

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

Nikolaos Antonakakis^{†‡} Christophe André[§] Rangan Gupta[¶]

Abstract

In this study we examine dynamic spillovers among the housing market, stock market, and economic policy uncertainty (EPU) in the United States in a unified empirical framework. Applying the Diebold and Yilmaz (2012) methodology 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.

JEL Classification: C32, E40, E50, G10

*The authors would like to thank the Editor (Lutz Hendricks) and two anonymous reviewers for their very insightful comments and suggestions that have substantially improved the paper.

[†]Corresponding author: Economics and Finance Subject Group, University of Portsmouth, Portsmouth Business School, Portland Street, Portsmouth, PO1 3DE, United Kingdom, phone: +44 (0)23 9284 4261 email: nikolaos.antonakakis@port.ac.uk.

[‡]Department of Business and Management, Webster Vienna Private University, Praterstrasse 23, 1020, Vienna, Austria, phone: +43 (1)2699293 4373, email: nikolaos.antonakakis@webster.ac.at.

[§]Economics Department, Organisation for Economic Co-operation and Development (OECD), 75775 Paris Cedex 16, France, email: christophe.andre@oecd.org.

[¶]Department of Economics, University of Pretoria, 0002, South Africa, email: rangan.gupta@up.ac.za.

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, as financial sector and housing market shocks, as well as economic policy uncertainty are highly intertwined with macroeconomic shocks.

There exists a large number of studies that have analysed the relationship between macroeconomic variables and monetary policy (see Aguiar-Conraria et al., 2008, and references cited therein), asset prices and the macroeconomy and monetary policy (see Nyakabawo et al., 2015; Simo-Kengne et al., 2015, and references cited therein), as well as interrelations between asset markets (see Li et al., 2015, and references cited therein).

In the wake of the recent financial crisis, there is a growing literature that attempts to model uncertainty (see Bloom, 2009; Baker et al., 2013; Jurado et al., 2015, and references cited therein), and then link it to the macroeconomy (Jones and Olson, 2013), monetary policy and asset prices (see Antonakakis et al., 2013; Chang et al., 2015; El Montasser et al., 2015; Jurado et al., 2015, and references cited therein).¹ However, there exists no analysis, to the best of our knowledge, of dynamic spillovers between macroeconomic variables, monetary policy, asset prices and uncertainty in a unified framework. Such an

analysis would provide a more correct and complete picture of the complex and intricate relationships between the aforementioned variables, but also provide better insights for policy making.

Against this background, this paper investigates how innovations in a set of key economic and financial variables spill over to the wider economy. Importantly, it also investigates how these spillovers vary over time and particularly to what extent they intensify during crisis periods. Indeed, stronger spillovers than in normal times may explain the depth of particular recessions, such as the Great Recession, and the difficulty of the economy to get back to a steady growth path. Periods of economic turmoil are characterised by the materialisation of tail risks and result in deviations from standard linear relationships, which may prevail in more normal times. Devising a full-fledged theoretical model to describe rare extreme episodes is extremely challenging. Hence, we adopt an empirical approach, based on the generalised spillover index approach of Diebold and Yilmaz (2012).

The VAR-based spillover index approach of Diebold and Yilmaz (2012) 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. This method is particularly suited to our analysis, as it is data-driven and does not require imposing theoretical restrictions on the parameters of the model. As explained above, designing a full theoretical model able to capture time-varying spillovers would be extremely challenging.² Intuitively, the method uses the historical co-variance structure of the variables to avoid the need to impose specific identifying restrictions on shocks. Being based on a VAR, the method allows for different speeds of reaction to shocks across variables. In

addition, as spillovers between variables are likely to be evolving due to structural breaks and nonlinearities, we conduct a rolling estimation of our model to obtain a time-varying picture of the spillovers.

The drawback of the Diebold and Yilmaz (2012) methodology is that it does not explicit all the economic mechanisms behind the spillovers. That is, it does not attempt to estimate a structural relationship. Put differently, the Diebold and Yilmaz (2012) approach does not identify the effects of structural shocks. For example, a fall in stock prices may result from expectations of weaker economic activity and hence lower profits and dividends. This would result in a spillover from stock market returns to industrial production. However, stock market returns may impact industrial production through other channels, such as wealth effects. They may also reflect disruptions in the financial system, which would spread to the real economy. These effects are difficult to disentangle, especially during troubled periods. While it falls short of providing a full theoretical explanation of spillovers, the analysis allows assessing the magnitude of the latter and sheds light on their evolution over time.

We draw on the literature to select a set of variables providing a stylised view of the economy and the shocks that contribute most to its volatility, while keeping the model tractable. Output (proxied by industrial production) and inflation are key business cycle indicators and are also among the main variables influencing macroeconomic policy making. Housing prices are included as the subprime meltdown was at the epicentre of the GFC and more generally as their influence on the US business cycle is well documented (Leamer, 2007). Econometric models of house prices generally include a measure of income or macroeconomic activity and a measure of the user cost of housing, as well as

demographic and supply-side variables (e.g. Meen, 2002; Muellbauer and Murphy, 2008). In our study, we use monthly data. Growth in industrial production is used as the measure of economic activity, while the real federal funds rate is used as a proxy for the user cost of housing. Demographic and supply-side variables, which are slow moving can be omitted in the context of dynamic spillover analysis. In addition, a strong and time-varying correlation between housing market returns and EPU has been found in the United States (Antonakakis et al., 2015). A similar negative and time-varying link has been documented between stock market returns and EPU (Antonakakis et al., 2013). Stock market shocks are important in their own right and also as they instantly reflect turmoil in other financial markets. The federal funds rate is one of the most important variables affecting the business cycle. Furthermore, it is one of the key instruments policymakers are using to stabilise the economy. Models using these variables are relatively standard. An important addition in our analysis is EPU. Uncertainties affect economic decisions, all the more recently as the exceptional magnitude of the downturn has driven economic policies into uncharted territory.

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 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

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. (2013) and measures policy-related economic uncertainty in the United States.³ 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 real FFR, we take the first differences so as to render the series stationary.

We define $y_t = (rIPgr_t, INF_t, DrFFR_t, rCSr_t, rS\&P500r_t, EPU_t)'$ as the vector consisting of US data on real industrial production growth, $rIPgr_t$, inflation, INF_t , real fed-

eral funds rate changes, $DrFFR_t$, real housing market returns, $rCSr_t$, real stock market returns, $rS\&P500r_t$, and economic policy uncertainty, EPU_t , in year t .⁴

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 Fig. 1, we observe that peaks of economic policy uncertainty tend to be associated with declining housing markets returns, falling industrial production growth, interest rate cuts and lower real stock markets returns and inflation (especially during US recessions).

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 the transformed (stationary) series in the VAR model.⁵

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

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

where y_t is the vector of endogenous variables defined above; $\Theta_k, k = 1, \dots, K$, 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: $A_p = \Theta_1 A_{p-1} + \Theta_2 A_{p-2} + \dots + \Theta_p A_{p-l}$, 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. This methodology is very well suited for our analysis, as the difficulty in identifying the relationship between housing markets, stock markets, economic policy uncertainty, inflation and policy responses is aggravated by their complex and intricate linkages. For instance, causality may run not only from e.g. housing markets (shocks) to financial markets (shocks), but also from financial markets to housing markets. Put differently, shocks (and spillovers) are highly intertwined/correlated, and this feature is very well captured by the methodology of Diebold and Yilmaz (2012) that uses a generalised vector autoregressive framework, in which forecast-error variance decompositions are invariant to the ordering of the variables, in contrast to Cholesky-factor identification used in Diebold

and Yilmaz (2009). In the context of the present study, this is particularly important, since it is hard if not impossible to justify one particular ordering of the aforementioned variables.⁶

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

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

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 $\phi(H) = [\phi_{ij}(H)]_{i,j=1,\dots,6}$, 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 matrix is normalized by its row sum, such that

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

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:

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

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:

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

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

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

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:

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

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.

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.⁷

[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.

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 developments, 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.

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.⁸ 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, the 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% of the forecast error variance and are bidirectional. Nevertheless, they behave rather 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]

We now turn our attention to net pairwise directional spillovers obtained from the 60-month rolling window estimation, which bring further insights into the transmission process of shocks. The strong spillover from industrial production in the early 2000s was linked to a big impact on the federal fund rates and EPU, and to a lesser extent to spillovers to the housing and stock markets. The positive net spillovers from the stock market since the turn of the century is mainly associated with an impact on federal fund rates and housing market returns. Spillovers from federal fund rates are increasingly associated with their impact on EPU. Inflation was also strongly affected by EPU in the wake of the GFC. The higher than usual interrelations between uncertainty and the federal fund rates and inflation are likely to reflect alterations to the monetary transmission process following the GFC. Spillovers from housing market returns to other variables are more evenly distributed across other variables, reflecting the various financial and real channels linking housing to the wider economy.

[Insert Fig. 6 here]

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. As the theory does not provide a clear cut guidance on the identification of the aforementioned variables, the Cholesky factorization with random

orderings serves as a robustness check. 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 7 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. 7 here]

4. Conclusions

In this study we examined the magnitude and the dynamic nature 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 in a time-varying fashion, 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 and is indeed time-varying. 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.

The fact that spillovers between major macroeconomic and financial variables are time-varying and tend to intensify during crises has important implications for forecasters and policymakers. During crises, forecasters tend to assume on the basis of linear relationships prevailing in normal times, that the economy will relatively rapidly return to equilibrium. However, the recovery often takes longer than expected. The intensification of spillovers between the macroeconomy, the financial system and the housing market in deep recessions partly accounts for the difficulty in returning the economy towards a steady growth path. Hence, it needs to be taken into account in forecasting and when formulating economic policy responses. Furthermore, EPU has a significant impact on the economy, as it affects most key economic and financial variables. This highlights the importance of clearly communicating strategies to fight crises and showing determination

to act forcefully to prop up the economy, to reduce uncertainty and restore confidence.

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.

References

- Aguiar-Conraria, L., N. Azevedo, and M. J. Soares. 2008. Using wavelets to decompose the time-frequency effects of monetary policy. *Physica A: Statistical Mechanics and its Applications* 387(12), 2863–2878.
- André, C., R. Gupta, and P. T. Kanda. 2012. Do house prices impact consumption and interest rate? Evidence from OECD countries using an agnostic identification procedure. *Applied Economics Quarterly* 58(1), 19–70.
- Antonakakis, N., I. Chatziantoniou, and G. Filis. 2013. Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters* 120(1), 87–92.
- Antonakakis, N., R. Gupta, and C. André. 2015. Dynamic co-movements between eco-

- conomic policy uncertainty and housing market returns. *Journal of Real Estate Portfolio Management* 21(1), 53–60.
- Baker, S., N. Bloom, and S. Davis. 2013. Measuring economic policy uncertainty. *Working Paper Series* 13-02, Chicago Booth Research Paper.
- Bjørnland, H. C. and D. H. Jacobsen. 2010. The role of house prices in the monetary policy transmission mechanism in small open economies. *Journal of Financial Stability* 6(4), 218–229.
- Bjørnland, H. C. and D. H. Jacobsen. 2013. House prices and stock prices: Different roles in the US monetary transmission mechanism. *Scandinavian Journal of Economics* 115(4), 1084–1106.
- Bloom, N.. 2009. The impact of uncertainty shocks. *Econometrica* 77(3), 623–685.
- Case, K. E., J. M. Quigley, and R. J. Shiller. 2005. Comparing wealth effects: The stock market versus the housing market. *The B.E. Journal of Macroeconomics* 5(1), 1–34.
- Chang, T., W.-Y. Chen, R. Gupta, and D. K. Nguyen. 2015. Are stock prices related to the political uncertainty index in OECD countries? Evidence from the bootstrap panel causality test. *Economic Systems* 39(2), 288–300.
- Diebold, F. X. and K. Yilmaz. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal* 119(534), 158–171.
- Diebold, F. X. and K. Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1), 57–66.

- El Montasser, G., A. N. Ajmi, T. Chang, B. D. Simo-Kengne, C. Andre, and R. Gupta. Forthcoming. Cross-country evidence on the causal relationship between policy uncertainty and house prices. *Journal of Housing Research*.
- Jones, P. M. and E. Olson. 2013. The time-varying correlation between uncertainty, output, and inflation: Evidence from a DCC-GARCH model. *Economics Letters* 118(1), 33–37.
- Jurado, K., S. C. Ludvigson, and S. Ng. 2015. Measuring uncertainty. *American Economic Review* 105(3), 1177–1216.
- Kennedy, M. and T. Sløk. 2005. Explaining risk premia on bonds and equities. *OECD Economic Studies* 2005(1), 111–125.
- Koop, G., M. H. Pesaran, and S. M. Potter. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74(1), 119–147.
- Leamer, E. E.. 2007. Housing is the business cycle. *Proceedings -Economic Policy Symposium- Jackson Hole, Federal Reserve Bank of Kansas City*, 149–233.
- Lettau, M. and S. C. Ludvigson. 2004. Understanding trend and cycle in asset values: Reevaluating the wealth effect on consumption. *American Economic Review* 94(1), 276–299.
- Li, X.-L., T. Chang, S. M. Miller, M. Balcilar, and R. Gupta. 2015. The co-movement and causality between the U.S. housing and stock markets in the time and frequency domains. *International Review of Economics & Finance* 38, 220–233.

- Meen, G.. 2002. The time-series behavior of house prices: A transatlantic divide? *Journal of Housing Economics* 11(1), 1–23.
- Muellbauer, J. and A. Murphy. 2008. Housing markets and the economy: The assessment. *Oxford Review of Economic Policy* 24(1), 1–33.
- Nyakabawo, W., S. M. Miller, M. Balcilar, S. Das, and R. Gupta. 2015. Temporal causality between house prices and output in the US: A bootstrap rolling-window approach. *The North American Journal of Economics and Finance* 33, 55–73.
- Pesaran, H. H. and Y. Shin. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58(1), 17–29.
- Simo-Kengne, B., S. Miller, R. Gupta, and M. Balcilar. Forthcoming. Evolution of monetary policy in the US: The role of asset prices. *Journal of Real Estate Finance and Economics*.
- Sims, C.. 1980. Macroeconomics and reality. *Econometrica* 48, 1–48.

Notes

¹A detailed literature review of all the above-mentioned relationships is beyond the scope of this paper, and hence, the reader is referred to the references in the most recent papers that we have cited.

²Even in more traditional VAR settings, identification can be challenging. For example, a “price puzzle” is often found in monetary VARs, where the initial response of inflation to higher interest rates is positive (Bjørnland and Jacobsen, 2010, 2013).

³In particular, it is 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.

⁴For 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.

⁵The ADF test statistic results for the series in levels (with and without an constant) indicate no rejection of the null hypothesis of a unit root; e.g. the series in levels are non-stationary. These results are not presented but available upon request.

⁶The results from the Diebold and Yilmaz (2009) approach remain qualitatively similar to those obtained using the methodology of Diebold and Yilmaz (2012), as discussed below.

⁷The 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)).

⁸Our results reported below remain robust to alternative choices of window length (i.e. 70 and 80 months).

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

<i>(i)</i>	<i>(j)</i>						Directional from others
	rIPgr	INF	DrFFR	rCSr	rS&P500r	EPU	
rIPgr	62.93	15.50	0.08	11.81	6.95	2.73	37.07
INF	14.98	50.04	2.02	29.26	1.53	2.17	49.96
DrFFR	9.20	1.59	63.86	8.39	6.47	10.48	36.14
rCSr	6.24	15.36	0.89	70.46	4.54	2.52	29.54
rS&P500r	2.85	1.49	0.65	0.92	83.24	10.86	16.76
EPU	2.36	3.15	0.35	4.78	22.04	67.32	32.68
Directional to others	35.62	37.08	3.98	55.16	41.53	28.76	Total Spillover
Directional including own	98.55	87.12	67.84	125.62	124.78	96.08	Index = 33.69%
Net directional spillovers	-1.45	-12.88	-32.16	25.62	24.77	-3.92	

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 captions

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

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

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

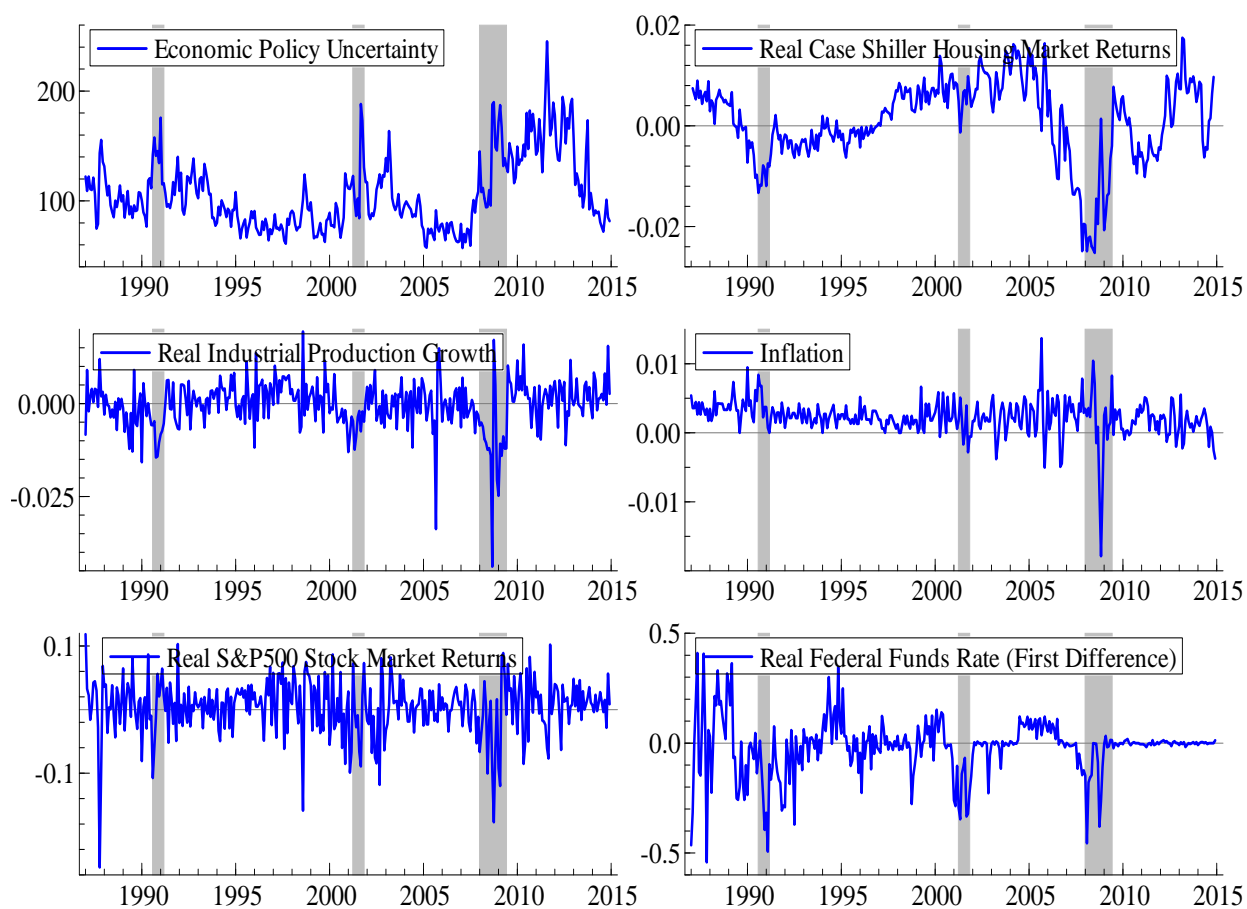
Figure 4: Directional spillovers *to* output growth, inflation, interest rates, house returns, stock market returns and EPU

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

Figure 6: Net pairwise directional spillovers of output growth, inflation, interest rates, house returns, stock market returns and EPU

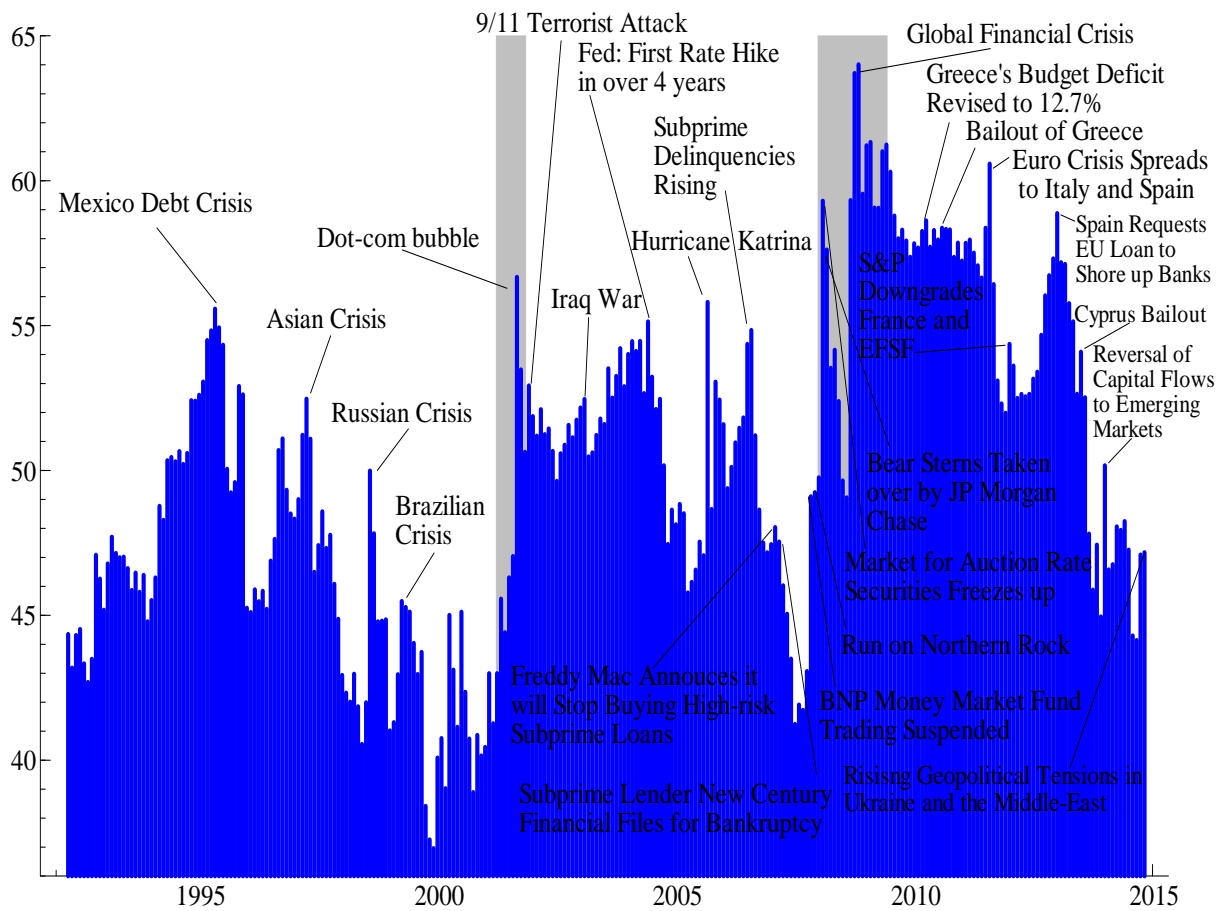
Figure 7: Maximum and minimum total spillovers based on Cholesky factorization with random permutations

Figure 1:



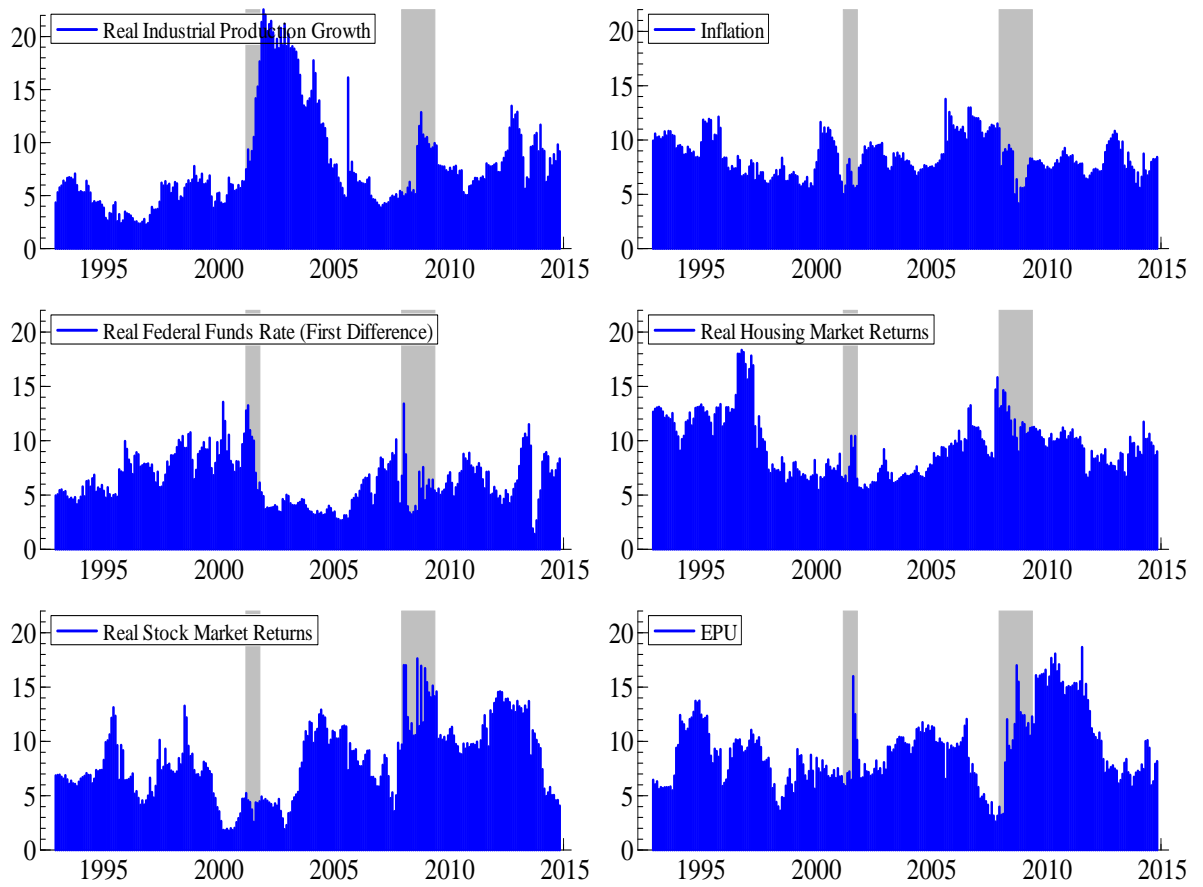
Notes: Grey shading denotes US recessions as defined by NBER.

Figure 2:



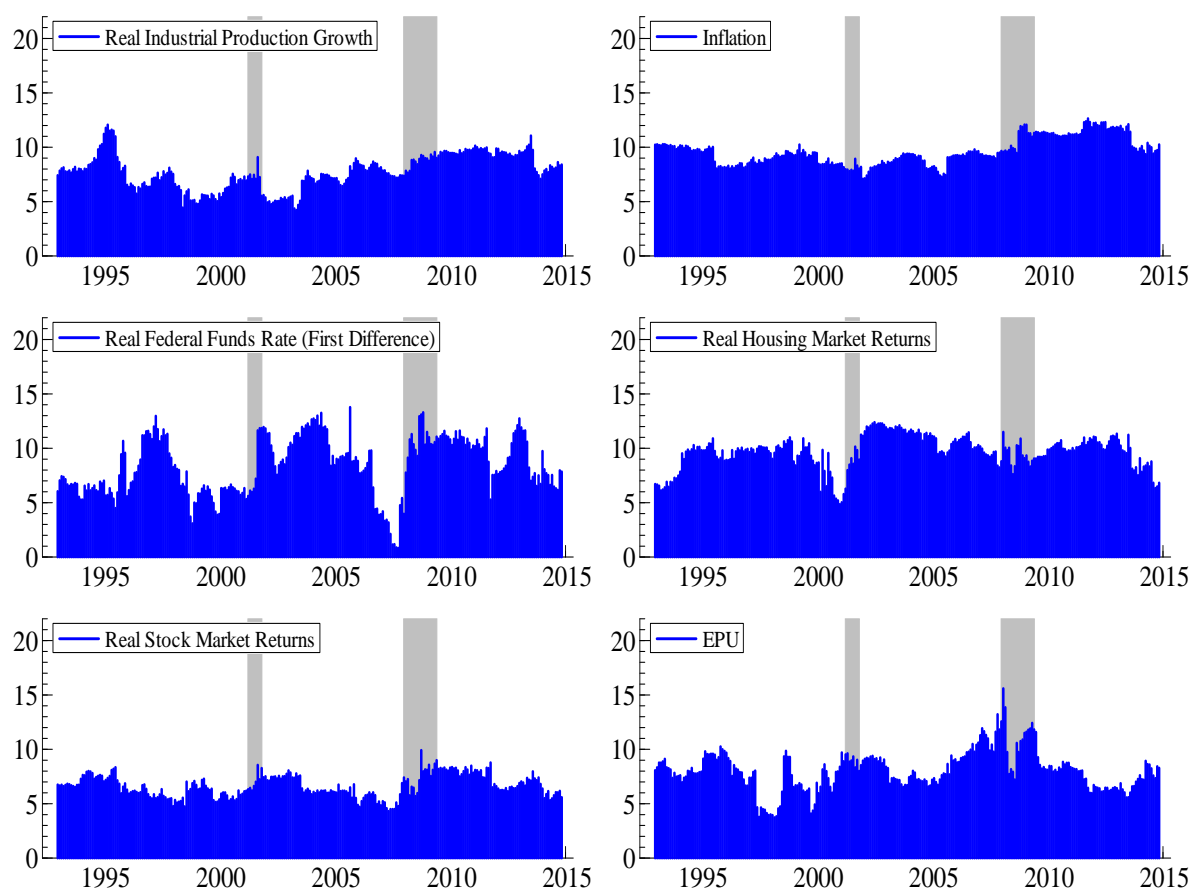
Notes: Plot of moving total spillover index estimated using 60-month rolling windows (and hence starting in 1992M4). Grey shading denotes US recessions as defined by NBER.

Figure 3:



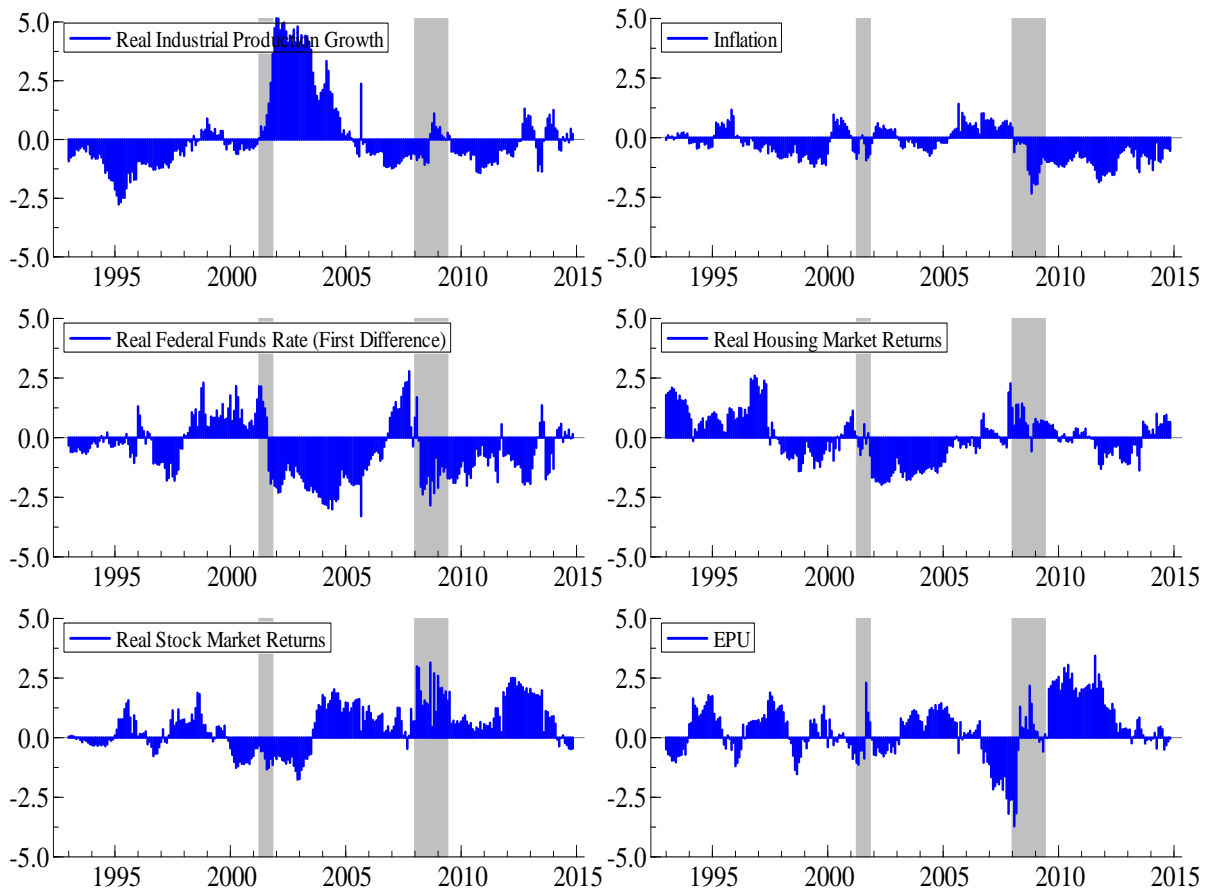
Notes: Plots of moving directional spillover indices estimated using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.

Figure 4:



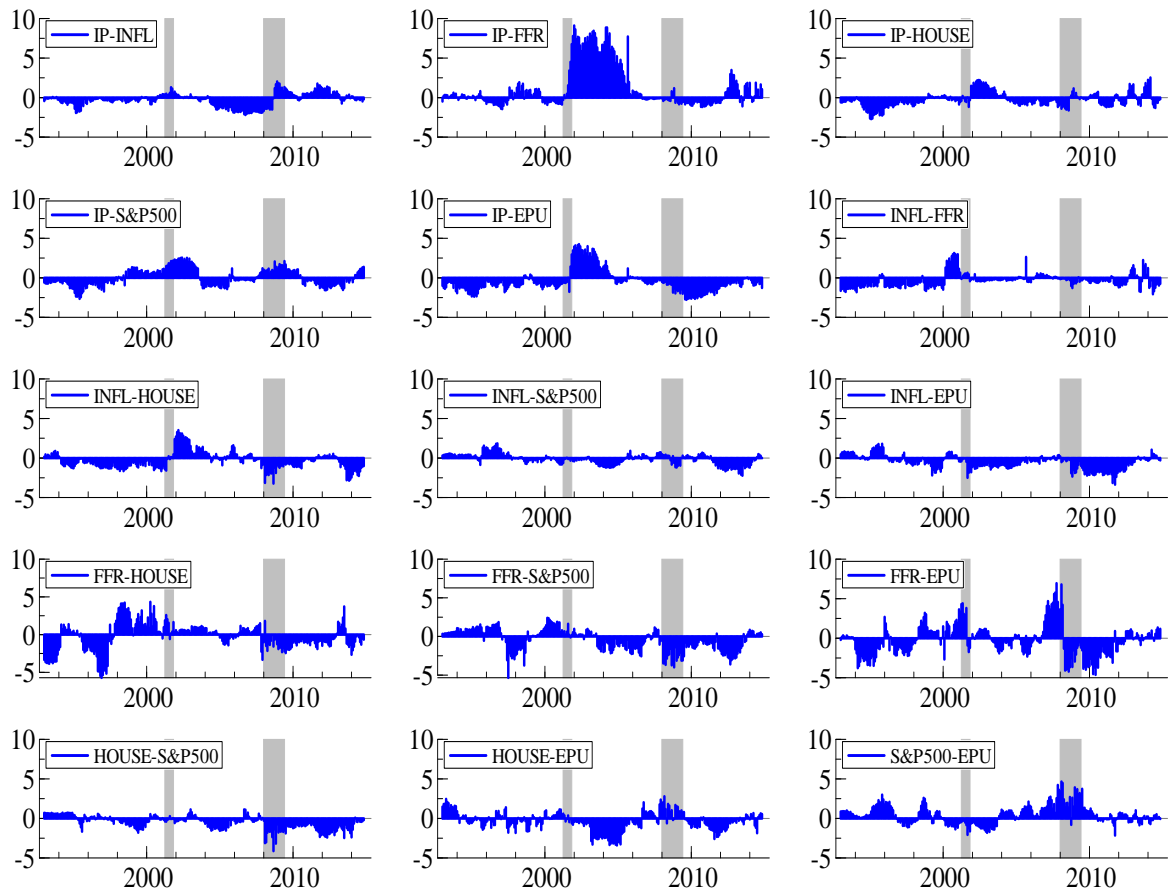
Notes: Plots of moving directional spillover indices estimated using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.

Figure 5:



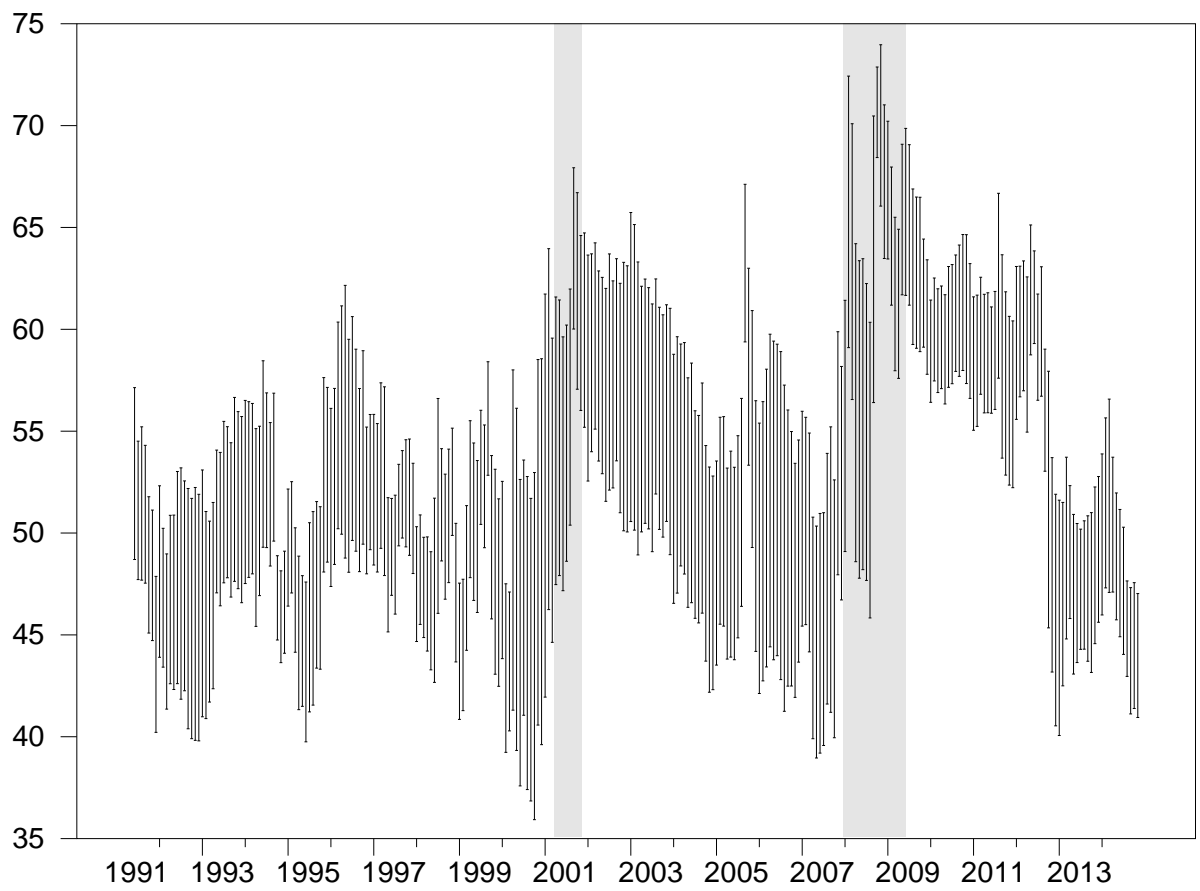
Notes: Plot of moving net directional spillover indices estimated using 60-month rolling windows. Grey shading denotes US recessions as defined by NBER.

Figure 6:



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

Figure 7:



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.