0.99 and the decay parameter for the innovation variance of the measurement equation to 0.99.

Table 1: Connectedness table

	$x_{1,t}$	$x_{2,t}$	...	$x_{N,t}$	From others
$x_{1,t}$	$d^H_{11,t}$	$d^H_{12,t}$	...	$d^H_{1N,t}$	$\sum_{j\neq 1} d^H_{1j,t}$
$x_{2,t}$	$d^H_{21,t}$	$d^H_{22,t}$	...	$d^H_{2N,t}$	$\sum_{j\neq 2} d^H_{2j,t}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
$x_{N,t}$	$d^H_{N1,t}$	$d^H_{N2,t}$	...	$d^H_{NN,t}$	$\sum_{j\neq N} d^H_{Nj,t}$
To others	$\sum_{i\neq 1} d^H_{i1,t}$	$\sum_{i\neq 2} d^H_{i2,t}$	...	$\sum_{i\neq N} d^H_{iN,t}$	$\sum_{i\neq j} d^H_{ij,t}$

A few additional comments are required. First, we do not use the TVP-FAVAR model outlined in Section 3 when performing the forecast error variance decomposition analysis, since we want to estimate connectedness at a daily frequency to capture high-frequency fluctuations in the connectedness measure (and the TVP-FAVAR model instead operates at a quarterly frequency since it includes macroeconomic variables). Moreover the innovations Ω in equation (5) have a diagonal covariance matrix, which rules out the propagation of sector-specific shocks across industries. Foerster et al. (2011) perform a structural factor analysis, modelling intersectoral linkages using data from the BEA's Input-Output table, which allows them to overcome the issue of zero off-diagonal elements in the innovation matrix of the measurement equation of the FAVAR model. However, assumptions about the functional form of the propagation mechanism of the intersectoral linkages need to be made. This is not appealing in our empirical application, since we want to put as little structure as possible on the propagation mechanism of sectoral shocks. Also, Foerster et al. (2011) do not model time-variation in the matrix modelling the propagation of sector-specific shocks, which is not attractive in the context of financial data.

Note that all connectedness measures are based on a time-varying vector autoregression model of order four and generalized forecast error variance decomposition of 2-day-ahead stock returns forecast errors. Figure 9 plots the total connectedness measure at a daily frequency. It is interesting to note that the total connectedness measure tends to peak during stock market turmoils (e.g., in October 1987 and October 2008). In the online appendix, we check the sensitivity of the connectedness measures to the VAR lag order and the forecast horizon of the variance decomposition analysis.

Figure 9 also reports the net connectedness measure (sample average) for each industry. It is interesting to note that the most connected industries are the Retail and Wholesale industries, which lines up with the results from Ahern (2014) obtained with network metrics calculated from Input-Output tables. In contrast, industries with the lowest net connectedness are in the energy sector (Oil and Coal). In both cases, their negative net connectedness measures reflect both low from and to connectedness measures, suggesting that these two industries are rather peripheral industries in that they both transmit and receive relatively little shocks to the rest of the network.

4.2 Explaining variation in the industry-specific responses to monetary policy shocks

We now investigate the determinants of industry-specific responses to monetary policy shocks, concentrating our analysis on the role of network metrics. We consider the following variables for explaining industry-specific responses to monetary policy shocks. First, we use the four concepts of connectedness described in the previous subsection to characterize the structure of the network. Second, we use an uncertainty measure from Jurado et al. (2015) to capture uncertainty in the economic environment. This measure is derived from the unpredictable component of a large set of macroeconomic and financial variables. Third, we include volatility as obtained from the sum of within quarter squared daily returns. Fourth, we use a dummy variable, which takes on a value of 1 if the U.S. economy is in recession according to the NBER business cycle dating committee. Finally, we consider industry-specific dividends series.

Figure 10 reports the average R-squared from pairwise regressions of the (time-varying) industry-specific response to monetary policy shocks with one of the aforementioned determinants. We use the one-step-ahead cumulative response (the median of the posterior distribution of the responses) obtained in the previous section. It is interesting to note that network metrics have the second strongest explanatory power (after the dividends series). This suggests that the structure of the network is an important factor in explaining the reaction to monetary policy shocks. Moreover, the explanatory power of network metrics is stronger for manufacturing and high-tech industries (as opposed to consumer and health industries). Besides, uncertainty and the business cycle dummy variables have a low explanatory power, suggesting that these variables are not relevant for explaining the industry-specific responses to monetary policy shocks.

The figure at the bottom of Figure 10 shows the slope coefficients from these regressions using net connectedness as an explanatory variable. It is interesting to note that for most industries, a stronger net connectedness is associated with a more adverse response to monetary policy shocks, suggesting that the more central industries tend to react the most negatively to monetary policy shocks.

5 Conclusions

In this paper, we evaluate the effects of monetary policy surprises on equity returns. Unlike most of the literature, a key aspect of our analysis is to use industry-level stock returns to provide a more comprehensive assessment of the linkages between monetary policy and stock prices. In doing so, we first use an event-study approach and uncover a substantial degree of heterogeneity in the responses to monetary policy surprises. In particular, while our estimates on the aggregate stock market (as proxied by the returns on the S&P500 index) lines up well with the previous literature – a 100 basis point surprise increase in the federal funds rate leads, on average, to a 4.25 per cent decline in the aggregate stock market – we find that responses vary substantially across industries.

Second, we trace out the dynamics of the responses using a FAVAR model that permits us to summarize the returns of the thirty industries in a single factor that captures the co-movements of industry-specific stock returns. To circumvent the potential time-instability in the relation between stock returns and monetary policy, we model time-variation in the coefficients of the autoregressive matrices of the model, and consider time-variation in the innovations of the VAR system using stochastic volatility estimates. The impulse response analysis finds evidence in favor of substantial variation in the responses to monetary policy shocks both over time and across industries. We also find that there is a high degree of concordance with the results from the event study regressions.

Finally, in the last section of the paper, we investigate the determinants of the industry responses to monetary policy shocks. We find the interdependence of industries – as measured by network metrics – help to understand the heterogeneity in the responses to monetary policy shocks. In particular, the most cyclical industries and the industries at the center of the network of equity returns tend to react the most to unexpected monetary policy changes.

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Table 2: Descriptive Statistics - 30-industry Fama-French portfolio returns

Abbreviation	Industry definition	Mean	Standard deviation
Food	Food Products	2.373	7.033
Beer	Beer and Liquor	2.413	7.837
Smoke	Tobacco Products	3.152	9.526
Games	Recreation	2.555	12.236
Books	Printing and Publishing	2.018	10.001
Hshld	Consumer Goods	2.079	7.620
Clths	Apparels	2.390	10.918
Hlth	Health care, Medical Equipment, Pharmaceutical Products	2.412	7.653
Chems	Chemicals	1.856	8.373
Txtls	Textiles	2.389	11.561
Cnstr	Construction and Construction Materials	1.806	9.575
Steel	Steel Works Etc	1.139	10.931
FabPr	Fabricated Products and Machinery	1.980	9.790
ElcEq	Electrical Equipment	2.486	9.508
Autos	Automobiles and Trucks	1.733	10.867
Carry	Aircraft, ships, and railroad equipment	2.366	10.397
Mines	Precious Metals, Non-Metallic, and Industrial Metal Mining	1.587	11.017
Coal	Coal	2.686	15.630
Oil	Petroleum and Natural Gas	2.099	7.776
Util	Utilities	1.692	5.980
Telcm	Communication	1.863	7.451
Servs	Personal and Business Services	2.331	10.462
BusEq	Business Equipment	2.104	10.802
Paper	Business Supplies and Shipping Containers	1.808	7.735
Trans	Transportation	2.052	9.220
Whlsl	Wholesale	2.236	9.418
Rtail	Retail	2.324	8.878
Meals	Restaurants, Hotels, Motels	2.550	10.752
Fin	Banking, Insurance, Real Estate, Trading	1.996	8.785
Other	Everything Else	1.473	9.498

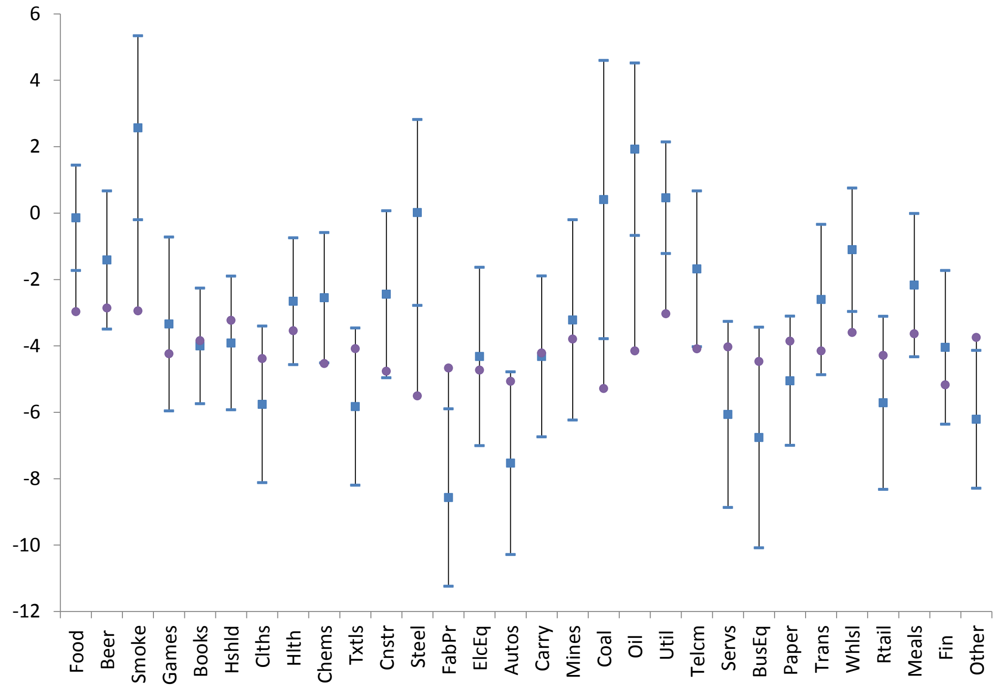
Note: Descriptive statistics are calculated over the period extending from 1958Q3 to 2014Q4.

Table 3: Responses of industry stock returns to monetary policy shocks - Daily data

Panel A: Sample size extends from February 1994 to December 2008									
AUTOS	BEER	BOOKS	BUSEQ	CARRY	CHEMS	CLTHS	CNSTR	COAL	ELCEQ
-7.38***	-1.36	-3.92***	-6.42***	-4.18***	-2.53***	-5.70***	-2.28*	0.50	-4.19***
(1.36)	(1.05)	(0.86)	(1.66)	(1.19)	(0.97)	(1.16)	(1.23)	(2.07)	(1.33)
FABPR	FIN	FOOD	GAMES	HLTH	HSHLD	MEALS	MINES	OIL	OTHER
-8.29***	-3.94***	-0.04	-3.25***	-2.42***	-3.82***	-2.18***	-3.13***	2.09	-6.08***
(1.32)	(1.14)	(0.79)	(1.31)	(0.94)	(1.01)	(1.09)	(1.48)	(1.29)	(1.03)
PAPER	RTAIL	SERVS	SMOKE	STEEL	TELCM	TRANS	TXTLS	UTIL	WHLSL
-4.92***	-5.48***	-5.45***	2.49*	0.11	-1.45	-2.24***	-5.74***	0.66	-0.65
(0.96)	(1.30)	(1.39)	(1.40)	(1.37)	(1.16)	(1.11)	(1.16)	(0.83)	(0.91)
S&P500									
-4.26***									
(1.01)									
Panel B: Sample size extends from October 2008 to December 2014									
AUTOS	BEER	BOOKS	BUSEQ	CARRY	CHEMS	CLTHS	CNSTR	COAL	ELCEQ
-5.07***	-1.59*	-1.56	-1.95	-0.66	-1.63	-4.37***	-3.84**	-2.48	-2.58
(1.36)	(0.93)	(1.27)	(1.18)	(1.24)	(1.42)	(1.38)	(1.80)	(2.43)	(1.59)
FABPR	FIN	FOOD	GAMES	HLTH	HSHLD	MEALS	MINES	OIL	OTHER
-2.03	-7.14***	0.98	-2.82*	0.29	-0.53	-4.39***	-4.25**	-0.62	-1.85
(1.47)	(1.58)	(0.87)	(1.55)	(0.83)	(0.92)	(1.04)	(2.03)	(1.23)	(1.14)
PAPER	RTAIL	SERVS	SMOKE	STEEL	TELCM	TRANS	TXTLS	UTIL	WHLSL
-2.53**	-2.50**	-0.90	-0.18	-4.89**	-2.16**	-1.29	0.80	-3.39***	-1.76
(1.16)	(0.98)	(1.07)	(1.10)	(2.05)	(0.91)	(1.26)	(1.54)	(1.07)	(1.10)
S&P500									
-1.79*									
(0.99)									

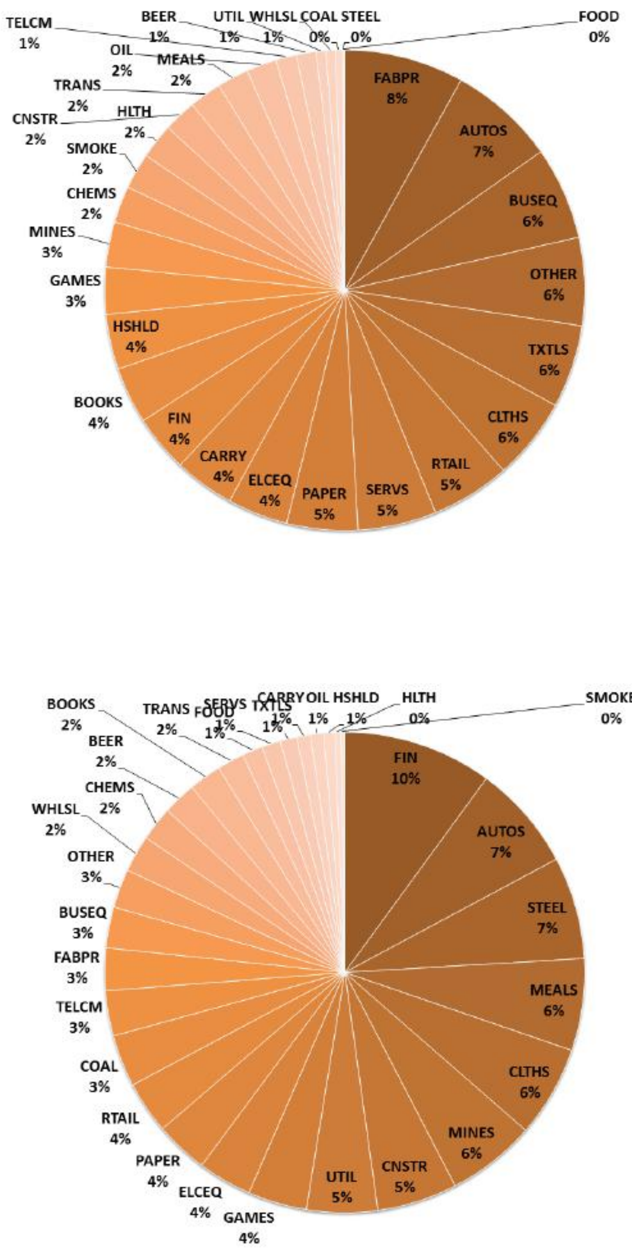
Note: Monetary policy surprises in Panel A are calculated from the change in the Federal Funds Future relative to the day prior the policy action (see equation (1)). Panel B instead calculates monetary policy surprises from the first principal component of the daily changes in the yields of the 2-year, 5-year, 10-year and 30-year Treasury Futures on the day of the monetary policy announcement to deal with the identification of monetary policy surprises when short-term interest rate are near zero (see Rogers et al. (2014)). Regressions in Panels A and B include 126 and 58 observations, respectively, and are based on robust regressions to mitigate the impact of outliers. Monetary policy surprises are scaled to represent a 100 basis point increase in the federal funds rate (Panel A), and a 100 basis point increase in the 10-year Treasury yields (Panel B). Standard errors are in parenthesis. *,**, *** denote significance at the 10, 5 and 1 per cent significant levels, respectively.

Figure 1: Estimated industry responses and asset pricing model implications



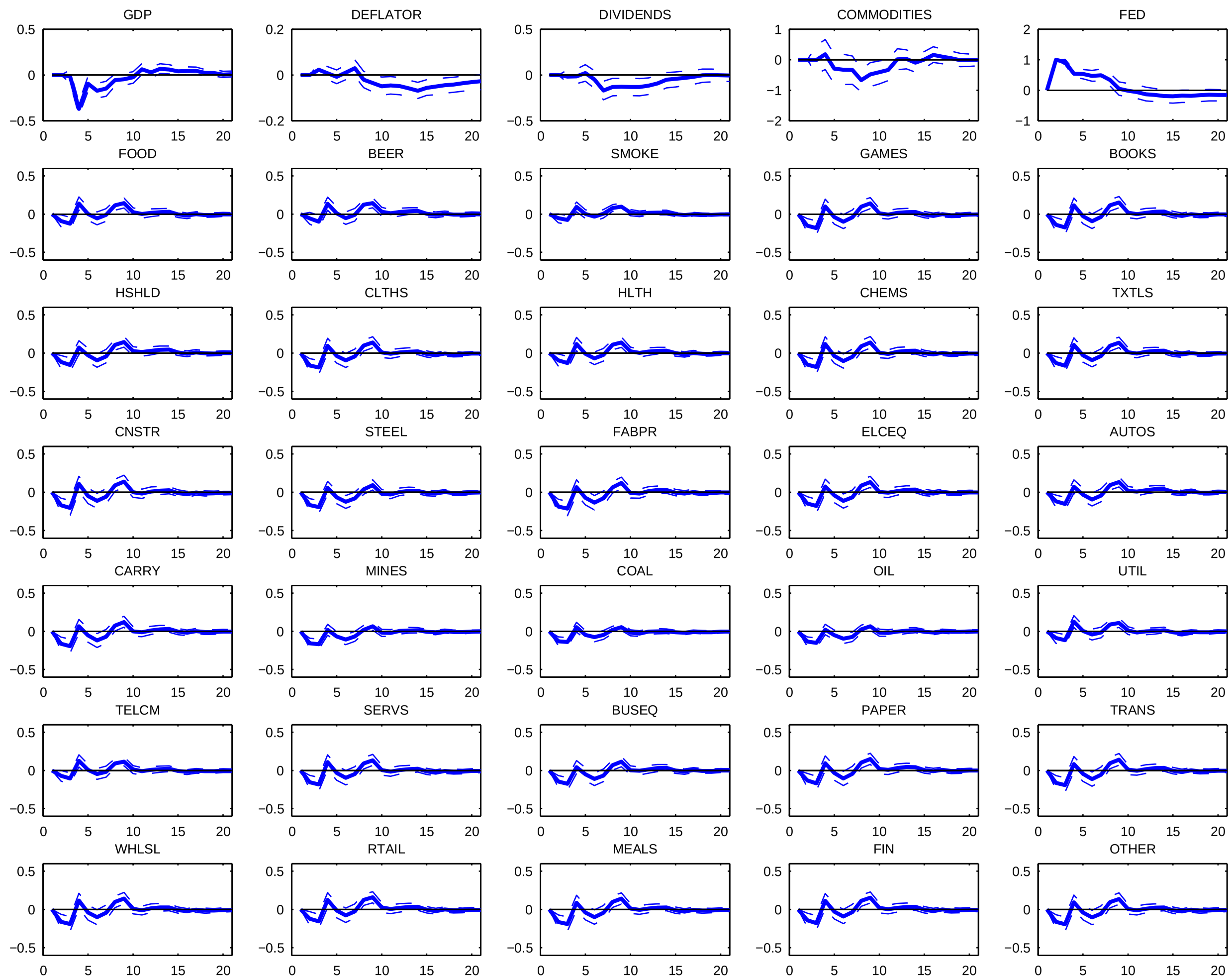
Note: This figure shows the industry responses to monetary policy surprises from the event study analysis (blue square dots) along with two standard errors confidence intervals markets with blue horizontal bars. The industry responses are obtained from the analysis performed when using the federal funds rate data as a measure of monetary policy surprises (i.e., for the sample extending from February 1994 to December 2008). The industry responses implied from the five-factor asset pricing model from Fama and French (2015) are represented in a purple circled dot.

Figure 2: Relative responsiveness of industries to monetary policy shocks before and at the ZLB



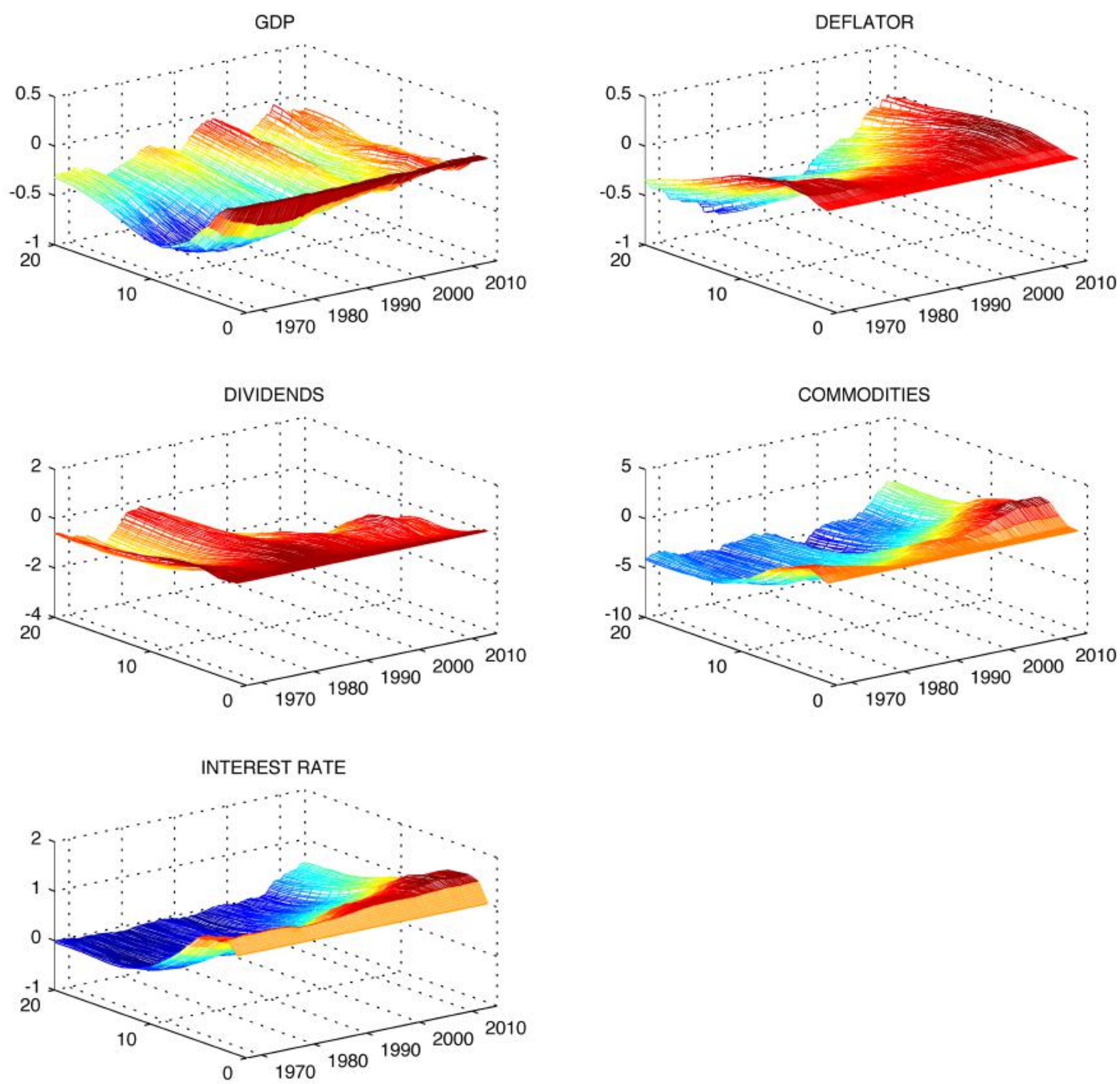
Note: The top chart shows the relative responsiveness before the ZLB (February 1994 - December 2008). The bottom chart shows the relative responsiveness at the ZLB (October 2008 - December 2014).

Figure 3: Estimated responses to a monetary policy shock from a Factor-augmented VAR model



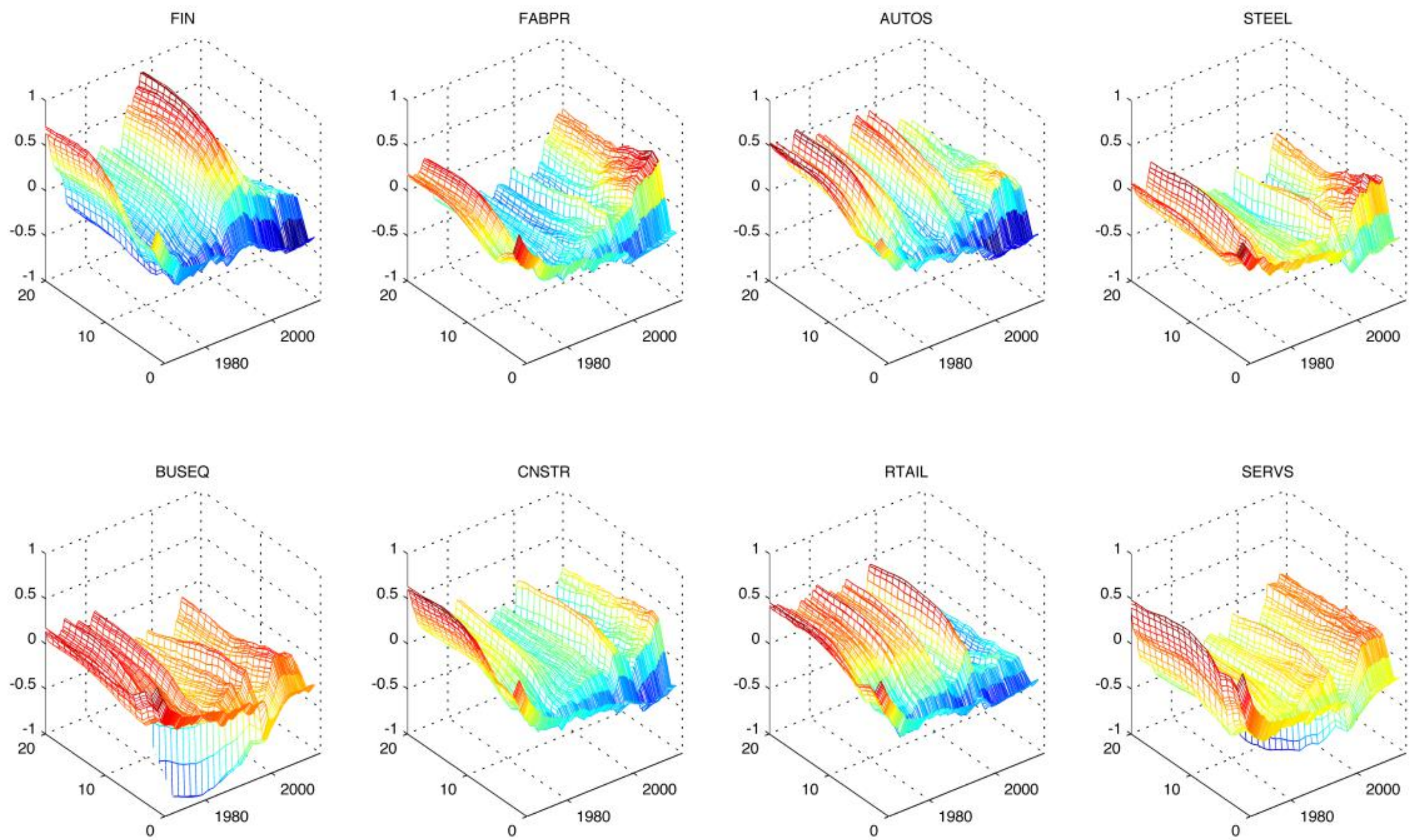
Note: This figure plots the impulse responses to an unexpected 100 basis point increase in the policy rate obtained from the linear FAVAR. The middle line represents the median estimates of the posterior distribution, the dotted lines represent the 16- and 84- percentile estimates of the posterior distribution.

Figure 4: Estimated responses of fundamentals to a monetary policy shock from a Time-Varying Coefficients Factor-augmented VAR model



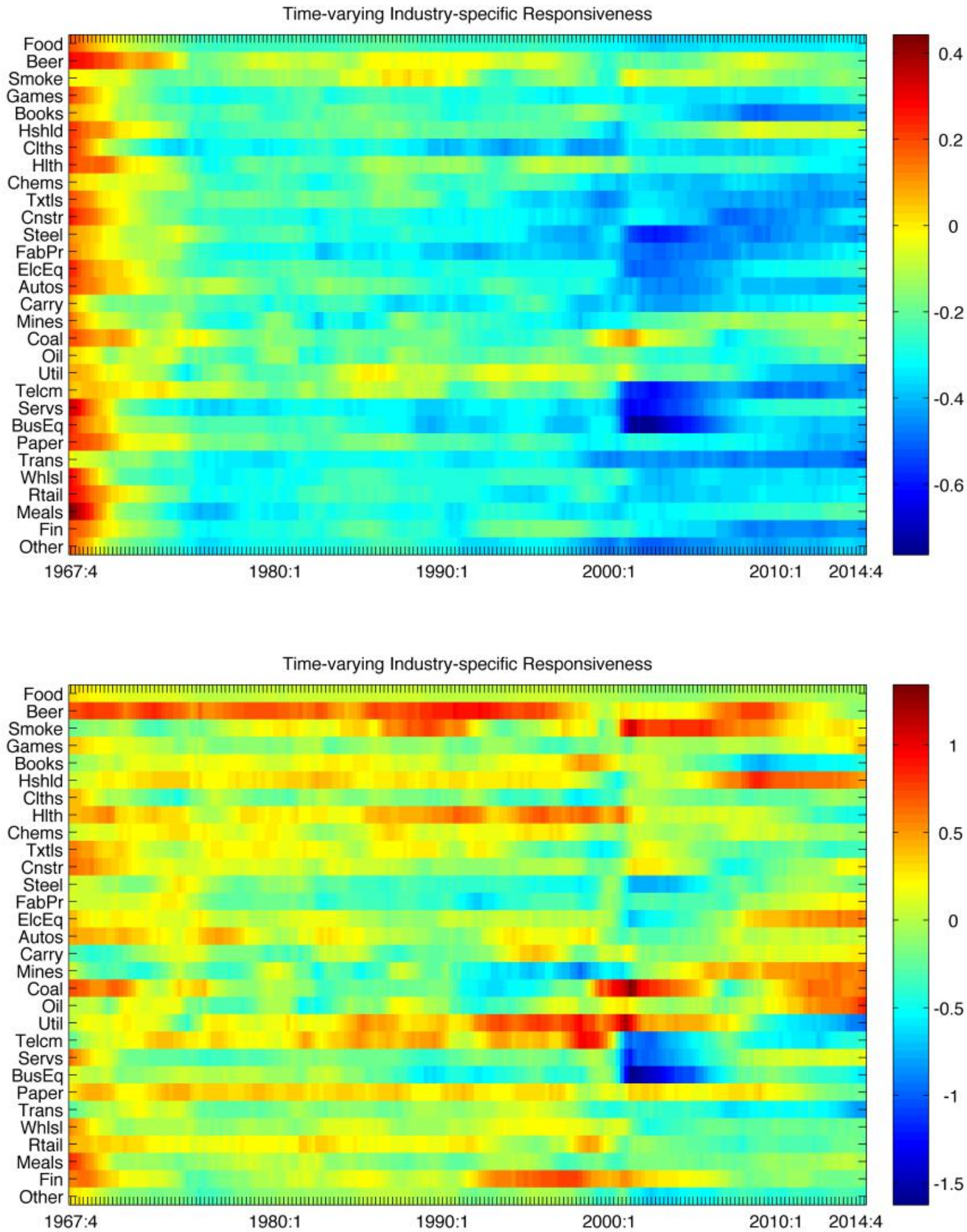
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 5: Estimated responses of industry-specific stock returns to a monetary policy shock from a Time-Varying Coefficients Factor-augmented VAR model



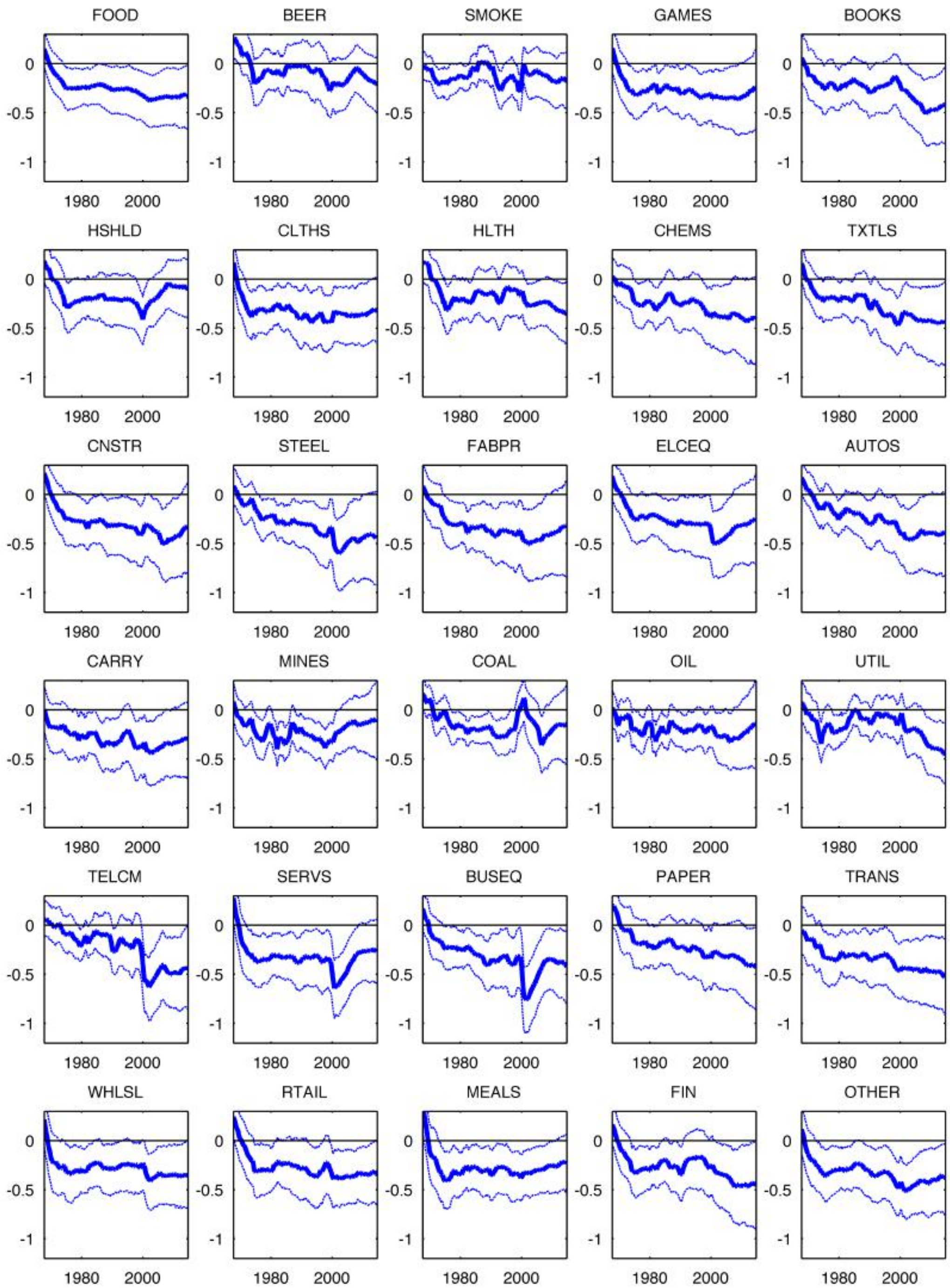
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 6: Heat map of Industry-specific responsiveness over time



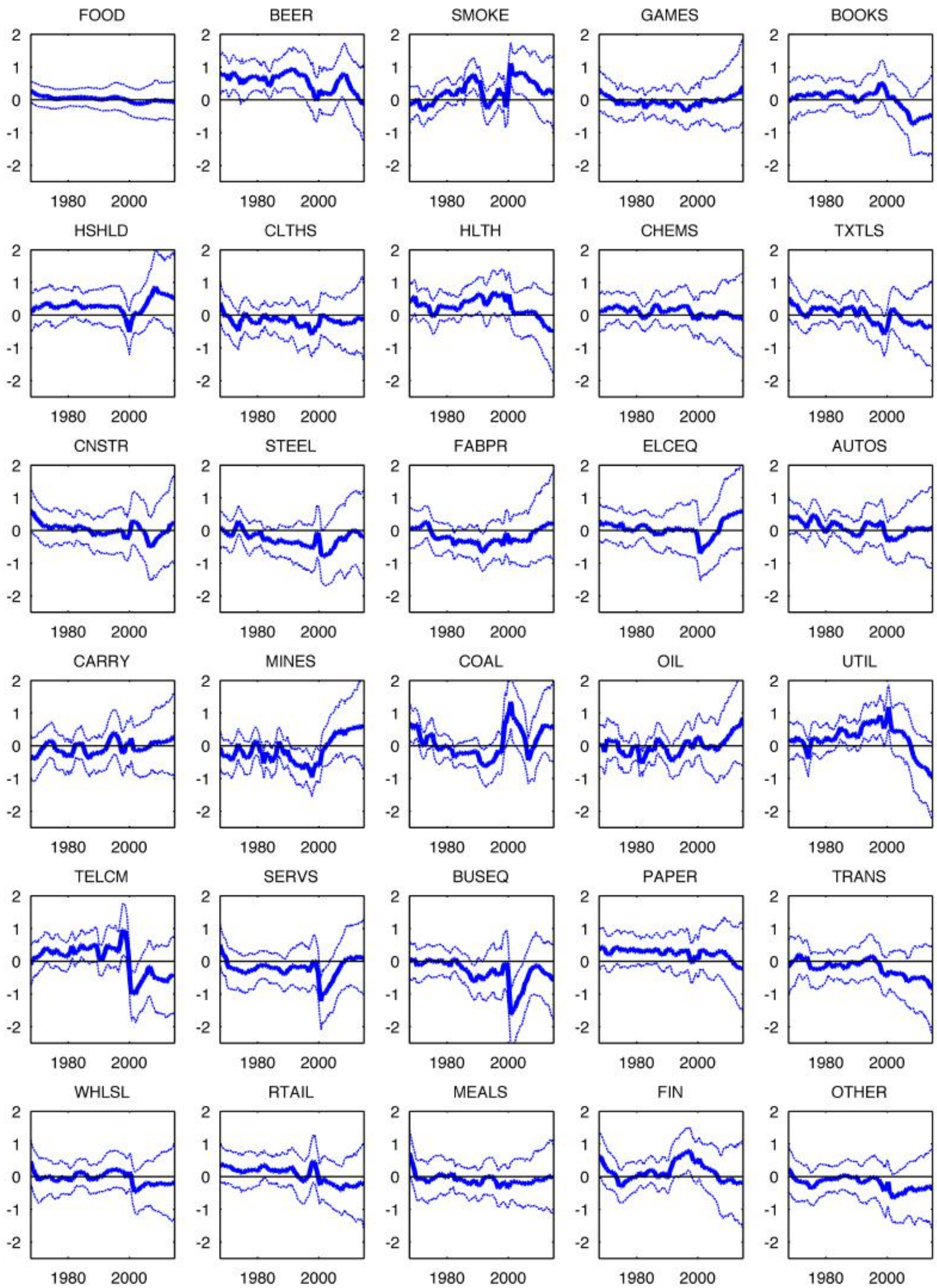
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 7: Estimated responses at an horizon of 2 quarters to a monetary policy shock from a Time-Varying Coefficients Factor-augmented VAR model



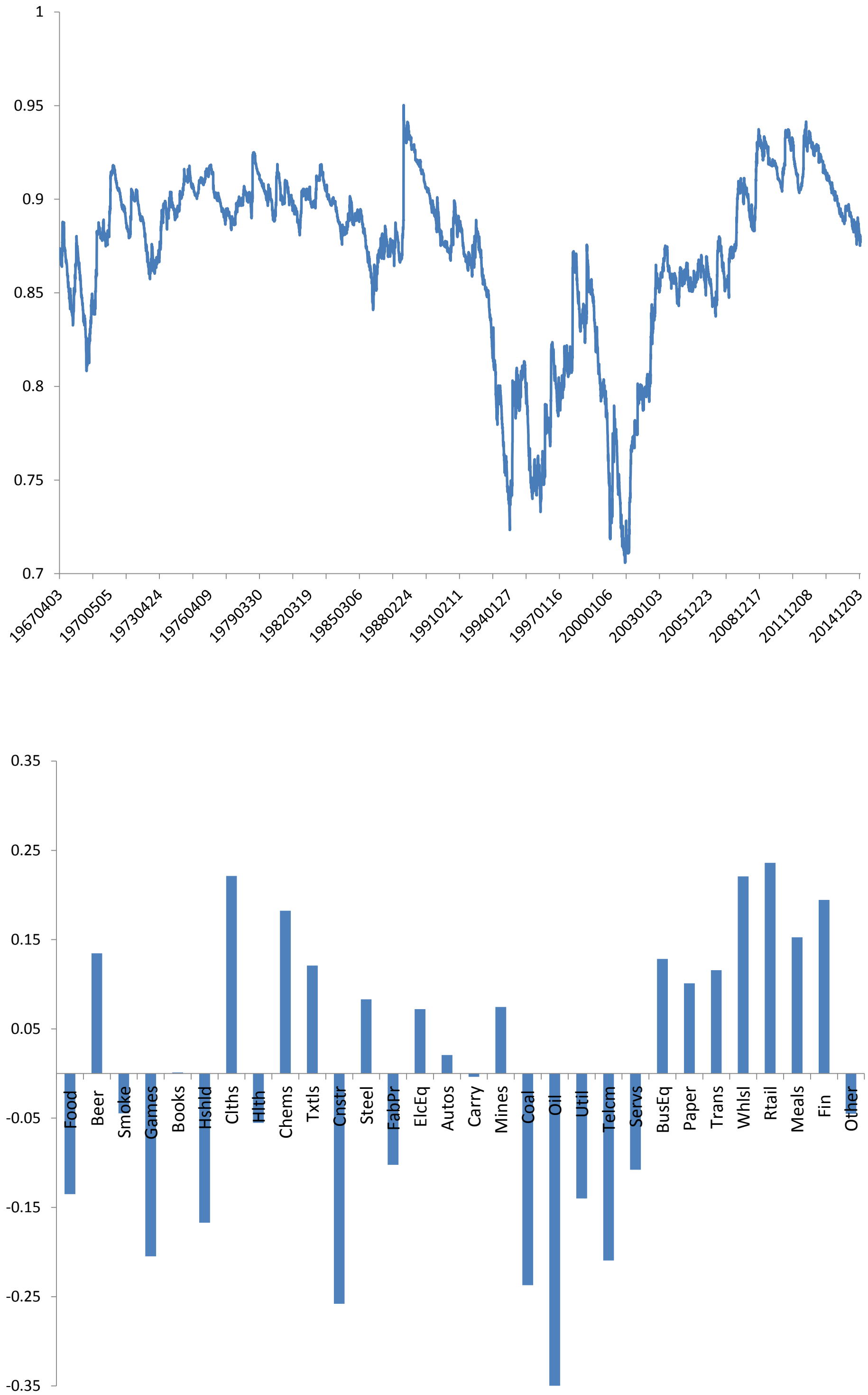
Note: The figure shows the time-varying responses to a monetary policy shock at a 10-quarter horizon. The middle line represents the median estimates of the posterior distribution, the dotted lines represent the 16- and 84- percentile estimates of the posterior distribution.

Figure 8: Estimated responses at an horizon of 10 quarters to a monetary policy shock from a Time-Varying Coefficients Factor-augmented VAR model



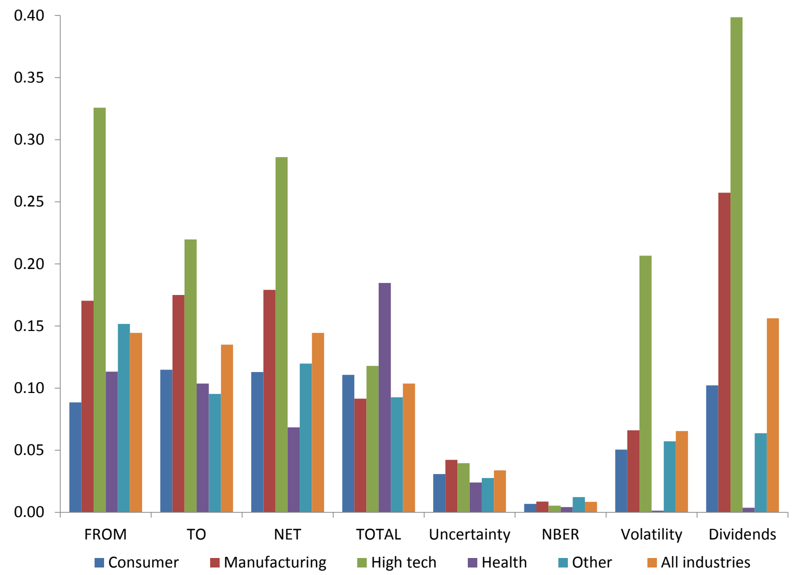
Note: The figure shows the time-varying responses to a monetary policy shock at a 10-quarter horizon. The middle line represents the median estimates of the posterior distribution, the dotted lines represent the 16- and 84- percentile estimates of the posterior distribution.

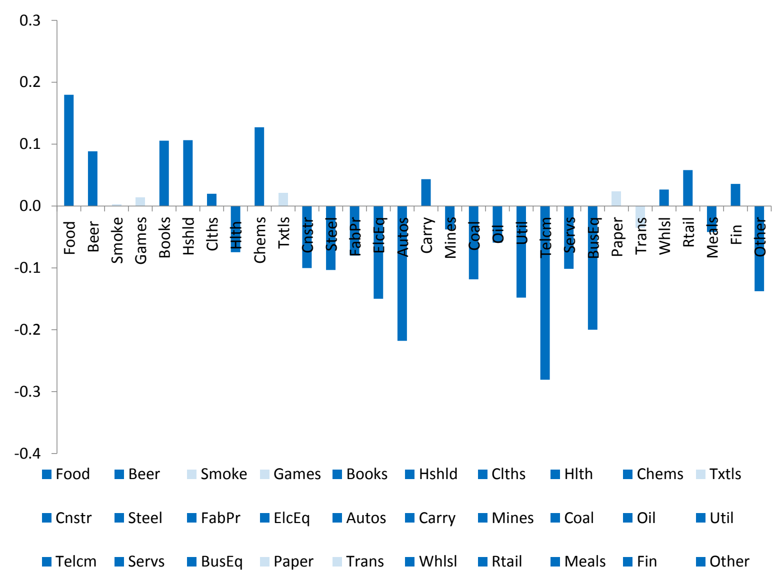
Figure 9: Total Connectedness



Note: The top figure shows the (daily) total connectedness measure obtained from the forecast variance decomposition analysis of the large TVP-VAR model as described in section 4.1. The figure at the bottom shows the net connectedness (average over the sample). A positive reading indicates that a given industry transmits more shocks than it receives.

Figure 10: Explaining industry-specific responses





Note: The top figure shows the averaged R-squared obtained from running thirty industry-specific regressions

$$IRF_{t+1}^{i} = \alpha_i + \beta_i X_{i,t} + \epsilon_{i,t},$$

where IRF_{t+1} is the one-step-ahead cumulative industry-specific response to a monetary policy shock for industry i at time $t+1$. $X_{i,t}$ is a single variable from the following list: macroeconomic uncertainty from Jurado et al. (2015), a dummy variable to capture U.S. recessions, industry-specific volatility as obtained from within-quarter daily squared returns, the four connectedness measures and industry-specific dividends. We show results aggregated over all industries and for five industry groupings: consumers, manufacturing, High-tech, Health, and Others. The figure at the bottom reports the slope coefficients of the industry-specific regressions using the net connectedness measure as a regressor (light blue bars indicate a not significant coefficient at the 10 per cent level).

Appendix for

The Effects of Monetary Policy on Industry-level Stock Returns in a Changing World

Pierre Guérin* Danilo Leiva-Leon†

February 12, 2016

*Bank of Canada, e-mail: pguerin@bank-banque-canada.ca
†Central Bank of Chile, e-mail: dleiva@bcentral.cl

Appendix A: Bayesian estimation

The factor-augmented time-varying parameter VAR model is estimated using Bayesian MCMC methods. Each iteration is composed of ten steps. The first seven steps follow the line of Del Negro and Primiceri (2013) and Galí and Gambetti (2015), and focus on sampling the elements of the VAR equation (6). The remaining three steps follow the line of Del Negro and Otrok (2008) and focus on sampling the elements of the Factor equation (5). At every iteration a draw of a set of parameters is obtained from the corresponding posterior density conditional on the rest of parameters of the model, i.e. the Gibbs sampling approach. A generic vector containing time-varying parameters is denoted by $\mathbf{z}^T = [z_1', z_2', ..., z_T']'$. The eleven steps can be briefly described as follows.

1. $P(h^T \mid Y^T, X^T, F_t, a^T, \phi^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, s^T, \Lambda^T, \Xi, \Omega)$
2. $P(a^T \mid Y^T, X^T, F_t, h^T, \phi^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, \Lambda^T, \Xi, \Omega)$
3. $P(\phi^T \mid Y^T, X^T, F_t, h^T, a^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, \Lambda^T, \Xi, \Omega)$
4. $P(\Theta_\phi \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_h, \Theta_{a,i}, \Lambda^T, \Xi, \Omega)$
5. $P(\Theta_h \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_\phi, \Theta_{a,i}, \Lambda^T, \Xi, \Omega)$
6. $P(\Theta_{a,i} \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_\phi, \Theta_h, \Lambda^T, \Xi, \Omega)$, $i = 1, 2, 3, 4, 5$
7. $P(s^T \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, \Lambda^T, \Xi, \Omega)$
8. $P(\Lambda^T \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, \Xi, \Omega)$
9. $P(\Xi \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, \Lambda^T, \Omega)$
10. $P(\Omega \mid Y^T, X^T, F_t, h^T, a^T, \phi^T, \Theta_\phi, \Theta_h, \Theta_{a,i}, \Lambda^T, \Xi)$

Prior distributions

There are three types of prior distributions. The first one corresponds to the Normal dstribution, and it is applied to the initial states of the time-varying parameters, h_0, a_{i0}, ϕ_0, and Λ_0. The second corresponds to the Wishart distribution, and it is used to model the variance-covariance matrices of the elements in the VAR equation, Θ_ϕ^{-1}, Θ_h^{-1}, $\Theta_{a,i}^{-1}$, Ξ^{-1}, Ω^{-1}. The third one is the Gamma distribution that is used to model the variance of the elements in the Factor equation. Specifically, the prior distributions are given by

1. $\log(h_0) \sim N(\log(\hat{h}_0), I_M)$

2. $a_{i0} \sim N(\hat{a}_i, \hat{V}_{a,i})$

3. $\phi_0 \sim N(\hat{\phi}, 4\hat{V}_\phi)$

4. $\Theta_\phi^{-1} \sim W(\underline{\Theta}_\phi^{-1}, \underline{\eta}_\phi)$

5. $\Theta_h^{-1} \sim W(\underline{\Theta}_h^{-1}, \underline{\eta}_h)$

6. $\Theta_{a,i}^{-1} \sim W(\underline{\Theta}_{a,i}^{-1}, \underline{\eta}_{a,i})$, $i = 1, 2, 3, 4, 5$

7. $\Lambda_0 \sim N(\hat{\Lambda}_0, \hat{V}_\Lambda)$

8. $\Xi^{-1} \sim G(\underline{\Xi}, \underline{\eta}_\Xi^2)$

9. $\Omega^{-1} \sim G(\underline{\Omega}, \underline{\eta}_\Omega^2)$

Let $Z^\tau = [Y^\tau, F_0^\tau]'$ be a sub-sample of size $\tau = 48$ observations. We run a time-invariant VAR for Z^τ and estimate by OLS the autoregressive coefficients, $\hat{\phi}$, their covariance matrix, $\hat{V}_\phi$, and the covariance matrix of the residuals, $\hat{\Upsilon} = \hat{F}\hat{D}\hat{F}'$. The log of the diagonal elements of $\hat{D}^{1/2}$ are given by $\log(\hat{h}_0)$. The OLS estimates obtained by regressing the $i+1$-th element of the residuals vector on the $1, t$-th, $2, t$-th,...,i, t-th elements, are given by $\hat{a}_i$, and its variance is denoted by $\hat{V}_{a,i}$.

The scale matrices are given by $\underline{\Theta}_\phi = \underline{\eta}_\phi(\varsigma_1 \hat{V}_\phi^f)$, $\underline{\Theta}_h = \underline{\eta}_h(\varsigma_2 I_M)$ and $\underline{\Theta}_{a,i} = \underline{\eta}_{a,i}(\varsigma_3 \hat{V}_{a,i}^f)$, where $\underline{\eta}_\phi$ and $\underline{\eta}_h$ are equal to the number of rows of $\underline{\Theta}_\phi$ and I_M plus one, respectively, while $\underline{\eta}_{a,i}$ is equal to $i+1$, for $i = 1, ..., M-1$. As in Gali and Gambetti (2014) we assume $\varsigma_1 = 0.005$, $\varsigma_2 = 0.01$, $\varsigma_3 = 0.01$. Also, $\hat{V}_\phi^f$ and $\hat{V}_{a,i}^f$ are estimated as $\hat{V}_\phi$ and $\hat{V}_{a,i}$ but using the full sample.

The mean and variance of the factor loadings prior distribution are given by $\hat{\Lambda}_0 = \mathbf{0}_{K \times M}$, and $\hat{V}_\Lambda = I_K$, respectively. Following Del Negro and Otrok (2008), the hyperparameters of the factor loading variances are given by $\underline{\Xi} = \underline{\eta}_\Xi T$, where $\underline{\eta}_\Xi = 0.1$. And the hyperparameters of the idiosyncratic terms variance are given by $\underline{\Omega} = \underline{\eta}_\Omega^2 T$, where $\underline{\eta}_\Omega^2 = 0.1$. Finally, for the prior distribution of the factor we use $\hat{F}_0 = \mathbf{0}_{K \times M}$, and $\hat{V}_F = I_K$.

Simulating the posterior distributions

In the sequel, we present the different steps of the MCMC algorithm to simulate the posterior distribution of the states and parameters of interest for the time-varying factor-augmented VAR model. Note that the algorithm closely follows the Gibbs sampling algorithm presented in the online appendix of Gali and Gambetti (2015), which is complemented by three steps to sample the elements in the factor equation.

- *Step 1:* Draw the stochastic volatility, h^T, using the Kim et al. (1998) (KSC) algorithm. KSC suggest to use a mixture of linear Gaussian distributions to approximate the (non-linear) stochastic volatility elements.[1] In doing so, they propose the use of seven Gaussian distributions, with mean $m_j - 1.2704$ and variance v_j^2 ($j = 1, ..., 7$), to match the moments of a log-χ_1^2 distribution (see Table 4 in Kim et al. (1998) for the values of m_j and v_j^2).

- *Step 2:* Draw the covariances, a^T, applying the Carter and Kohn (1994) (CK) algorithm equation by equation.

- *Step 3:* Draw the time-varying VAR coefficients, ϕ^T, using the CK algorithm.

- *Step 4:* Draw the time-varying VAR coefficients innovation variance, Θ_ϕ, by letting $\Theta_\phi = (Q_\phi Q_\phi')^{-1}$, where Q_ϕ is a matrix whose columns are independent draws from a $N(0, \underline{\Theta}_\phi + \sum_{t=1}^T \Delta\phi_t(\Delta\phi_t)')$.

- *Step 5:* Draw the stochastic volatility innovation variance, Θ_h, by letting $\Theta_h = (Q_h Q_h')^{-1}$ where Q_h is matrix whose columns are independent draws from a $N(0, \underline{\Theta}_h + \sum_{t=1}^T \Delta\log(h_t)(\Delta\log(h_t))')$.

- *Step 6:* Draw the stochastic covariance innovation variance, $\Theta_{a,i}$, by letting $\Theta_{a,i} = (Q_{a,i} Q_{a,i}')^{-1}$ where $Q_{a,i}$ is matrix whose columns are independent draws from a $N(0, \underline{\Theta}_{a,i} + \sum_{t=1}^T \Delta a_{i,t}(\Delta a_{i,t})')$.

- *Step 7:* Draw, from a discrete density, the random variable, s^T, that serves as a mixture component indicator that is used for drawing the stochastic volatility elements h^T.

- *Step 8:* Draw the time-varying factor loadings, Λ^T, using the CK algorithm.

[1] Sampling the stochastic volatility elements is not straightforward in that a standard linear Kalman filter cannot be directly implemented given that the error term for the dynamics of h^T is not Gaussian, but instead follows a log-χ_1^2 distribution.

- *Step 9:* Draw the innovation variance of the time-varying factor loadings, Ξ^{-1}, from the posterior gamma distribution $G(T + \underline{\Xi}, (\epsilon_t \epsilon_t' + \underline{\eta}_{\Xi}^2)^{-1})$.

- *Step 10:* Draw the variance of the innovations in the factor equation, Ω^{-1}, from the posterior gamma distribution $G(T + \underline{\Omega}, (e_t e_t' + \underline{\eta}_{\Omega}^2)^{-1})$.

The MCMC algorithm simulates the posterior distribution of the states and hyperparameters, iterating over steps 1 to 10. We use a burn-in period of 20,000 iterations to converge to the ergodic distribution, and run further 2,000 iterations sampling every 2 iterations to reduce the autocorrelation across draws. The results presented in the paper are therefore based on 1,000 draws from the posterior distributions. To assess convergence, we examine the recursive means of the retained draws. Recursive means vary little, suggesting evidence in favor of convergence.

Appendix B: Estimated industry responses and asset pricing model implications

To further understand the heterogeneity in the responses of industries to monetary policy surprises, we compare the industries' responses to monetary policy shocks against the ones that are implied by a standard asset pricing model. In doing so, we follow Bernanke and Kuttner (2005) and run the following regression of the excess return in industry i, $y_{i,t}$ on the five-factor model from Fama and French (2015), that is, we run the following regressions

$$y_{i,t} = a_i + b_i y_{M,t} + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + v_{i,t}, \tag{1}$$

where $y_{M,t}$ is the market excess return, SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on a diversified portfolios of high and low B/M (book-to-market equity ratio) stocks, RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, CMA_t is the difference between the returns on diversified portfolios of the stocks of low and high investment firms and $v_{i,t}$ is the regression residual term. The regression model is estimated at a daily frequency for a sample extending from February 1, 1994 to December 31, 2008.

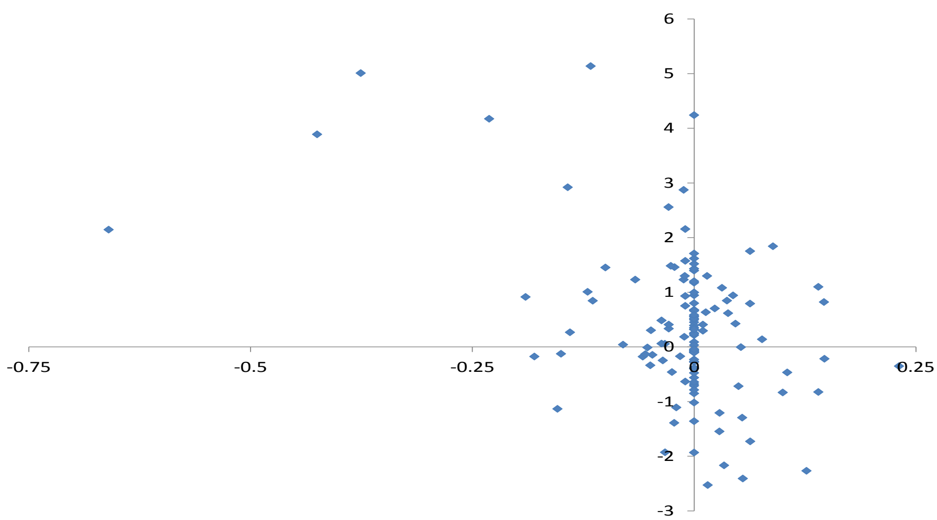
The industry response that is consistent with the five-factor model ($\hat{b}_i^u$) is therefore given by

$$\hat{b}_i^u = \hat{b}_i \times \hat{\beta}^u, \tag{2}$$

where $\hat{\beta}^u$ is the estimated response of S&P 500 returns to monetary policy surprises. Figure 8 plots the responses as implied by the 5-factor asset pricing model against the responses obtained from the event study analysis. It is interesting to note that for most industries, the five-factor asset pricing model does a reasonably good job at explaining the industry responses to monetary policy surprises in that the responses implied by the asset pricing model described by equation (2) typically lies within the confidence bands of the actual responses estimated from the data. There are, however, few noticeable exceptions in that the following industries responses are not well captured by the Fama and French (2015) model: "Food", "Smoke", "Steel", "FabPr", "Coal, "Oil", "Util", "Whlsl" and "Other".

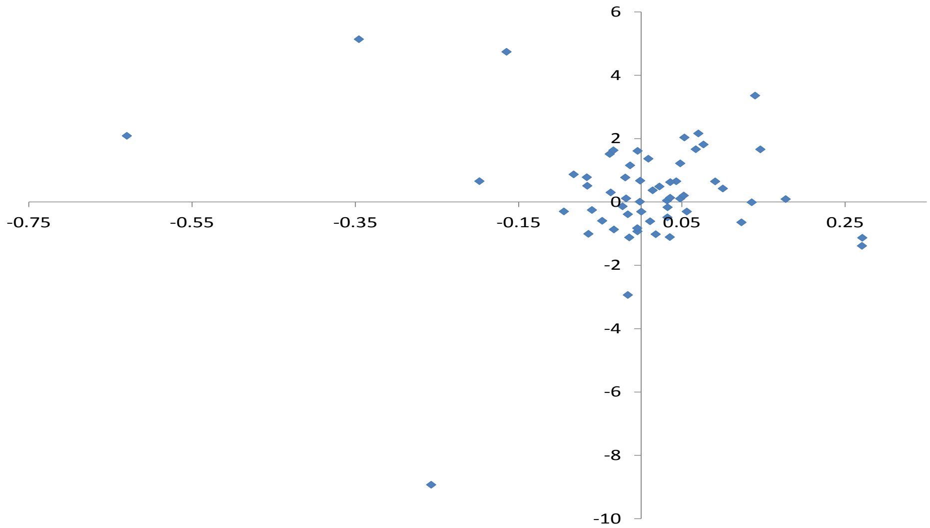
Appendix C: Figures

Figure 1: Federal funds rate surprises and equity returns (daily data)



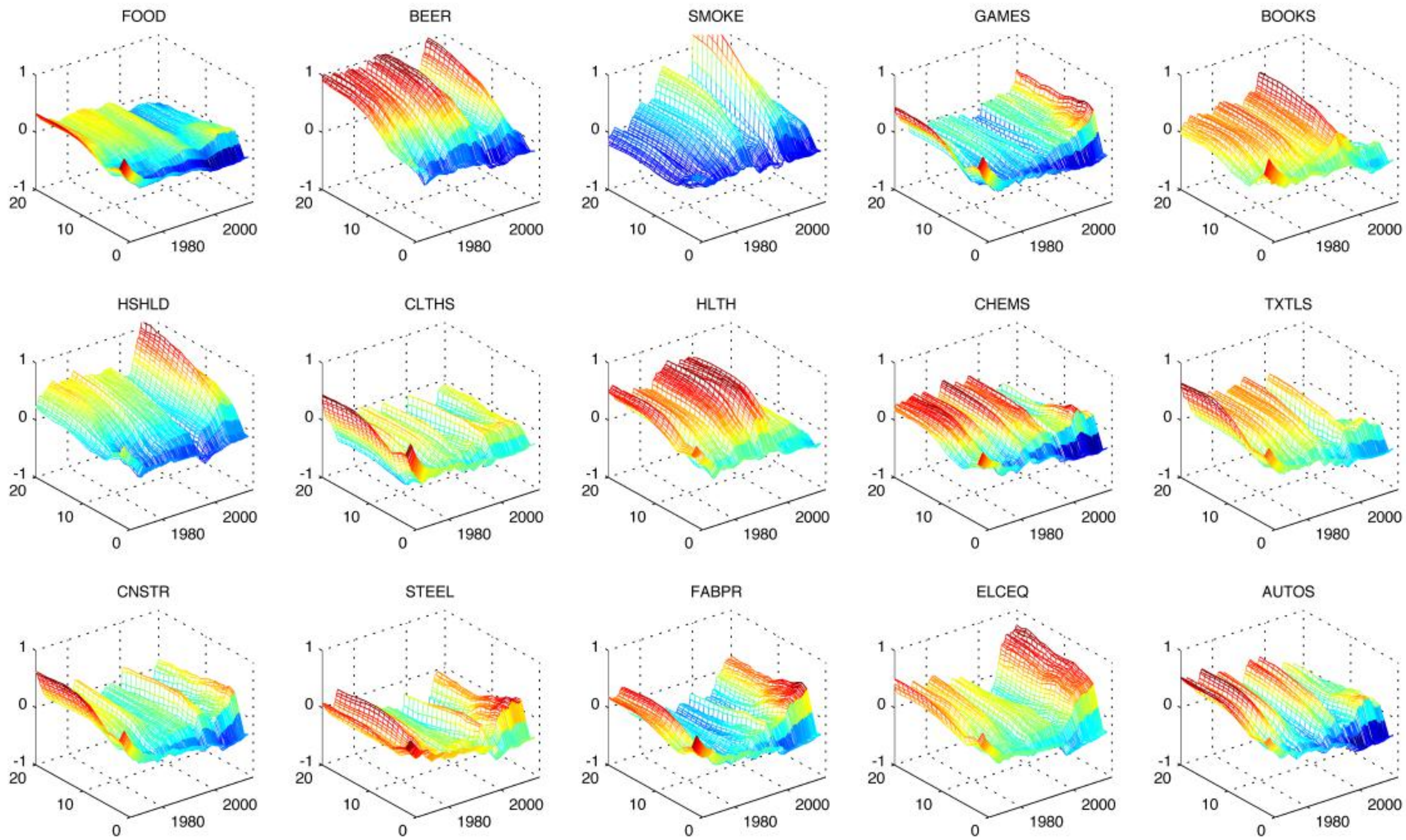
Note: This figure is a scatterplot of the S&P500 returns (on the y-axis) against the monetary policy surprises calculated from equation (1) (on the x-axis) over the sample extending from February 1994 to December 2008.

Figure 2: Unconventional monetary policy surprises and equity returns (daily data)



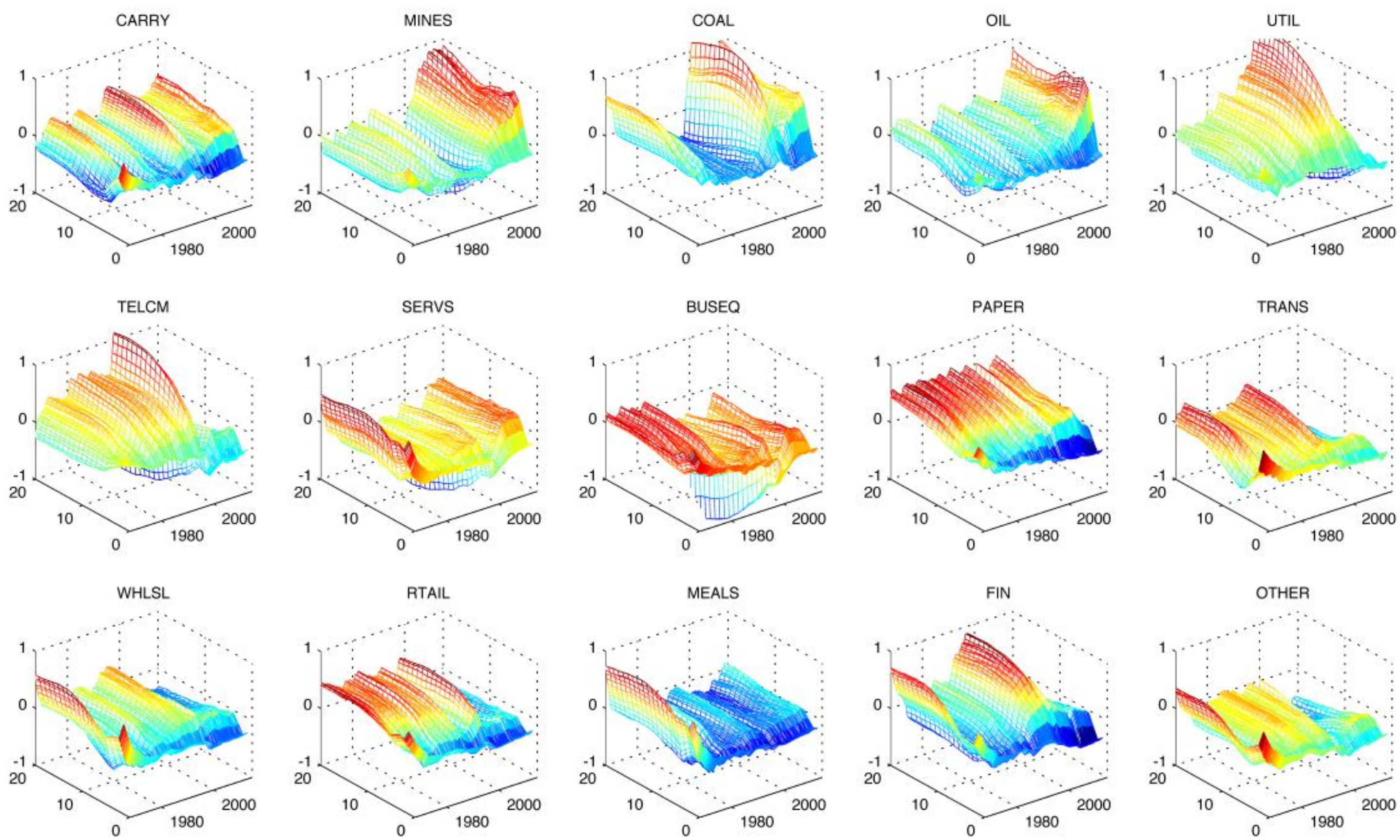
Note: This figure is a scatterplot of the S&P500 returns (on the y-axis) against the monetary policy surprises calculated as in equation (1) (on the x-axis) over the sample extending from October 2008 to December 2014.

Figure 3: Industry-specific Responsiveness to Monetary policy shocks based on Cholesky identification



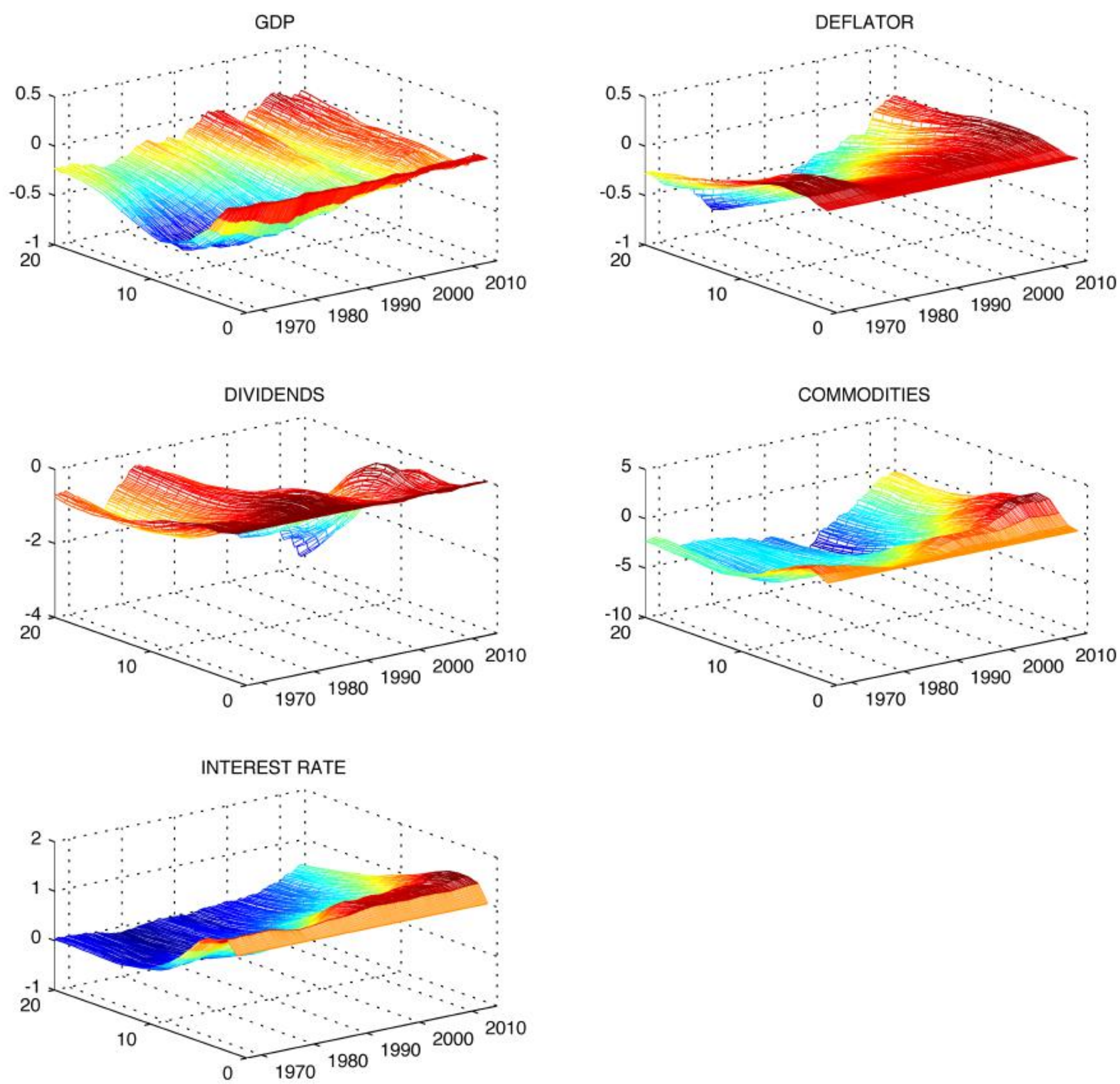
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 4: Industry-specific Responsiveness to Monetary policy shocks based on Choleski identification (cont.)



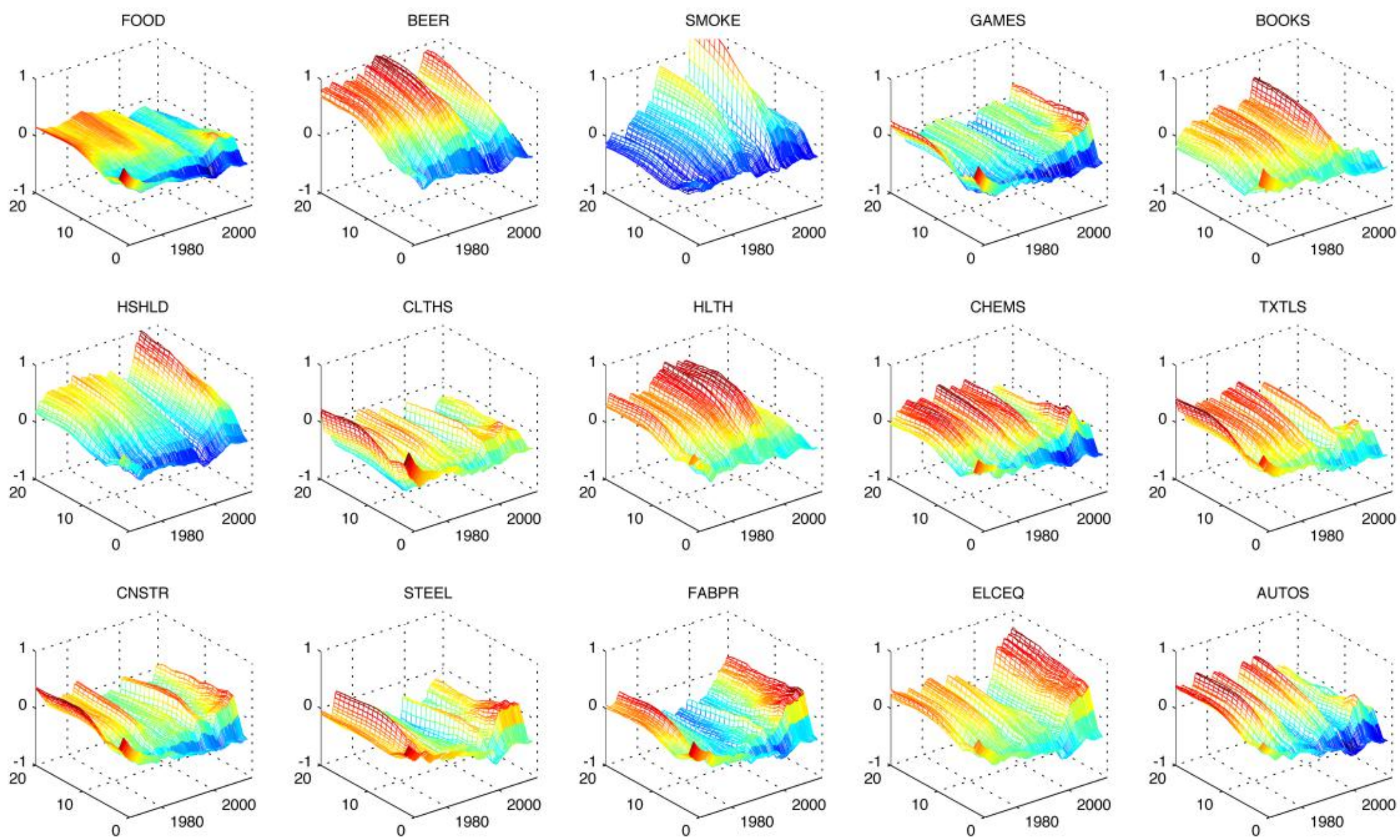
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 5: Fundamentals Responsiveness to Monetary policy shocks based on simultaneous responses identification



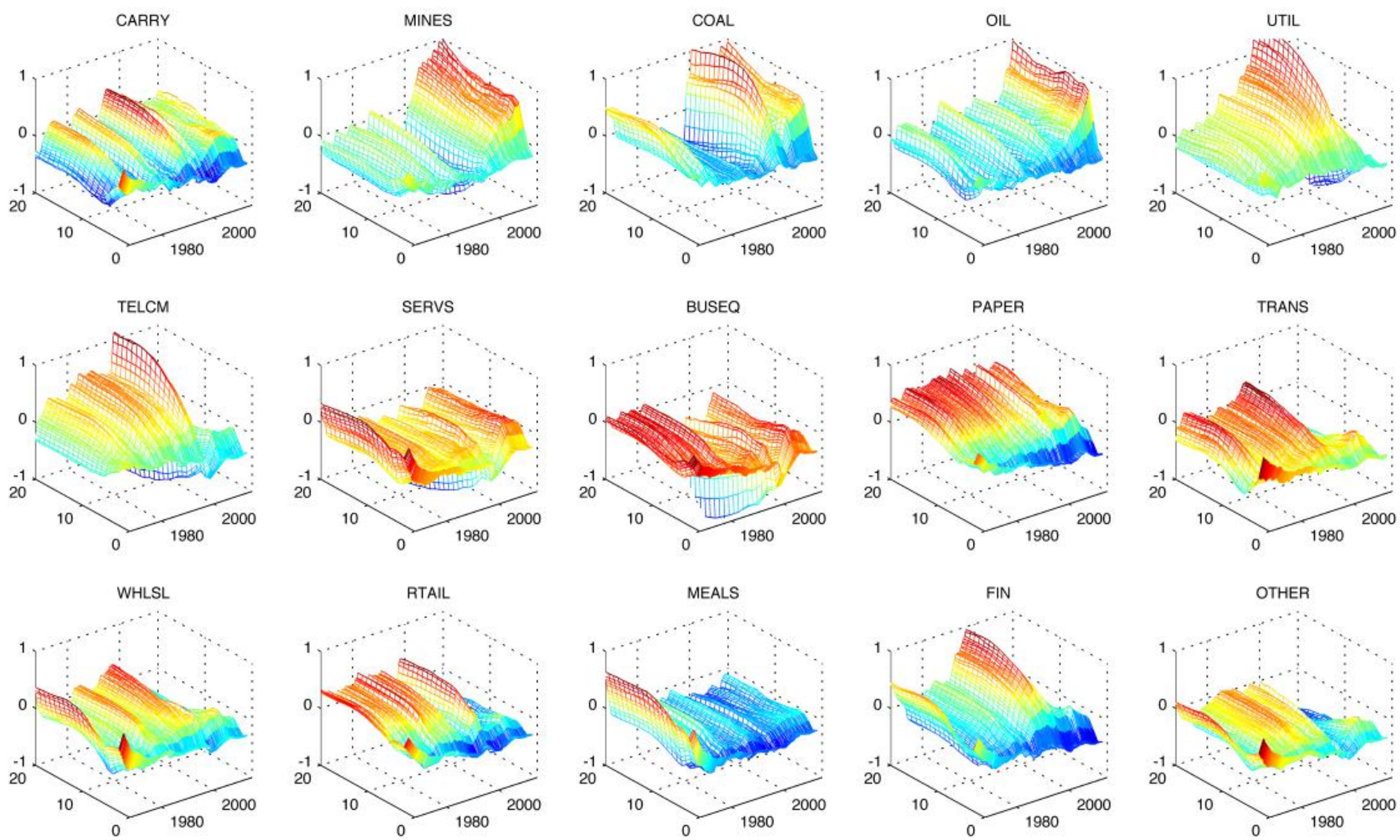
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 6: Industry-specific Responsiveness to Monetary policy shocks based on simultaneous responses identification



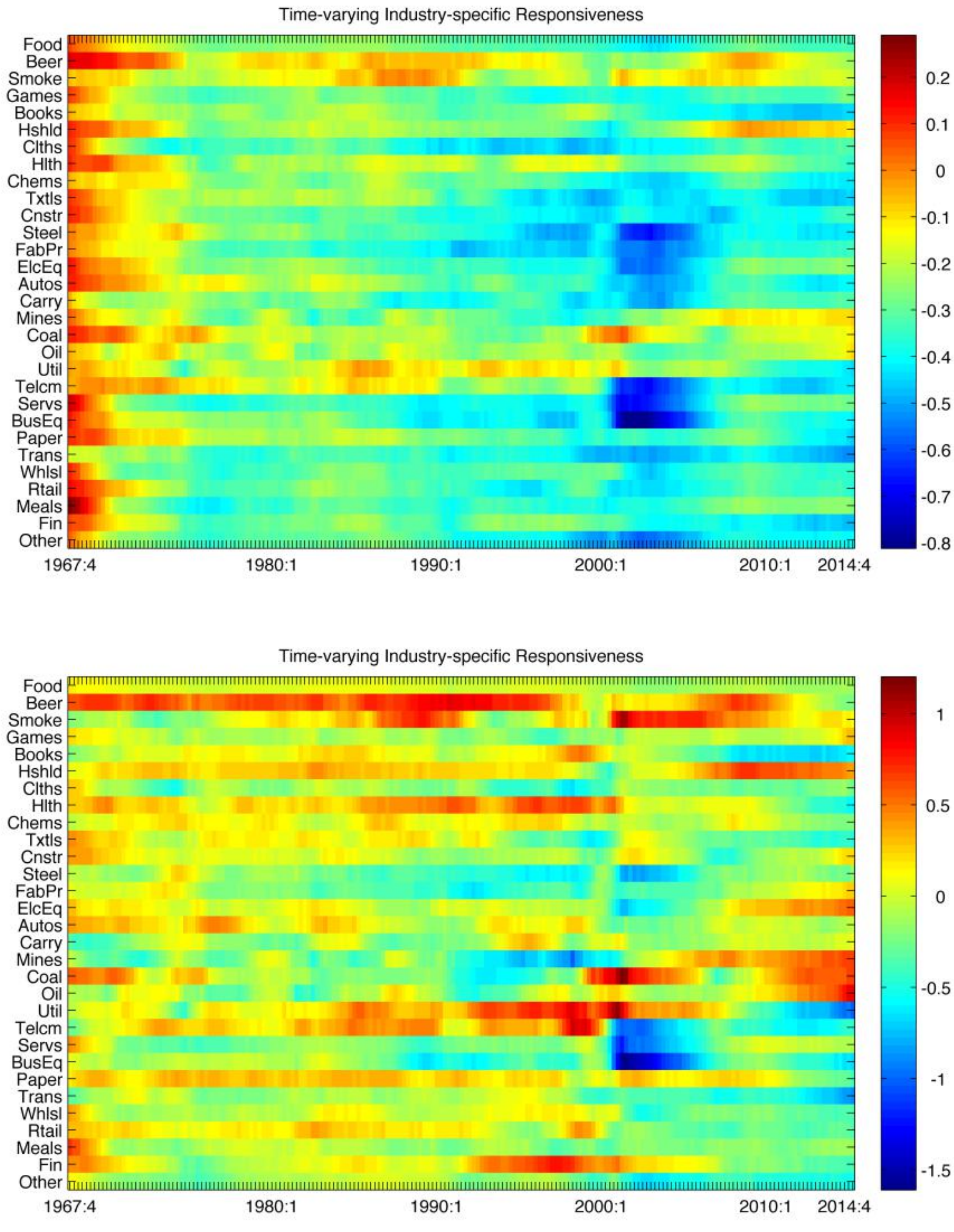
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 7: Industry-specific Responsiveness to Monetary policy shocks based on simultaneous responses identification (cont.)



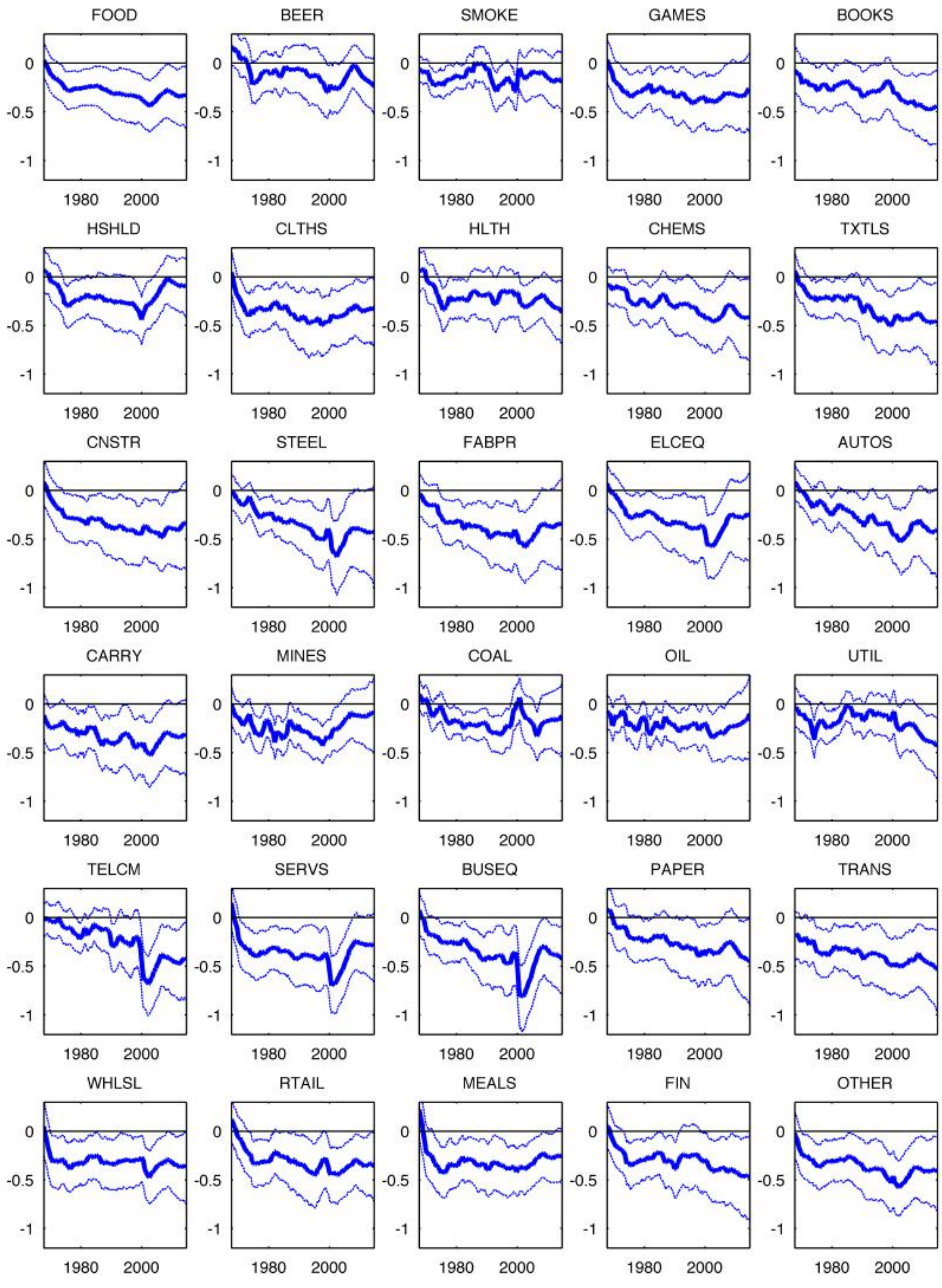
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 8: Heat map of Industry-specific responsiveness over time based on simultaneous responses identification



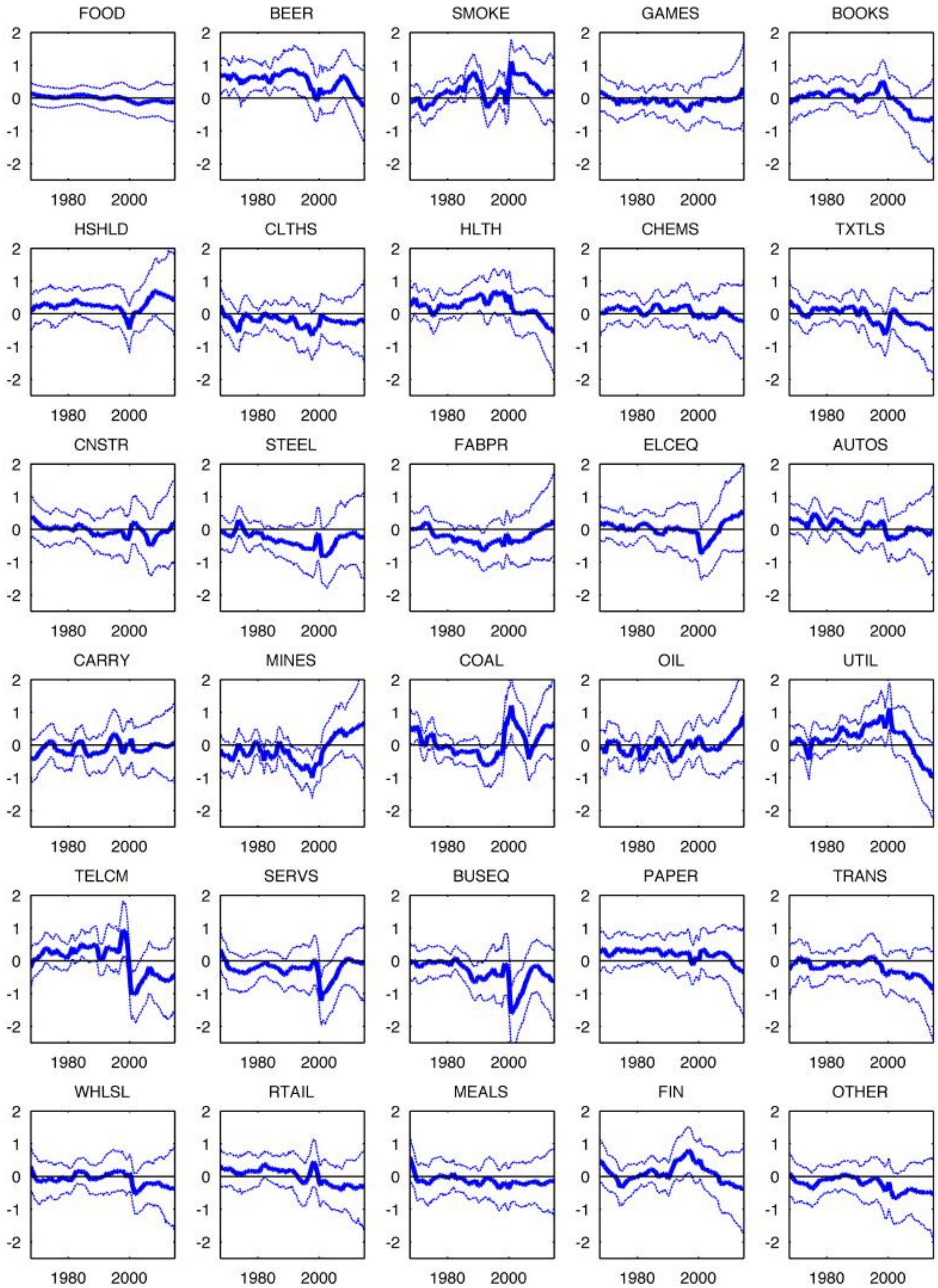
Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 9: Industry-specific Responsiveness at a horizon of 2 quarters to Monetary policy shocks based on simultaneous responses identification



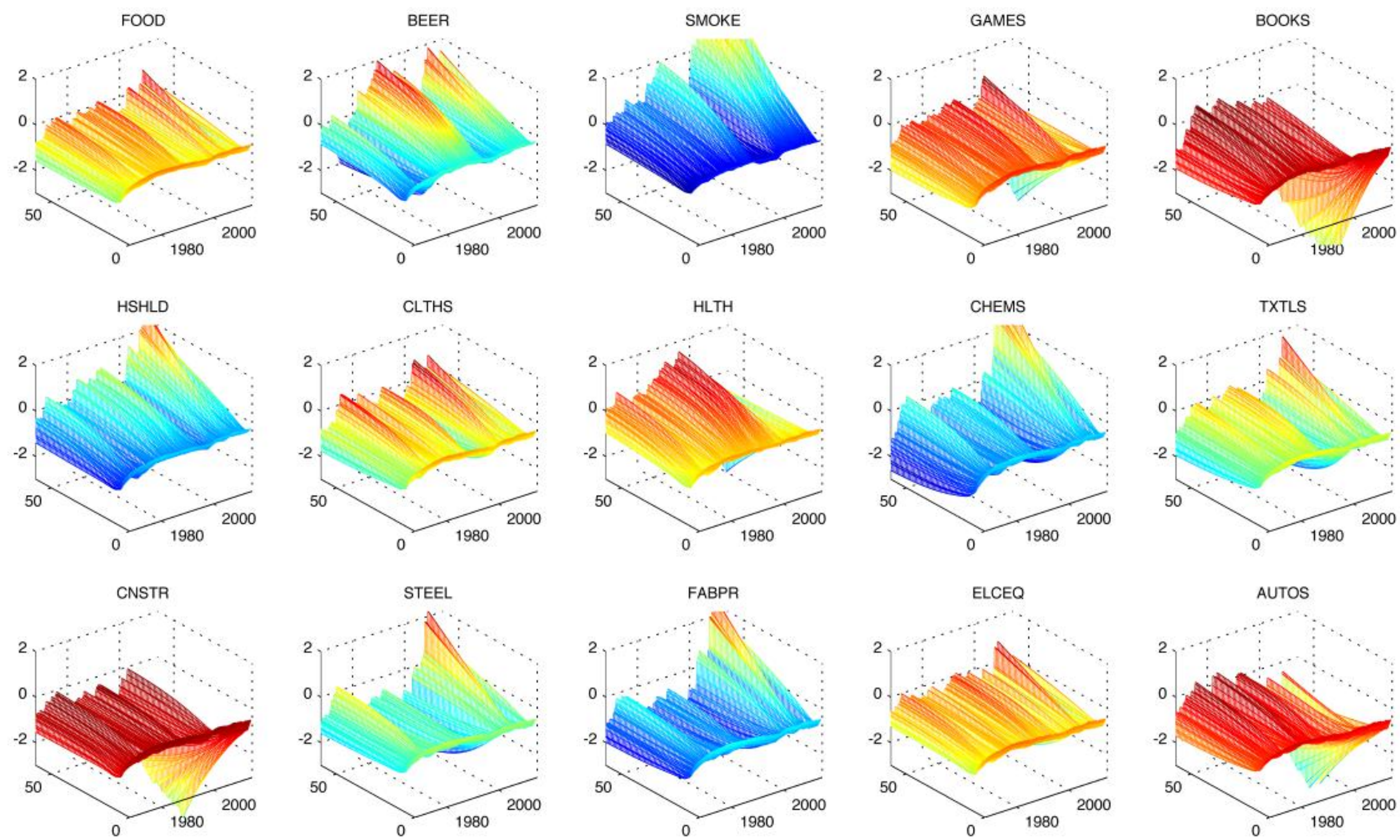
Note: The figure shows the time-varying responses to a monetary policy shock at a 10-quarter horizon. The middle line represents the median estimates of the posterior distribution, the dotted lines represent the 16- and 84- percentile estimates of the posterior distribution.

Figure 10: Industry-specific Responsiveness at a horizon of 10 quarters to Monetary policy shocks based on simultaneous responses identification



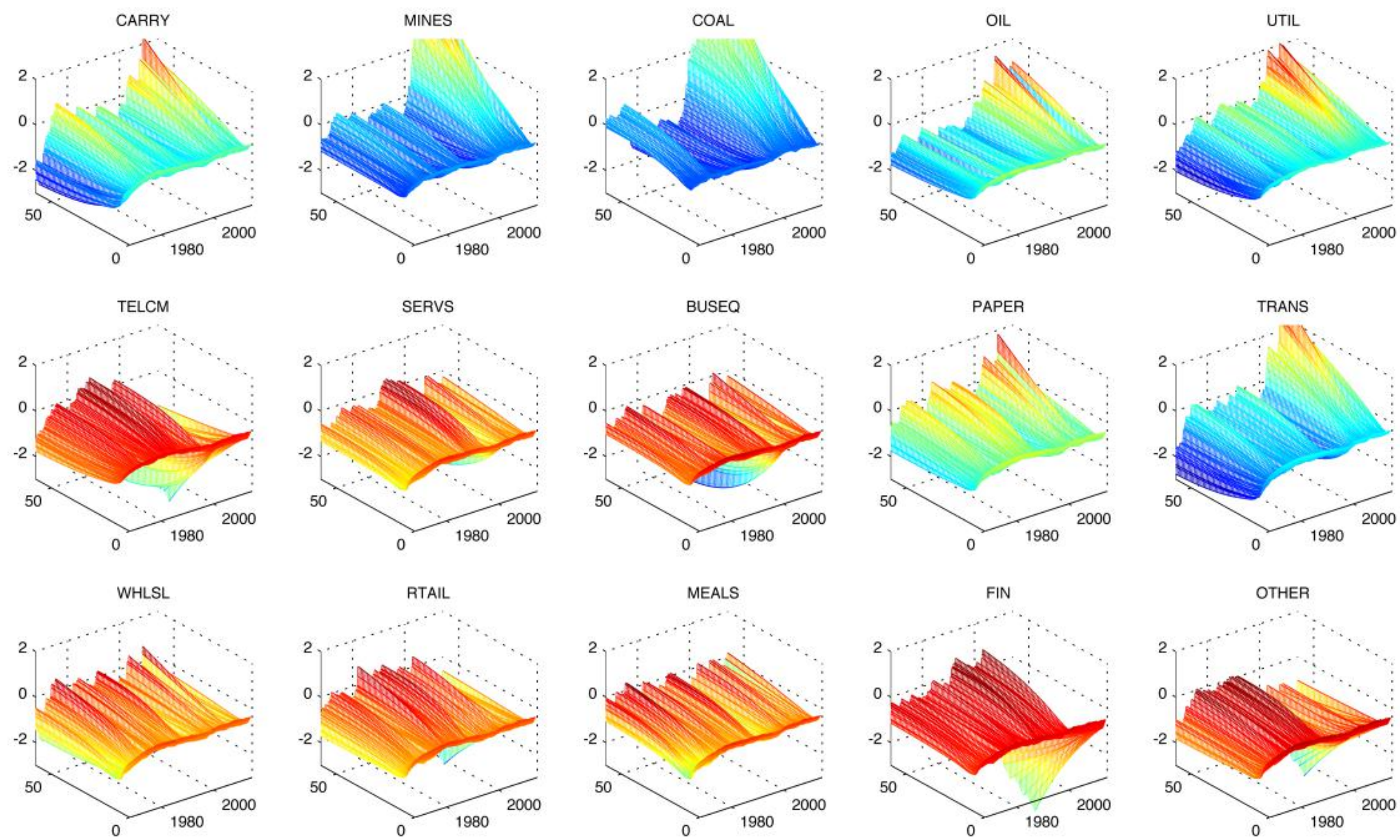
Note: The figure shows the time-varying responses to a monetary policy shock at a 10-quarter horizon. The middle line represents the median estimates of the posterior distribution, the dotted lines represent the 16- and 84- percentile estimates of the posterior distribution.

Figure 11: Industry-specific Responsiveness to Monetary policy shocks based on monthly frequency



Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

Figure 12: Industry-specific Responsiveness to Monetary policy shocks based on monthly frequency (cont.)



Note: This figure shows the median estimates of the time-varying impulse responses to a surprise 100 basis point increase in the policy rate.

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