Dynamic spillovers in the United States: Stock market, housing, uncertainty and the macroeconomy

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Abstract

In this study we examine dynamic macroeconomic spillovers in the United States, with a particular focus on the stock market, housing and economic policy uncertainty (EPU). Based on monthly data over the period 1987M1 to 2014M11, our findings reveal the following features. First, the transmission of various types of shocks contributes significantly to economic fluctuations in the United States. Second, spillovers show large variations over time. Third, in the wake of the global financial crisis, spillovers have been exceptionally high in historical perspective. In particular, we find large spillovers from EPU, as well as stock market and housing returns to other variables, in particular inflation, industrial production and the federal funds rate. These results illustrate the contagion from the housing and financial crisis to the real economy and the strong policy reaction to stabilise the economy.

Keywords: Housing market, Spillover, Stock market, Variance decomposition, Vector autoregression, Economic policy uncertainty, US recession

JEL codes: C32; E40; E50; G10; G20

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1. Introduction

Since the 2007 subprime mortgage market meltdown and the global financial crisis (GFC) that followed, the US economy has been exceptionally volatile. The contraction in output during the latest recession was the deepest since the Great Depression, falls in national indices of housing prices were unprecedented and the stock market dropped sharply before rebounding on the back of steep falls in interest rates. Policy responses to the crisis were exceptional, notably in terms of monetary policy and interventions to buttress the financial system. In this context, isolating sources of macroeconomic volatility is particularly challenging. In this paper, we identify dynamic spillovers among a set of key US economic indicators, which are chosen to provide a fairly comprehensive view of the economy, while keeping the model tractable. In addition to output and consumer price inflation, which are standard business cycle indicators, we include a stock market and a housing price index, a measure of economic policy uncertainty (EPU) and a key policy variable, the federal funds rate.

Our results indicate that over the period 1987M1 to 2014M11 roughly one third of the forecast error variance across our set of indicators comes from spillovers from shocks to other variables of the model. Moreover, the strength of spillovers varies widely over time and reaches a peak in November 2008 at the climax of the GFC. Over the whole sample, the variables at the origin of the largest net spillovers are real stock market and housing returns. The variables most affected by net spillovers are inflation and the federal funds rate. Industrial production and EPU are generating and receiving spillovers of roughly similar magnitude and hence have on average a relatively small net effect on other variables volatility. Looking at the post-GFC period, we find large spillovers from EPU as well as stock market and housing returns to other variables, in particular inflation, industrial production and the federal funds rate. These results illustrate the contagion from the housing and financial crisis to the real economy and the strong policy reaction to stabilise the economy.

The remainder of the article is organized as follows. Section 2 discusses the application

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of the spillover index approach and describes the data used. Section 3 presents the empirical findings. Section 4 summarizes the main results and concludes.

2. Data and Methodology

2.1. Data

We collect monthly series of the economic policy uncertainty index (EPU), S&P/Case-Shiller 10-City composite home price index (CS), consumer price index (CPI), industrial production index (IP), S&P500 stock market price index (S&P500), and the federal funds rate (FFR), over the period January 1987 to November 2014. The EPU comes from Baker et al. (2012) and measures policy-related economic uncertainty in the United States.[1] The remaining series are obtained from FRED, and converted to real returns (apart from the FFR) by taking the annualized monthly change of the natural logarithm of the real variable (i.e. deflated by CPI), e.g. for the Case-Shiller home price index (rCS_t): $1200 \times (\log(rCS_t) - \log(rCS_{t-1}))$. In the case of the FFR, we take the first differences so as to render the series stationary. The motivation for including these series is to look at which shocks contributed most to macroeconomic volatility over time. Housing prices are included as the subprime meldown was at the epicentre of the GFC and more generally as their influence on the US business cycle is well documented (e.g. Leamer, 2007). Stock market shocks are important in their own right and also as they instantly reflect turmoil in other financial markets. Finally, EPU accounts for uncertainties, which affect economic decisions, all the more recently as the exceptional magnitude of the downturn has driven economic policies into uncharted territory. Innovations in output (proxied by industrial production) account for supply shocks, those in inflation for demand shocks and those in interest rates for monetary policy shocks.

We define $y_t = (EPU_t, rCSr_t, rIPgr_t, INF_t, rS\&P500r_t, DrFFR_t)'$ as the vector consisting of US data on economic policy uncertainty, EPU_t, real housing market returns,$rCSr_t$,

[1] In particular, it's a constructed index based on three components. The first component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty.

real industrial production growth, $rIPgr_t$, inflation, INF_t, real stock market returns, $rS\&P500r_t$, and real federal funds rate changes, $DrFFR_t$, in year t.[2]

Fig. 1 and Table 1 illustrate and provide descriptive statistics on the underlying series in the United States.

[Insert Fig. 1 here]

[Insert Table 1 here]

According to this figure, we observe that peaks of economic policy uncertainty tend to be associated with declining housing markets returns, industrial production growth and interest rate changes, real stock markets returns and inflation (especially during US recessions). A feature which we explore further below.

Table 1 presents the descriptive statistics of our data. According to this table, we observe large variability in our main variables. The augmented Dickey-Fuller (ADF) test with just a constant, rejects the null hypothesis of a unit root for each series (i.e. all series are stationary), which motivates the use of a VAR model in these series.

2.2. Empirical Methodology

Our analysis is based on the spillover index approach introduced by Diebold and Yilmaz (2009, 2012) which builds on the seminal work on VAR models by Sims (1980) and the notion of variance decompositions. It allows an assessment of the contributions of shocks to variables to their own forecast error variance and those of the other variables of the model. Using rolling-window estimation, the evolution of spillover effects can be traced over time and illustrated by spillover plots.

The starting point for the analysis is the following K^{th} order, N variable VAR

$$y_t = \sum_{k=1}^{K} \Theta_k y_{t-k} + \varepsilon_t \tag{1}$$

[2]For robustness, we have checked the results using the real housing returns based on the housing price index from the Federal Housing Finance Agency (FHFA). The findings are qualitatively very similar and thus omitted for the sake of brevity.

where $y_t = (EPU_t, rCSr_t, rIPgr_t, INF_t, rS\&P500r_t, DrFFR_t)'$ is a vector of endogenous variables defined above; $\Theta_k, k = 1, ..., K$, are $N \times N$ parameter matrices and $\varepsilon_t \sim (0, \Sigma)$ is a vector of disturbances that are assumed to be independently (though not necessarily identically) distributed over time; t is the month index, ranging from 1987M1 to 2014M11.

Key to the dynamics of the system is the moving average representation of model (1), which is given by $y_t = \sum_{p=0}^{\infty} A_p \varepsilon_{t-p}$, where the $N \times N$ coefficient matrices A_p are recursively defined as follows: $A_p = \Theta_1 A_{p-1} + \Theta_2 A_{p-2} + \ldots + \Theta_p A_{p-l}$, where A_0 is the $N \times N$ identity matrix and $A_p = 0$ for $p < 0$.

We use the variant of the spillover index in Diebold and Yilmaz (2012), which is based on the generalized VAR framework (Koop et al., 1996; Pesaran and Shin, 1998), in which forecast error variance decompositions are invariant to the ordering of the variables. Of course, this has advantages and drawbacks. Given our goal to assess the magnitude of macroeconomic spillovers (as determinants of (the share of) forecast error variances) rather than identifying the causal effects of structural shocks, this appears to be the preferred choice in the present context.[3]

In the generalized VAR framework, the H-step-ahead forecast error variance contribution is

$$\phi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \tag{2}$$

where Σ is the (estimated) variance matrix of the error vector ε, σ_{jj} the (estimated) standard deviation of the error term for variable j, and e_i a selection vector with 1 as the i^{th} element and zeros otherwise. This yields a 6×6 matrix $\phi(H) = [\phi_{ij}(H)]_{i,j=1,\ldots,6}$, where each entry gives the contribution of variable j to the forecast error variance of variable i. The main diagonal elements contain the (own) contributions of shocks to variable i to its own forecast error variance, the off-diagonal elements represent cross-variable spillovers, defined here as contributions of other variables j to the forecast error variance of variable i.

Since the own and cross-variable variance contribution shares do not sum to 1 under the generalized decomposition, i.e., $\sum_{j=1}^{N} \phi_{ij}(H) \neq 1$, each entry of the variance decomposition

[3]However, we explore the robustness of our results by using Cholesky factorization with alternative orderings of the variables, as discussed below, and our results remain very similar.

matrix is normalized by its row sum, such that

$$\tilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)} \tag{3}$$

with $\sum_{j=1}^{N} \tilde{\phi}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H) = N$ by construction.

This ultimately allows to define a total spillover index, which is given by the following:

$$TS(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{4}$$

which measures, on average over all variables, the contribution of spillovers from shocks to all other variables to the total forecast error variance.

This approach is quite flexible and allows to obtain a more differentiated picture by considering directional spillovers: Specifically, the directional spillovers received by variable i from all other variables j are defined as follows:

$$DS_{i\leftarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{5}$$

and the directional spillovers transmitted by variable i to all other variables j as follows:

$$DS_{i\rightarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ji}(N)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ji}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ji}(H)}{N} \times 100. \tag{6}$$

Notice that the set of directional spillovers provides a decomposition of total spillovers into those coming from (or to) a particular variable.

By subtracting Equation (5) from Equation (6) the net spillovers from variable i to all other variables j are obtained as follows:

$$NS_i(H) = DS_{i\rightarrow j}(H) - DS_{i\leftarrow j}(H), \tag{7}$$

providing information on whether a variable is a receiver or transmitter of shocks in net terms. Put differently, Equation (7) provides summary information about how much each variable in the US contributes to the other variables in net terms.

3. Empirical Findings

In the following, we present the results from our empirical analysis. We start with the estimates of the static spillover index (i.e. an average estimate for the full sample period), and then consider the dynamic nature of spillovers using rolling window estimation.

3.1. Spillover Indices

Table 2 presents the estimation results for the spillover indices defined in Equations (4)-(7), based on 12-month-ahead forecast error variance decompositions. Before discussing the results, let us first describe the structure and elements of Table 2. The ij^{th} entry is the estimated contribution *to* the forecast error variance of variable i coming *from* shocks (innovations) to variable j (see Equation (2)). The diagonal elements ($i = j$) measure intra-variable spillovers of shocks (over time), while the off–diagonal elements ($i \neq j$) capture inter-variable (i.e., cross–variable) spillovers of shocks.

In addition, the row sums excluding the main diagonal elements (labelled 'Directional from others', see Equation (5)) report the total spillovers *to* (received by) the particular variable in the respective row, whereas the column sums (labelled 'Directional to others', see Equation (6)) report the total spillovers *from* (transmitted by) the particular variable in the respective column. The difference between each variable's (off-diagonal) column sum and the same variable's row sum gives the net spillovers of the respective variable to all other variables (see Equation (7)). Finally, the total spillover index defined in Equation (4), is given in the lower right corner of Table 2, is approximately equal to the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals), expressed in percentage points.[4]

[Insert Table 2 here]

Table 2, that summarizes the average spillovers for the full sample period reveals several interesting findings. First, intra-variable spillovers explain the highest share of forecast error variance, as the diagonal elements receive higher values compared with the off-diagonal elements. For instance, innovations to real housing market returns in the United States explain 70.46% of the 12-month-ahead forecast error variance of real housing market returns in the United States, but only 29.26% and 11.81% of the 12-month-ahead forecast error variance of inflation and real industrial production growth.

[4]The approximate nature of the result is due to the fact that the contributions of the variables do not sum to 1 under the generalized decomposition framework and have to be normalized (see Equation (3)).

Second, the most important sources of net spillovers are real housing and stock market returns. Home price changes influence inflation, industrial production and the federal funds rate. This is consistent with the well-known spillovers from housing prices to the wider economy, especially through residential investment as well as wealth and collateral effects on private consumption (Leamer, 2007; Lettau and Ludvigson, 2004; Case et al., 2005). Inflation also has an effect on housing prices, in particular through its effect on borrowing constraints. As they affect activity and inflation, variations in home prices also naturally tend to spill over to the policy rate (André et al., 2012). The largest spillover from stock market returns concerns EPU, which in turn feeds back to the stock market and influences the federal funds rate. The variables receiving the largest net spillovers are inflation, which is traditionally lagging the business cycle, and the federal funds rate, which is adjusted according to economic and financial developments to stabilise the economy. Industrial production and EPU are generating and receiving spillovers of roughly similar magnitudes and hence have on average a relatively small net effect on other variables volatility. EPU is most affected by stock market developements, while industrial production is mainly impacted by inflation and the housing market. Both variables have a notable influence on federal funds rates

Third, according to the total spillover index reported at the lower right corner of Table 2, which effectively distils the various directional spillovers into one single index, on average, 33.69% of the forecast error variance in our set of variables comes from cross-variable spillovers of shocks.

In sum, the results reported in Table 2 suggest that, on average, both the total and directional spillovers across our set of variables are relatively high during our sample period, highlighting interrelations between the stock market, housing, uncertainty and the macroeconomy.

3.2. Spillover Plots

While the average results for the full sample period in Table 2 are indicative, they might mask interesting changes in the pattern of inter-variable spillovers, given the long time span of three decades considered. Hence, we estimate the model in Equation (1) using 60-

month rolling windows and calculate the variance decompositions and spillover indices.[5] As a result, we obtain time-varying estimates of spillover indices, allowing us to assess the intertemporal evolution of total and directional spillovers between the various variables in the model.

[Insert Fig. 2 here]

Fig. 2 presents the results for the time-varying total spillover index obtained from the 60-month rolling windows estimation. According to this figure, we observe a large variation in the total spillover index, which turns out very responsive to extreme economic events and closely associated with US recessions. In particular, he total spillover index reaches peaks during the Mexican, Asian, Russian and Brazilian crises during the 1990s. Higher peaks are reached after the dot-com bubble burst and the terrorist attacks on the United States in 2001, and especially after the global financial crisis of 2008, which followed the meltdown of the US subprime market. Even though the spillover index came down progressively afterwards, new spikes correspond to different episodes of the euro crisis. Overall, the index captures well spillovers from both domestic and external shocks.

Although the results for the total spillover index are informative, they might mask directional information that is contained in the "Directional to others" row (Equation (5)) and the "Directional from others" column (Equation (6)) in Table 2. Fig. 3 presents the estimated 60-month rolling windows directional spillovers from each of the variables to others (corresponding to the "Directional to others" row in Table 2), while Fig. 4 presents the estimated 60-month rolling windows directional spillovers from other variables to each variable (corresponding to the "Directional from others" column in Table 2).

[Insert Fig. 3 here]

[Insert Fig. 4 here]

According to these two figures, directional spillovers from or to each variable range between 2% and 20% and are of bidirectional nature. Nevertheless, they behave rather

[5] Our results reported below remain robust to alternative choices of window length (i.e. 70 and 80 months).

heterogeneously over time and follow a similar pattern as the one found for the total spillover index. That is, directional spillovers from or to each variable generally peak during the extreme economic events, such as housing bubble bursting and US recessions. Spillovers from variables show more volatility than spillovers to them, suggesting that the impact of specific shocks tend to partially offset each other, reflecting stabilising forces in the economy. Spillovers to Federal fund rates and EPU vary the most over time, which could be expected from a policy instrument and policy related variable.

Net directional spillover indices obtained from the 60-month rolling window estimation show which shocks have caused most volatility in the economy or at least the group of variables considered in this paper at specific points in time. According to Fig. 5, which plots the time-varying net directional spillovers across variables, we observe that all variables frequently switch between a net transmitting and a net receiving role. Most notable over the sample period are: the large spillover from industrial production after the bursting of the dot-com bubble and the associated adjustment of productivity growth expectations; the almost always positive net spillovers from the stock market since the early 2000s, which may reflect an increasing role of financial shocks on the economy; the large spillover from the federal fund rates to the economy in periods preceding recessions and in the opposite direction during and after downturns, reflecting proactive policy to avoid overheating during booms and strong reactions by monetary authorities to dampen recessions; the sizeable spillovers to inflation since the GFC, which contribute to justifying unconventional monetary policy as the Federal fund rates are close to zero; the unusually high spillovers from EPU since the GFC, which follows a period of negative spillovers, which sent EPU to historically low levels during the preceding boom, a period during which risk spreads on a wide range of assets also turned exceptionally low (Kennedy and Sløk, 2005). Spillovers from real housing returns tend, as for inflation and the federal funds rate, to turn positive before recessions, illustrating the important role of housing in the business cycle.

[Insert Fig. 5 here]

3.3. Robustness analysis

In an attempt to check the robustness of the results obtained based on the generalised version of the spillover index by Diebold and Yilmaz (2012), we also employ the spillover index approach of Diebold and Yilmaz (2009), which is based on the Cholesky decomposition and in which the forecast error variance decomposition is sensitive to the ordering of the variables in the VAR. In particular, we analyse 100 random permutations (different orderings of the variables in the VAR) and construct the corresponding spillover indices for each ordering. Figure 6 presents the minimum and maximum values that the total spillover index receives based on Cholesky factorization. According to this figure, the results are in line with those of our main approach reported in Figure 2. In particular, the spillover index varies between 35% and 75% and reaches a peak during (extreme) economic events identified in the baseline analysis.

[Insert Fig. 6 here]

4. Conclusions

This study has examined the magnitude and evolution of spillovers within a set of macroeconomic indicators, including stock and housing market returns and economic policy uncertainty (EPU), using monthly data over the period January 1987 to November 2014. Methodologically, we employed the VAR-based spillover index by Diebold and Yilmaz (2012), which is well suited for the investigation of macroeconomic spillovers, but has rarely been used in this strand of the literature so far.

We find that the transmission of shocks between variables is an important source of macroeconomic fluctuations in the United States. On average over the whole sample period, 34% of forecast error variance across variables is due to spillovers. Over the whole sample, the variables at the origin of the largest net spillovers are real stock market and housing returns. However, spillovers show large variations over time. In particular, we identify large spillover from industrial production after the bursting of the dot-com bubble and the associated adjustment of productivity growth expectations; mostly positive net spillovers from the stock market since the early 2000s, which may reflect an increasing role of financial shocks on the economy; large spillovers from the federal fund rates to the economy in periods preceding recessions and in the opposite direction during and after downturns, reflecting proactive policy to avoid overheating during booms and strong reactions by monetary authorities to dampen recessions; sizeable spillovers to inflation since the GFC, which contribute to justifying unconventional monetary policy as the Federal fund rates are close to zero; unusually high spillovers from EPU since the GFC, which follows a period of negative spillovers, which sent EPU to historically low levels during the preceding boom. Spillovers from real housing returns, as for inflation and the federal funds rate, tend to turn positive before recessions, illustrating the important role of housing in the business cycle. These results are robust to several robustness checks.

A straightforward avenue for future research would be to extend the analysis to other countries to examine if specific structural and institutional features of economies, housing and financial markets affect the strength of spillovers and their evolution over time.

Disclaimer

The views expressed in this paper are those of the authors and do not necessarily reflect those of the Organisation for Economic Co-operation and Development (OECD) or its member countries.

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Table 1: Descriptive statistics

	EPU	rCS returns	rIP growth	Inflation	rS&P500r	DrFFR
Min	57.203	-0.0252	-0.0438	-0.0179	-0.2454	-0.5419
Mean	106.33	0.0010	-0.0003	0.0023	0.0060	-0.0172
Max	245.13	0.0175	0.0194	0.0137	0.1058	0.4098
Std	33.061	0.0080	0.0068	0.0026	0.0440	0.1262
ADF[a] (constant)	-5.298**	-3.981**	-14.98**	-11.47**	-16.46**	-10.49**

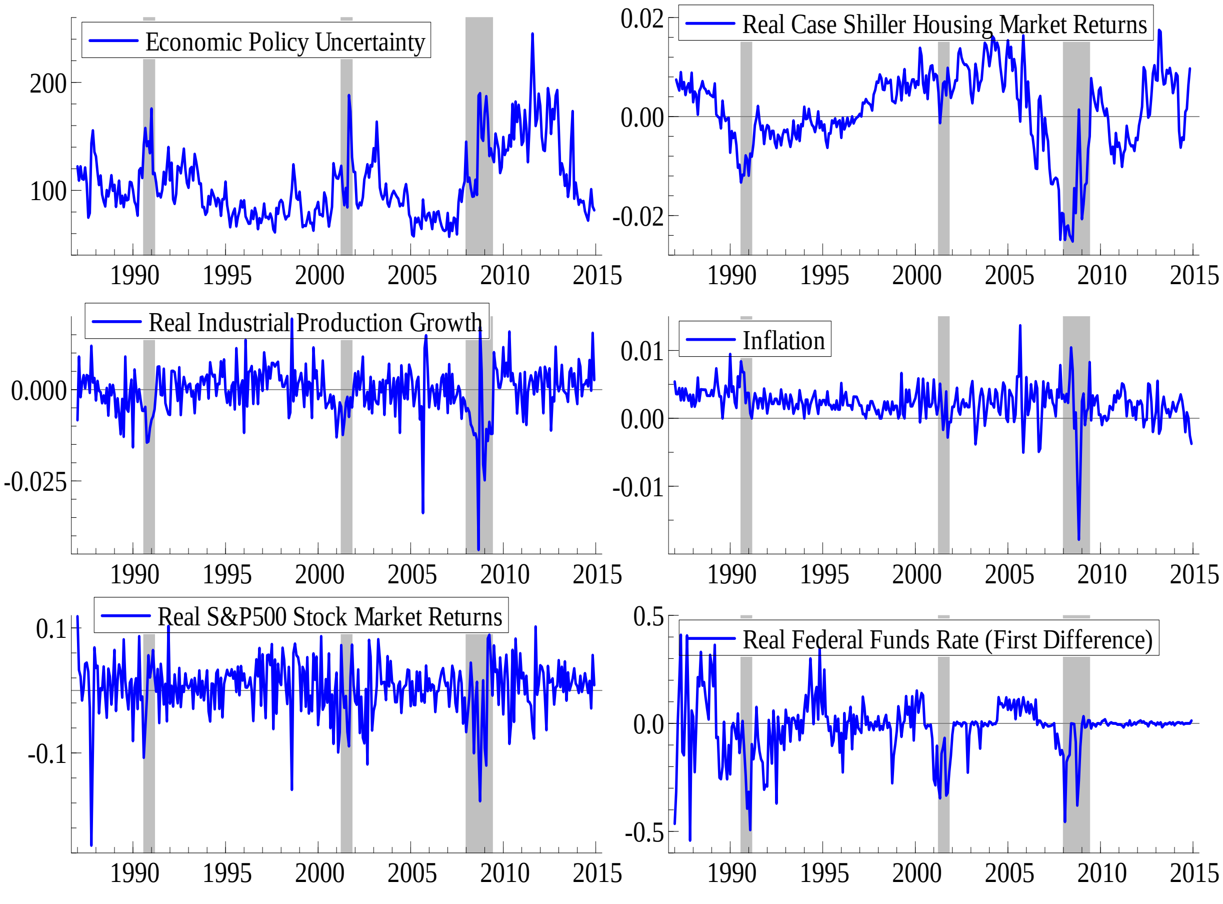
Note: [a] The 5% and 1% critical values are -2.87 and -3.45, respectively. * and ** indicate significance at 5% and 1% level, respectively.

Table 2: Estimation Results for Spillover Indices

	(j)						
(i)	EPU	rCSr	rIPgr	INF	rS&P500r	DrFFR	Directional from others
EPU	67.32	4.78	2.36	3.15	22.04	0.35	32.68
rCSr	2.52	70.46	6.24	15.36	4.54	0.89	29.54
rIPgr	2.73	11.81	62.93	15.50	6.95	0.08	37.07
INF	2.17	29.26	14.98	50.04	1.53	2.02	49.96
rS&P500r	10.86	0.92	2.85	1.49	83.24	0.65	16.76
DrFFR	10.48	8.39	9.20	1.59	6.47	63.86	36.14
Directional to others	28.76	55.16	35.62	37.08	41.53	3.98	Total Spillover
Directional including own	96.08	125.62	98.55	87.12	124.78	67.84	Index = 33.69%
Net directional spillovers	-4.82	25.62	-1.45	-12.38	24.77	-32.16	

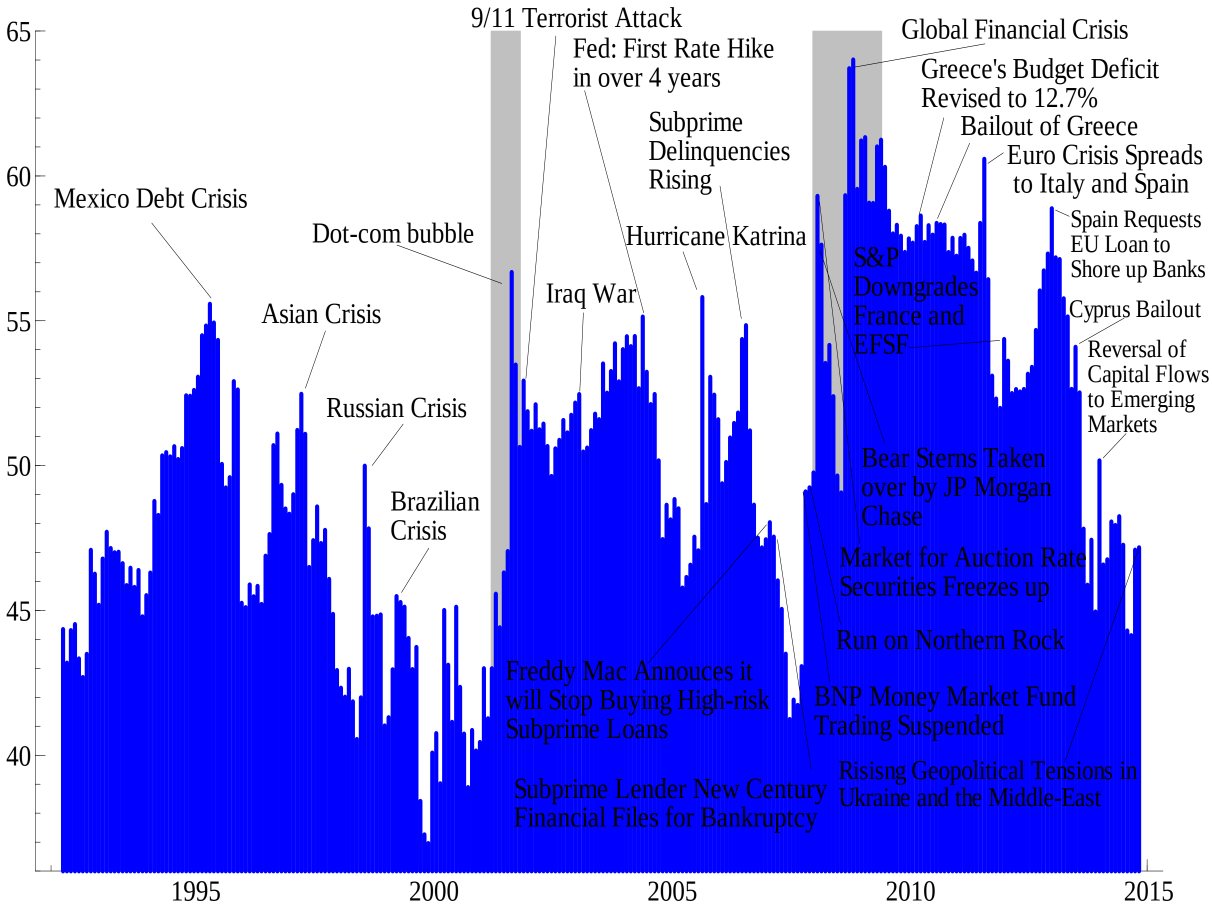
Notes: The underlying variance decomposition is based upon a monthly VAR of order 3. The number of lags (3) have been selected based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Spillover indices, given by Equations (2)-(7), calculated from variance decompositions based on 12-month ahead forecasts.

Figure 1: EPU, house returns, output growth, inflation, stock market returns and interest rates



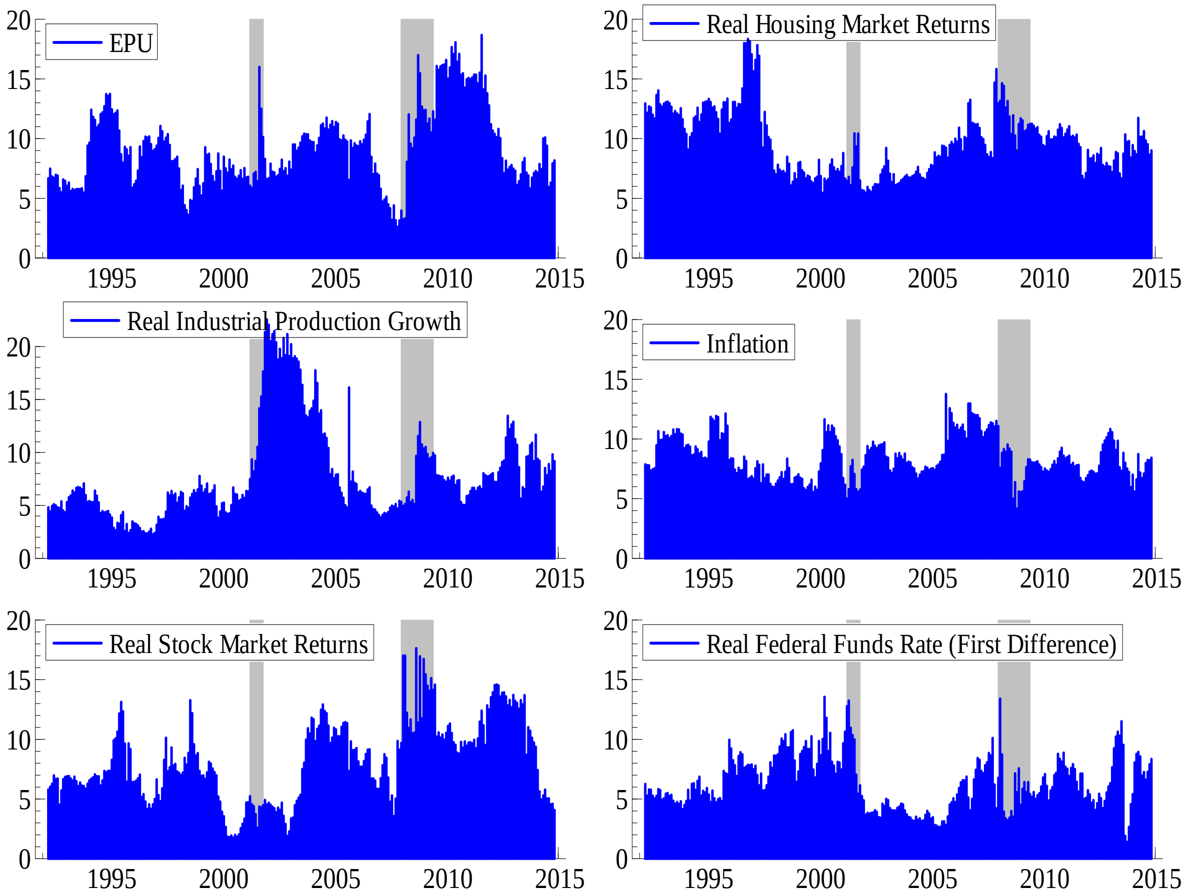
Notes: Grey shading denotes US recessions as defined by NBER.

Figure 2: Total spillover index of EPU, house returns, output growth, inflation, stock market returns and interest rates



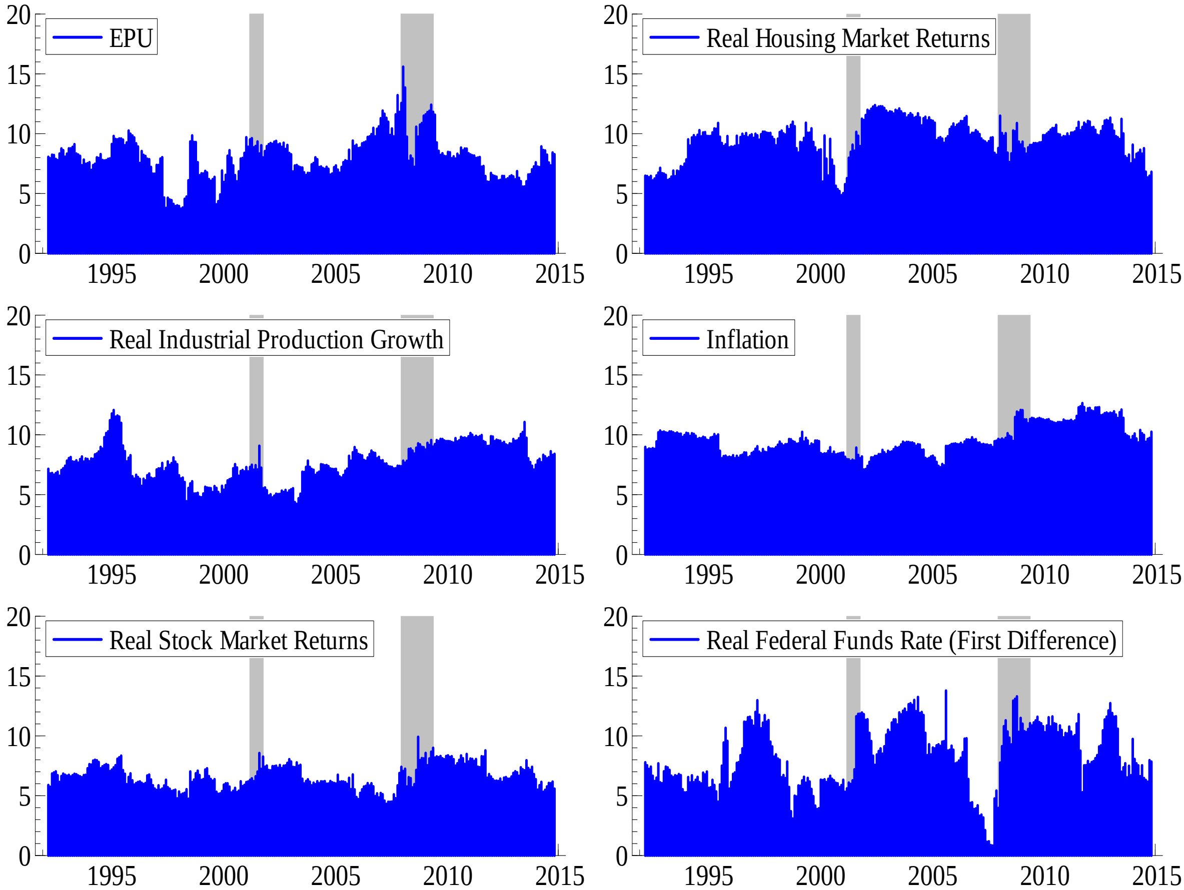
Notes: Plot of moving total spillover index estimated using 60-month rolling windows (and hence starting in 1992M4). Grey shading denotes US recessions as defined by NBER.

Figure 3: Directional spillovers *from* EPU, house returns, output growth, inflation, stock market returns and interest rates



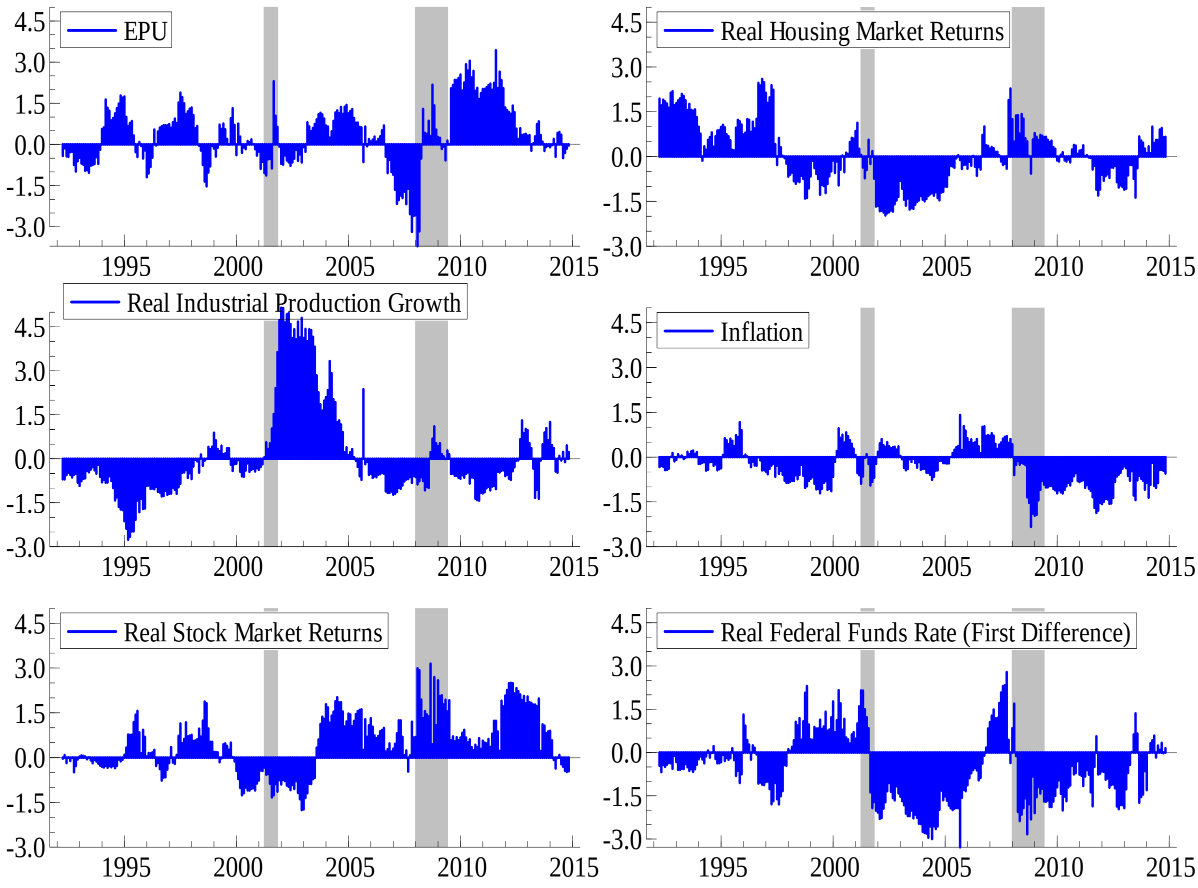
Notes: Plots of moving directional spillover indices estimated using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.

Figure 4: Directional spillovers *to* EPU, house returns, output growth, inflation, stock market returns and interest rates



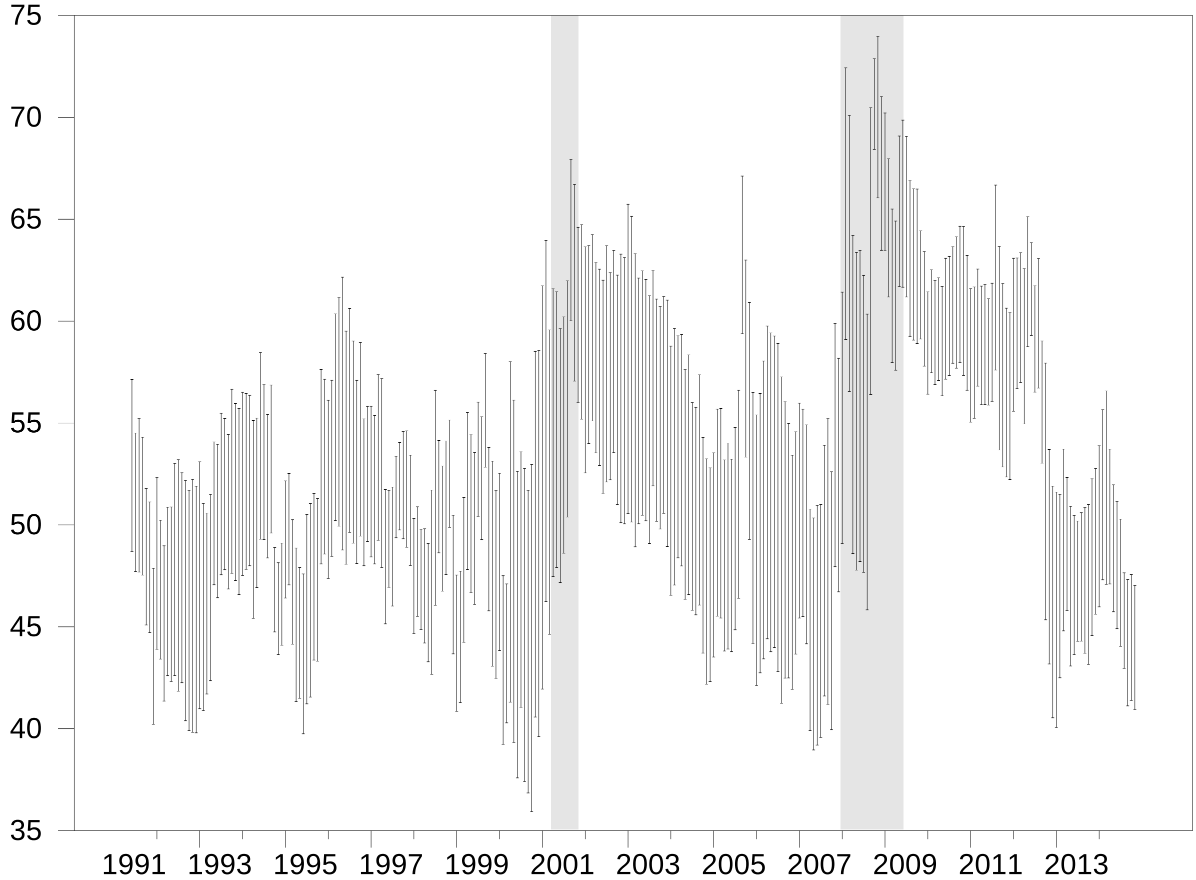
Notes: Plots of moving directional spillover indices estimated using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.

Figure 5: Net directional spillovers of EPU, house returns, output growth, inflation, stock market returns and interest rates



Notes: Plot of moving net directional spillover indices estimated using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.

Figure 6: Maximum and minimum total spillovers based on Cholesky factorization with random permutations



Notes: Plot of maximum and minimum moving total spillover index estimated based on Cholesky factorization with 100 randomly chosen orderings using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.