UCD GEARY INSTITUTE FOR PUBLIC POLICY
DISCUSSION PAPER SERIES

Mixed-frequency macro-financial spillovers

John Cotter
School of Business and Geary Institute for Public Policy,
University College Dublin

Mark Hallam
Essex Business School,
University of Essex

Kamil Yilmaz
Koç University

Geary WP2017/04
January 26, 2017

Mixed-Frequency Macro-Financial Spillovers

John Cotter
University College Dublin

Mark Hallam*
University of Essex

Kamil Yılmaz
Koç University

09 January 2017

Abstract

We develop a new methodology to analyse spillovers between the real and financial sides of the economy that employs a mixed-frequency modelling approach. This enables high-frequency financial and low-frequency macroeconomic data series to be employed directly, avoiding the data aggregation and information loss incurred when using common-frequency methods. In a detailed analysis of macro-financial spillovers for the US economy, we find that the additional high-frequency information preserved by our mixed-frequency approach results in estimated spillovers that are typically substantially higher than those from an analogous common-frequency approach and are more consistent with known in-sample events. We also show that financial markets are typically net transmitters of shocks to the real side of the economy, particularly during turbulent market conditions, but that the bond and equity markets act heterogeneously in both transmitting and receiving shocks to the non-financial sector. We observe substantial short and medium-run variation in macro-financial spillovers that is statistically associated with key variables related to financial and macroeconomic fundamentals; the values of the term spread, VIX and unemployment rate in particular appear to be important determinants of macro-financial spillovers.

Keywords: spillovers, connectedness, macro-financial, mixed-frequency

1 Introduction

In recent decades, markets on both the real and financial sides of the economy have become increasingly interconnected at the national and international level, allowing the

*Corresponding author: Essex Business School, University of Essex, England. E-mail: mark.hallam@essex.ac.uk. John Cotter and Mark Hallam gratefully acknowledge the support of Science Foundation Ireland under grant number 08/SRC/FMC1389. Kamil Yılmaz and Mark Hallam gratefully acknowledge the support of The Scientific and Technological Research Council of Turkey under grant number TUBITAK 114K954. The authors wish to thank participants of the 2016 FMA Annual Meeting in Las Vegas, the Financial Econometrics and Empirical Asset Pricing Conference at Lancaster University, the Barcelona GSE Summer Forum at Universitat Pompeu Fabra and seminar participants at Bilkent University, Boğaziçi University, University College Dublin, University of Essex and University of Konstanz for valuable feedback and comments.

effects of idiosyncratic adverse economic or financial shocks to spread more easily across markets and countries. The potential dangers that this presents were demonstrated by the recent financial and economic crisis, which has highlighted the need to develop a better understanding of market spillovers, systemic risk and contagion.

Although comovement and contagion in financial markets in a general sense are established topics of research in the finance literature and more recent post-crisis work such as Longstaff (2010), De Bruyckere et al. (2013), Bekaert et al. (2014) that substantially predate the recent crisis, one specific problem that has attracted significant attention since the crisis is the development of new quantitative measures and tests for spillovers and systemic risk[1]. A large number of methodologies have been proposed for this task, with some examples including Brown and Hund (2007), Billio et al. (2012), Corradi et al. (2012), Diebold and Yılmaz (2012a), Engle and Kelly (2012), Diebold and Yılmaz (2014), Adams et al. (2014), Chiu et al. (2015), Engle et al. (2015), Adrian and Brunnermeier (2016) and Brownlees and Engle (2016).

The empirical analysis of these previous studies has suggested an important role for financial spillovers and systemic stress, both at the level of financial markets and individual financial institutions and both within and across national borders. Significant time variation is observed in the level of spillovers and systemic risk that is strongly related to market conditions, with the vast majority of studies finding that they increase substantially during volatile periods or financial crises (see for example Diebold and Yılmaz, 2012a, Engle and Kelly, 2012, Adams et al., 2014). Furthermore, there appears to be significant cross-sectional variation, with certain financial markets or institution types found to play larger roles in the transmission of shocks than others. As a result, such methods have been advocated as potential tools for identifying the key sources of spillovers and systemic risk, the channels through which they are transmitted and monitoring their buildup during periods of market stress. Based on this information, regulatory policy can be revised in an attempt to more effectively limit the spread of market distress or crises and minimise their adverse effects.

While the existing work on the measurement of spillovers focuses on financial markets, it ignores the linkages that exist between the real and financial sides of the economy[2]. Such an approach arguably results in an incomplete picture of the structure of spillovers, since there is clearly the potential for adverse conditions in financial markets to negatively impact the real side of the economy; the most obvious example is through a reduction in willingness of financial firms to extend credit to corporate clients, with the resulting tightening of financial constraints in turn suppressing corporate investment, as documented empirically by work such as Almeida and Campello (2007) and Ivashina and Scharfstein (2010). Likewise, adverse macroeconomic shocks affecting non-financial firms may feed back into the financial markets, by increasing corporate defaults or reducing firm equity values. More generally, work such as Braun and Larrain (2005),

[1] For pre-crisis treatments of the topic see for example Forbes and Rigobon (2002), Bekaert et al. (2005), Baele (2006).

[2] Across the finance and econometrics literatures the terms 'spillovers' and 'connectedness' have both been used to describe effects of the type studied here and are used interchangeably in the current work.

Claessens et al. (2009) and Claessens et al. (2012a) find evidence of interactions between financial market conditions including crashes and real economic fluctuations. Furthermore, such macro-financial linkages may lead to adverse feedback loops forming between the two sides of the economy, which can be formalised in concepts such as the financial accelerator first proposed by Bernanke et al. (1996).

The importance of macro-financial connectedness is frequently noted in the literature on financial spillovers and systemic risk by work such as Brunnermeier et al. (2011), however formal study of these effects in the context of market spillover measurement has received little attention. An extensive literature does exist on macro-financial linkages more generally, but the vast majority considers other aspects of the interaction between financial and real variables, rather than the measurement of spillovers as such. One example is the attempt to identify macroeconomic determinants of financial return volatility, including Engle and Rangel (2008), Paye (2012), Engle et al. (2013), who find that the levels and volatilities of GDP, industrial production and inflation all play important roles. A large literature also exists on the effects of macroeconomic news and announcements on financial markets, including Green (2004), Brenner et al. (2009) and Jiang et al. (2012), and concerning the effects of financial conditions on macroeconomic variables, particularly the effects of financial volatility on the rate and volatility of economic growth (see for example Ramcharan et al., 2014 and Chauvet et al., 2015), where it has again been found that the financial sector has a significant effect on the real economy.

Whilst these studies have undeniably provided valuable insights into connectedness between markets on the financial and real sides of the economy, they do not represent direct macro-financial generalisations of earlier work on financial spillovers and systemic risk. As previously noted, they focus on specific aspects of the linkages of interest, rather than the problem of quantitatively measuring the strength and structure of spillovers or connectedness in a general sense. A key conceptual difference that results from this choice is that they employ unidirectional analyses of macro-financial linkages (either the effects of real variables on the financial sector or vice versa), rather than the type of multidirectional approach that would be required in light of the complex linkages expected between financial and real variables.

A small number of existing works whose aims are more closely aligned with that of the current work are those of Baur (2012), Claessens et al. (2012b), Dungey et al. (2013) and Chauvet et al. (2014), which specifically address the issue of measuring or testing for spillovers and include both the financial and real sides of the economy in some form. A significant limitation of the first three examples is that the real side of the economy enters the analysis only via financial data for non-financial firms (typically equity returns augmented with data on other firm characteristics), rather than actual macroeconomic variables of interest such as industrial production, unemployment or inflation. This makes it harder to draw policy implications from the results obtained, since a policy maker such as a government or regulatory authority is likely to care how these variables are affected by spillovers transmitted from the financial sector. The most recent study of Chauvet et al. (2014) does incorporate a genuine economic variable in the form of industrial production growth, however the specific methodology employed is only allows for bivariate analysis and only tests for the statistical significance of causal linkages, rather than quantifying their size.

Given this gap in the literature, we propose and apply a new methodology for measuring macro-financial spillovers that simultaneously addresses the limitations outlined above and thus allows new aspects of macro-financial connectedness to be studied. In contrast to the unidirectional analysis in most earlier studies of macro-financial spillovers, the resulting methodology is naturally multivariate in nature, allowing us to study the spillovers transmitted from any variable to any other variable, conditional on the presence of other variables. Furthermore, our method allows for the inclusion of true macroeconomic variables of interest, rather than simply financial variables for non-financial firms, whilst also permitting the use of variables at non-common or mixed sampling frequencies. This permits each variable to be included at the optimal or most informative sampling frequency and minimises the loss of relevant information occurring due to data aggregation. This is achieved by using the recent mixed-frequency econometric methods of Ghysels (2016) to extend the existing Diebold-Yilmaz (DY) spillover framework developed by Yilmaz (2012a, 2014) for measuring financial spillovers, in order to make it more appropriate for a macro-financial context.

We apply our methodology to perform a detailed empirical investigation of the joint structure of macro-financial connectedness in the US economy, focusing initially on connectedness between equity and bond markets on the financial side of the economy and the key variable of industrial production on the real side. Both the dynamics and magnitude of spillover estimates obtained from our new mixed-frequency extension of the DY approach differ significantly from those obtained from a more traditional common-frequency modelling approach.

Perhaps most notably, the estimated magnitude of spillovers implied by our new mixed-frequency DY approach is typically substantially higher than that implied by the existing common-frequency DY approach. For example, the average value of the most aggregated measure of macro-financial spillovers, the total spillover index, is nearly twice as large when employing our mixed-frequency approach than in the common-frequency case, with the average values of the more disaggregated spillover measures often exhibiting even larger differences. This finding suggests that the discarding of additional high-frequency information for one or more variables that occurs with the common-frequency approach results in estimated connectedness being lower on average. During many sub-periods, the differences in estimated spillovers between the common-frequency and mixed-frequency approaches are also sufficiently large that the choice of approach changes whether a given variable is classed as a net transmitter or net receiver of spillovers.

Furthermore, the estimated spillover measures obtained from our mixed-frequency approach correctly identify several key events during our sample period that are not reflected in the corresponding common-frequency measures. Perhaps most notably, both Black Monday in October 1987 and the collapse of Bear Stearns in March 2008 are visible as large spikes in macro-financial spillovers originating in the equity market using the mixed-frequency approach, but not the common-frequency case. The conclusions reached concerning the structure of macro-financial spillovers and connectedness thus depend significantly on which approach is used, with our new mixed-frequency approach producing results that are intuitively more consistent with economic and financial events during the sample period.

We also identify a set of financial and macroeconomic factors widely used in the literature as indicators of market conditions that have substantial explanatory power for our macro-financial spillover measures. Our results suggest that our spillover measures are closely associated with macro-financial fundamentals, particularly the term spread, VIX and unemployment rate, but that the explanatory power of these factors substantially during the recent crisis. Furthermore, for our mixed-frequency approach we find evidence that financial factors have relatively higher explanatory power than macro factors for spillovers originating in financial markets and the converse is true for spillovers originating on the real side of the economy. The first of these two patterns is however not observed for the simpler common-frequency approach, suggesting that the loss of high-frequency financial information occurring due to data aggregation to some extend decouples the spillover measures from financial fundamentals.

Our work thus adds to and complements existing work in several subfields of the finance and econometrics literature. Our methodological and empirical contributions add to the existing literature on the measurement and analysis of market spillovers and market interactions between the financial and real sides of the economy more generally. Although the primary benefit of our approach is to allow spillovers between low-frequency macroeconomic and high-frequency financial series to be estimated directly, it may also have benefits even when financial spillovers are the subject of interest; for example, it enables low and high-frequency financial series to be used simultaneously, or for low-frequency macroeconomic series to be included as endogenous control variables within the system. Given that our work also represents the first consideration of the forecast error variance decomposition in the MF-VAR context, we also contribute to the growing literature on mixed-frequency multivariate econometric methods.

2 Mixed-Frequency Spillover Methodology

As previously noted, our methodology is based on the established DY spillover methodology of Diebold and Yilmaz, (2009, 2012a); this approach has been applied extensively to study financial spillovers, but has not been employed to study macro-financial spillovers. The fundamental problem encountered in such an application is that the DY approach relies on the forecast error variance decomposition from a VAR model, in which all series are observed at a common sampling frequency. However, the combinations of macroeconomic and financial variables of interest here will contain variables available at very different sampling frequencies.

The traditional solution would be to aggregate all high-frequency data to the sampling frequency of the lowest frequency variable present, before applying the standard DY methodology to the transformed data. Whilst simple to implement, the obvious draw-back of such an approach is the potentially relevant information lost when aggregating the higher frequency series. Instead, we avoid these issues by replacing the standard VAR model of the original DY approach with the mixed-frequency VAR model of Ghysels (2016). After introducing some additional techniques to link these two components of the methodology, we are able to directly estimate our spillover measures from macroeconomic and financial data recorded at non-common frequencies and thus minimise any loss of information occurring through data transformation.

2.1 The Mixed-Frequency VAR Model

To permit the use of mixed-frequency macro-financial data, we substitute the standard common-frequency VAR model used in the existing DY methodology with the mixed-frequency VAR model of Ghysels (2016)[3]. In contrast to earlier approaches for implementing MF-VAR models employed in work such as Mariano and Murasawa (2010) and Schorfheide and Song (2015) (see also the survey by Foroni et al., 2013), that of Ghysels (2016) does not involve latent variables or shocks. Whilst this advantage may be unimportant in other applications, it is critical in the current context, since the presence of latent shocks would prevent us from obtaining the forecast error variance decomposition (FEVD) values that are required to compute our spillover measures.

For simplicity we assume that there are only two distinct sampling frequencies; high-frequency and low-frequency. We also assume that the number of observations for the high-frequency series is always the same within each low-frequency time period, as would be true for a combination of monthly and quarterly data, but not for a combination of daily and monthly data. Both of these assumptions can however be relaxed at a cost of more complex notation and exposition.

Formally, we observe a K-dimensional mixed-frequency vector process, which contains $K_L < K$ low-frequency and $K_H = K - K_L$ high-frequency series. The K_L low-frequency series are observed every m high-frequency time periods, or equivalently once per low-frequency time period, and collected in the K_L-dimensional vector process $x_L(\tau_L)$, where τ_L is the time index of the low-frequency observations. Each of the K_H high-frequency series is observed every high-frequency time period, or equivalently m times every low-frequency time period. At this stage we diverge slightly from Ghysels (2016), by grouping the high-frequency observations into vectors on a variable-by-variable basis within each low-frequency time period, rather than according to the high-frequency time period they are observed in as in Ghysels (2016)[4]. This change is made to simplify the implementation of the FEVD aggregation process discussed in the following section for cases when $K_H > 1$.

[3]Various extensions and additional issues in the MF-VAR framework are explored in subsequent work, including the problem of testing for Granger causality (Chauvet et al., 2014 and Ghysels et al., 2015) and issues of error correction and cointegration (Götz et al., 2013 and Ghysels and Miller, 2015).

[4]Because we follow the later work on the DY approach and employ the generalised VAR approach of Pesaran and Shin (1998) when computing the FEVD, changes in the ordering of the variables within the VAR will have no effect on the quantities of interest.

We thus have K_H m-dimensional vectors $x_{H,1}(\tau_L), \ldots, x_{H,K_H}(\tau_L)$ within each low-frequency time period, where these vectors are defined as:

$$x_{H,i}(\tau_L) \equiv \begin{bmatrix} x_{H,i}(\tau_L, 1) \\ \vdots \\ x_{H,i}(\tau_L, m) \end{bmatrix} \quad \text{for} \quad i = 1, \ldots K_H$$

where $x_{H,i}(\tau_L, j)$ is used to denote the (scalar) value of the i-th high-frequency variable observed for the j-th high-frequency time period within the τ_L-th low-frequency time period. Next we stack the K_L-dimensional vector of low-frequency observations together with the K_H m-dimensional vectors of high-frequency observations that are observed *within the same low-frequency time period.* This results in a K_x-dimensional stacked variable vector, where $K_x \equiv (mK_H + K_L)$, which we denote by $\underline{x}(\tau_L)$:

$$\underline{x}(\tau_L) \equiv \left[x_{H,1}(\tau_L), \ldots, x_{H,K_H}(\tau_L), x_L(\tau_L)\right]'$$

The general form of the p-th order MF-VAR is then given by:

$$\underline{x}(\tau_L) = A_0 + \sum_{j=1}^{p} A_j \underline{x}(\tau_L - j) + \underline{\varepsilon}(\tau_L) \tag{2.1}$$

where A_0 is an K_x-dimensional parameter vector, $A_j, j = 1, \ldots p$ are $(K_x \times K_x)$ parameter arrays and $\underline{\varepsilon}(\tau_L)$ is an K_x-dimensional vector of errors.

The key advantage of the stacked MF-VAR in equation (2.1) is that despite the somewhat non-standard composition of variables within the vector $\underline{x}(\tau_L)$, the model is mathematically equivalent to a standard VAR. As such, standard methods for estimation and analysis of VAR models can be employed, with the main differences arising in the interpretation of some of the quantities obtained.

In addition to the stacked mixed-frequency vector process $\underline{x}(\tau_L)$ introduced above, we will also consider the associated K-dimensional low-frequency vector process denoted by $\overline{x}(\tau_L)$, which contains both the K_L low-frequency variables and the K_H high-frequency variables *all observed at the low frequency*:

$$\overline{x}(\tau_L) \equiv \left[x_{HtL}(\tau_L), x_L(\tau_L)\right]'$$

where $x_{HtL}(\tau_L)$ is used to denote the set of high-frequency variables aggregated to the lower frequency in the τ_L-th time period. The precise relationship between the elements of $\underline{x}(\tau_L)$ and those in $\overline{x}(\tau_L)$ will vary depending on whether the individual variables are stocks or flows, but we do not need to be explicit about this in the current context.

We can specify a standard VAR model for the low-frequency vector process $\overline{x}(\tau_L)$, which we will refer to as the common-frequency VAR (CF-VAR). This model has the general form:

$$\overline{x}(\tau_L) = \overline{A}_0 + \sum_{j=1}^{p} \overline{A}_j \overline{x}(\tau_L - j) + \overline{\varepsilon}(\tau_L) \tag{2.2}$$

where $\overline{A}_0$ is a K-dimensional parameter vector, $\overline{A}_j, j = 1, \ldots p$ are $(K \times K)$ parameter arrays and $\overline{\varepsilon}(\tau_L)$ is an K-dimensional vector of errors. The CF-VAR in (2.2) is the model that would be estimated if using the alternative approach in which all high-frequency series are first aggregated down to the lower frequency

It should be noted that whilst the MF-VAR and CF-VAR are both technically specified at the lower sampling frequency, the MF-VAR also incorporates all higher frequency information available within each low frequency time period that is ignored by the CF-VAR. During the empirical exercise we will directly compare the DY spillover measures obtained from the traditional CF-VAR in (2.2) with those obtained from the new approach employing the MF-VAR in (2.1) to investigate how expanding the information set in this way changes the values obtained.

2.2 Aggregation of the Forecast Error Variance Decomposition Arrays

After the specified VAR model has been estimated, the next step in producing the DY spillover measures is to compute the forecast error variance decomposition arrays. The elements of these arrays measure the fraction of the error variance in forecasting each variable that is attributable to shocks in each other variable and thus clearly characterise the structure of spillovers between the variables.

From a purely mathematical perspective the FEVD arrays for the MF-VAR model are computed exactly as in the simple common-frequency case and so this aspect does not need to be discussed in detail[5]. However, the MF-VAR FEVD arrays have a non-standard structure arising from the non-standard composition of the stacked variable vector, that prevents the DY spillover measures from being computed directly from the arrays as in the common-frequency case.

As previously discussed, the MF-VAR is specified for the K_x-dimensional stacked variable vector $\underline{x}(\tau_L)$, which results in $(K_x \times K_x)$ FEVD arrays of the form:

$$\begin{bmatrix} \theta_{11}(H) & \cdots & \theta_{1K_x}(H) \\ \vdots & \ddots & \vdots \\ \theta_{K_x1}(H) & \cdots & \theta_{K_xK_x}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \ldots \tag{2.3}$$

in which the generic element $\theta_{ij}(H)$ is the fraction of the H-step-ahead error variance in forecasting variable i attributable to shocks in variable j. The corresponding CF-VAR, in which all higher frequency series are aggregated to the lowest common sampling frequency, is specified in terms of the smaller (non-stacked) K-dimensional variable vector $\overline{x}(\tau_L)$, resulting in $(K \times K)$ FEVD arrays of the form:

$$\begin{bmatrix} \phi_{11}(H) & \cdots & \phi_{1K}(H) \\ \vdots & \ddots & \vdots \\ \phi_{K1}(H) & \cdots & \phi_{KK}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \ldots \tag{2.4}$$

[5]Note that throughout we follow Diebold and Yılmaz (2012a) and the subsequent literature on the DY methodology by employing the generalised VAR approach of Pesaran and Shin (1998) to compute the FEVD values as detailed in Appendix A.1.

where again $\phi_{kl}(H)$ for $k, l = 1, \ldots, K$ is the fraction of the H-step-ahead error variance in forecasting variable k attributable to shocks in variable l, with the difference in notation used only to distinguish the FEVD elements for the MF-VAR from those of the CF-VAR.

Whilst it is immediately clear that the FEVD arrays obtained from the corresponding MF-VAR and CF-VAR models have different dimensions, they also have different structures. For the CF-VAR, each of the K variables contained in the vector $\overline{x}(\tau_L)$ corresponds to a variable in the conventional sense, which is observed at the low sampling frequency. Each element $\phi_{kl}(H)$ of the resulting $(K \times K)$ FEVD arrays therefore completely characterises the spillovers at the chosen forecast horizon between a given (directional) pair of variables. For the MF-VAR however, the multiple observations for the high-frequency variable(s) observed in each low-frequency time period are treated mathematically as distinct variables, despite being in reality multiple observations of the same variable in the conventional sense. This fact can be seen from the structure of the stacked variable vector $\underline{x}(\tau_L)$. As a result, for the MF-VAR the directional shock dynamics between a given pair of variables will generally be characterised not by a single element of the FEVD array, as is the case for the CF-VAR, but by multiple array elements.

This last point highlights the key theoretical difference between the FEVD arrays in (2.3) obtained from the MF-VAR and those from the CF-VAR in (2.4); the former incorporate information on the dynamics of shocks within each low-frequency period for any variables observable at the higher frequency, whereas the latter does not, with this information being lost when the data for the high-frequency series are aggregated down to the lower frequency. It has already been demonstrated by Ghysels (2016) using appropriate simulation exercises that this allows the MF-VAR approach to provide more accurate estimates than the alternative in which all higher frequency series are aggregated, in the sense that the estimates obtained from the MF-VAR are closer to those for the practically unachievable but optimal case where *all* variables are observed at the highest sampling frequency.

From a practical perspective however, the non-standard structure of the MF-VAR FEVD arrays means that DY spillover measures computed directly from them in the conventional manner do not have the desired interpretation and are incomparable with those obtained from the corresponding common-frequency VAR. To solve this problem we develop a method for aggregating the elements of the FEVD arrays obtained from the MF-VAR, in order to produce arrays with the same dimensions and structure as those from the corresponding common-frequency VAR. The aggregation scheme we propose is discussed in Appendix A.2 and is straightforward to implement, generally applicable and follows directly from the structure of the FEVD arrays, which is in turn determined solely by the sampling frequencies of the chosen variables.

The conventional DY spillover measures can then be computed as normal from these aggregated MF-VAR FEVD arrays, with the resulting measures incorporating information concerning the high-frequency dynamics of shocks within each low-frequency period.

The use of mixed-frequency methods thus allows us to estimate our spillover measures from a larger information set than is achievable when using common-frequency methods in which the data themselves are aggregated before specifying and estimating the model.

2.3 Diebold-Yilmaz Spillover Measures

Although the individual elements of the FEVD arrays could be used directly to study the structure of spillovers between the variables, the large number of elements makes interpretation somewhat difficult. The various DY spillover measures that can be computed from these arrays condense and summarise this information into a set of relevant and easily interpretable measures that more effectively characterise spillover structure. The large set of DY measures obtainable enables the structure of spillovers between the variables of interest to be mapped out in great detail, using different levels of aggregation and taking into account the direction of spillovers.

We denote the elements of the $(K \times K)$ aggregated FEVD arrays obtained from the method presented in Appendix A.2 by $\tilde{\psi}_{ij}(H)$ $(i, j = 1, \ldots, K)$ for a given forecast horizon H. Given that these aggregated FEVD arrays have the same dimensions and structure as those from the common-frequency VAR, we can the various DY connectedness measures from them in the normal manner.

The first measure is the total spillover (or connectedness) index, which measures the proportion of the total H-step-ahead error variance in the entire system that is due to shocks *across* variables (note $i \neq j$ in the index of the summation below) expressed as a percentage and is computed as:

$$S(H) = \frac{100}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\psi}_{ij}(H) \tag{2.5}$$

Total spillovers can also be decomposed into various directional measures to better understand the transmission of shocks between the variables of interest. We measure the directional spillovers received by variable i *from* all other variables, and the directional spillovers transmitted by variable i *to* all other variables, as:

$$S_{Fi}(H) = \frac{100}{N} \cdot \sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\psi}_{ij}(H) \qquad \text{and} \qquad S_{Ti}(H) = \frac{100}{N} \cdot \sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\psi}_{ji}(H) \tag{2.6}$$

respectively. In an analogous way to the total spillover index, the values of $S_{Fi}(H)$ and $S_{Ti}(H)$ measure the proportion of the total H-step-ahead error variance in the entire system that is attributable to shocks received by variable i from all others and transmitted by variable i to all others respectively, again expressed as percentages. Summing the set of K 'to all others' spillover values or the set of K 'from all others' spillover values gives the value of the total spillover index $S(H)$. Taking the difference between these two measures gives the *net* spillovers from variable i to all other variables:

$$S_{Ni}(H) = S_{Ti}(H) - S_{Fi}(H) \tag{2.7}$$

where positive (negative) values of the net spillover measure imply that variable i is a net transmitter (receiver) of shocks to (from) all other variables.

Finally, it is also possible to compute pairwise analogues of the above measures, rather than to/from a specific variable to/from *all* other variables. These pairwise measures may permit additional details in the structure of spillovers to observed, that are not visible from the more aggregated measures above. Perhaps the most informative of the pairwise measures is the net pairwise measure, which is the net spillover transmitted from variable i to variable j:

$$S_{Nij}(H) = 100 \cdot \left(\frac{\tilde{\psi}_{ji}(H) - \tilde{\psi}_{ij}(H)}{N} \right) \tag{2.8}$$

3 US Macro-Financial Spillovers

We employ our extended mixed-frequency version of the DY spillover approach to analyse connectedness between the real and financial sides of the United States economy. Much of the recent literature on financial connectedness focuses on analysing connectedness in the time period surrounding the recent financial crisis, which is understandable given the central role that market linkages appeared to play in the development of the crisis. Whilst our methodology could be employed in a similar manner, we focus on how the long-run level and structure of macro-financial connectedness has evolved over a longer period of time. Specifically, our sample period for empirical analysis spans January 1975 to September 2015, thus including many significant economic and financial events of the past decades.

On the real side of the economy our variable of interest is industrial production (IP), due to its significant academic and practical interest, its clear relevance for the macro-financial feedback effects described previously and its widespread use in previous empirical analysis on macro-financial linkages. We transform the monthly IP level series to obtain a series of month-on-month percentage growth rates, under the assumption that changes in conditions on the financial side of the economy are more likely to be connected to relative, rather than absolute, changes in IP. Following the existing literature, particularly that concerning the effects of macroeconomic variables on financial markets such as Engle and Rangel (2008), Paye (2012) and Engle et al. (2013), we also studied the volatility of industrial production growth, with IP growth volatility computed as in Engle et al. (2013). The results for IP volatility are broadly similar to those obtained for IP growth and so they have been omitted from the current version of the paper to keep the discussion of empirical findings concise, but are available upon request.

On the financial side we focus on equity and bond markets, represented by the S&P500 equity index and the 10-year US Treasury Note respectively. The choice of the S&P500 to represent US equity markets needs little defence, however the choice of suitable variables to represent the bond market is a more complex issue. In particular, the strength and structure of connectedness between bond markets and the real economy may vary with bond maturity and type (see e.g. Brenner et al., 2009). For simplicity we restrict our attention to US sovereign bonds of a single maturity, with the 10-year Treasury Note seeming appropriate considering our focus on macro-financial connectedness over relatively long horizons[6].

We follow the existing literature on financial spillovers and macro-financial linkages by focusing primarily on return volatilities for the financial variables, rather than their corresponding return levels. This is typically justified by arguing that volatility spillovers are intuitively and empirically more relevant in both financial and macro-financial contexts. We do however repeat the core analysis of Section 3.1 using return levels for the sake of completeness, with the results found in Appendix C.2. Whilst some differences are visible relative to the results for return volatilities presented in the main text, such as the dynamics of the indexes during the recent crisis, the key empirical findings follow through mostly unchanged.

The raw data for the two financial variables consist of daily closing prices, which are transformed to produce a closing price series at a weekly frequency. To sidestep the practical issues introduced by the number of weeks per month varying from month to month, we employ a data pre-processing and transformation approach to produce weekly series with a constant four weeks per month[7]. The details of this data pre-processing method can be found in Appendix B.1. Finally, we use these weekly close prices to compute weekly returns and finally (logarithmic) return volatility. The latter is of course latent, but could be approximated here in various ways, including realised volatility type approaches or taking the squared value of the weekly returns. We follow Diebold and Yılmaz (2012a), Diebold and Yılmaz (2014) and others by using a range-based proxy of return volatility, which is detailed in Appendix B.2.

[Figure 1 about here.]

The resulting series are plotted for the full sample period in Figure 1. Major economic and financial events during the sample period are clearly visible in the plots, either as substantial increases in financial volatility, large drops in industrial production or increases in IP volatility; examples include the 1980-1981 recession, Black Monday and the junk bond crash in the late 1980's, the Asian and Russian financial crisis and the collapse of Long-Term Capital Management in the late 1990's, the dotcom bubble and

[6]Simultaneously including bonds of different maturities would however allow us to investigate how macro-financial connectedness varies with bond maturity. This would have some parallels with the work of Chaieb et al. (2014), who study the so-called 'term structure of integration' in sovereign bond markets.

[7]This is again not strictly necessary, since the MF-VAR framework can accommodate deterministic time variation in the number of high-frequency observations per low-frequency period (as discussed by Ghysels, 2016), but significantly simplifies the exposition and implementation.

9/11 in the early 2000's and the recent global financial crisis in the late 2000's and early 2010's.

3.1 Levels and Dynamics of US Macro-Financial Spillovers

Although we do report static results for the full sample period in Appendix C.1, our interest lies primarily in obtaining dynamic estimates of macro-financial spillovers[8]. This will allow us to investigate how the strength and structure of spillovers has varied over time and whether the changes appear to relate to specific economic and financial events.

To achieve this we use a standard rolling window estimation approach in which the parameters of the MF-VAR, the FEVD arrays and the connectedness measures are re-estimated each time the window is rolled forward. A window length of 60 months is employed, since it appears to offer a good balance between providing a sufficient sample size to estimate the parameters of the underlying MF-VAR to an appropriate level of accuracy, and allowing dynamics of connectedness to be captured. The study of business cycle connectedness by Diebold and Yılmaz (2012b) also employed the same rolling window length with a monthly dataset of industrial production series. We have however checked the robustness of our results to reasonable changes in the window length, with these results available upon request.

When computing the connectedness measures we considered forecast horizons of 3, 6 and 12 months, thus including a range of forecast horizons that seem relevant for plausible applications of the resulting measures. We found however that the estimates did not show significant sensitivity to the choice of forecast horizon within this range, and so report results only for the intermediate horizon of 6 months. In addition, estimated spillover indexes obtained for longer forecast horizons, such as the 12-36 month horizons often used in the macroeconomics literature, differ only very slightly from those at the 6 month horizon and so are not reported here.

Throughout we include direct comparisons between the estimates obtained from our new mixed-frequency DY approach and those obtained from the existing common-frequency DY approach. This enables us to gauge the practical effects of ignoring the availability of weekly data for the financial series that occurs when specifying a VAR at the lower monthly sampling frequency. Figure 2 begins with the total connectedness indexes obtained from both the mixed-frequency and common-frequency DY approaches over the complete sample period at a forecast horizon of 6 months.

[Figure 2 about here.]

We see from Figure 2 that the estimated total spillover indexes obtained from the mixed-frequency DY approach and the common-frequency approach show broadly the same movements over the sample period. More striking however is that, despite the high correlation between the indexes obtained from the two approaches, the level of total

[8] The full-sample results are broadly consistent with the dynamic results discussed below. Again, we find that estimated spillovers for the MF approach are higher than those for the CF approach and that spillovers transmitted from our financial variables are greater than those transmitted from IP.

connectedness implied by the new mixed-frequency approach is, with one or two exceptions, consistently higher than that obtained from the common-frequency approach. For example, the average value of total connectedness for the mixed-frequency and common-frequency DY approaches are 22.75% and 13.36% respectively, representing the proportion of the total forecast error variance in the entire system that is due to shocks *across* variables[9]. This suggests that by aggregating the financial data to monthly frequency and ignoring the additional intra-monthly information it contains, one underestimates the true level of connectedness across real and financial sectors. Furthermore, in certain periods CF-based approach results in very low levels (5-10 percentage points) of connectedness, irrespective of whether financial returns or return volatilities are used in the analysis.

It should be noted however that the common-frequency approach does not always produce lower estimates of connectedness than the mixed-frequency approach. In the final part of the sample, once the time periods corresponding to the peak of the global financial crisis are dropped out of the rolling sample estimation window both total spillover indices drop significantly. In this period however the value of the mixed-frequency total spillover index drops slightly faster than its common-frequency counterpart. In this case, the extra informational content employed by the mixed-frequency approach relative to the common-frequency approach allows it to respond faster to changes in conditions once these extreme periods are dropped out of the window.

Considering next the dynamics of the total spillover indexes, we see substantial fluctuations over the sample period, most of which coincide with major economic or financial events. As with the sample average of the spillover index levels, as discussed below there is often a substantial difference between the levels of the mixed-frequency and common-frequency indexes in the periods surrounding these events. Similar differences are also observed for the disaggregated spillover indexes plotted in subsequent figures, but are not discussed in detail.

The most visible spikes in spillovers occur during the recent global financial crisis, with the total spillover index for the mixed-frequency approach peaking at 41.55% and the common-frequency index at 33.54% in November 2008 (point G), coinciding with the collapse of Lehman Brothers, the bailout of AIG and Fannie Mae and Freddie Mac being placed in government conservatorship. As the crisis progressed, further spikes in connectedness are clearly visible in May 2009 (point H, index levels 37.95% and 34.27%) with the announcement of results for the SCAP stress tests and announcement of large Q1 losses for Fannie Mae and Freddie Mac, followed by the start of the EU debt crisis in April 2010 and flash crash of May 2010 (point I, index levels 32.91% and 26.07%). The final spike in connectedness occurring around October 2011 appears to be due to a combination of the threat of US government shutdown and deteriorating market conditions in Europe that culminated in the Greek Prime Minister announcing

[9]It is interesting to note that the size of the total spillover index for our macro-financial application is smaller than the total spillover index typically observed in previous studies using purely financial datasets, which often reach values of 75% or 80%. This stems from the lower levels of connectedness present between the financial and real economic series employed here.

a referendum on the debt deal from the Eurozone. Following the recent global financial crisis, the overall level of macro-financial spillovers appears to have fallen substantially and to be slowly returning to pre-crisis levels. The observed drop in spillover levels could be at least partially attributed to changes in monetary and financial regulatory policy since the start of the crisis.

We also observe smaller peaks in total spillovers around other key events: there is a visible increase in connectedness during the period 2000-2002 due to a combination of the dotcom crash, September 11 and the associated economic downturn, peaking at 28.18% in September 2001 (point E) and remaining in the range 25-30% until mid-2002. Similar patterns are observed from 2000 to 2002 for the common-frequency index, although the index clearly attains much lower levels, with the local maximum in September 2001 being just 18.24%, compared to the value of 28.18% attained by the mixed-frequency index. In addition, the impact of the East Asian crisis (point C and surrounding months) is captured in the mixed-frequency total spillover index with an approximately 5 percentage point increase, from levels of around 17% in the early months of 1997 up to 21-22% from August 1997 onwards. The common-frequency index during the same period is by contrast decreasing on average, remaining approximately 15 percentage points lower than the mixed-frequency index during this period.

We see a somewhat elevated index level from Black Monday in October 1987, through the 1989 savings and loan crisis, Iraq's invasion of Kuwait (point B) and the 1990-1991 recession that followed. Black Monday itself is visible in the mixed-frequency index as a small but sharp spike in October 1987 (point A) up to a value of 27.56%, but is not visible in the index for the common-frequency method that exhibits a value of just 6.33% in the same month. A possible explanation for this is that this event was largely financial in nature, rather than macro-financial, and so the loss of information concerning the financial component of spillovers caused by aggregating the financial data is particularly detrimental in this period. The same explanation could also be relevant for the previously discussed differences between the index levels during the Asian financial crisis and the Russian financial crisis and collapse of LTCM in August and September 1998 (point D), which are clearly visible as a period of elevated spillovers in the mixed-frequency case, but not for the common-frequency approach.

Despite the sizeable short-run fluctuations in the total spillover indexes, the long-run average level remains more or less stable for the majority of the sample period, with no clear long-run trend. Although this lack of a long-run trend may seem somewhat surprising, since one might intuitively expect the level of macro-financial connectedness to be rising steadily over time as markets become more integrated, it is broadly consistent with the empirical findings of previous studies applying the common-frequency DY approach to purely financial or purely macroeconomic datasets[10].

The total spillover index provides an informative but highly aggregated measure

[10] Even ignoring the more contentious question of whether we expect connectedness between markets on the real and financial sides of the economy to have increased over the preceding decades, an increase solely in financial connectedness arising from increased financial market integration should be sufficient to drive up total connectedness over time.

that hides many potentially interesting details of the structure of spillovers between the variables. For a more detailed analysis we now turn to the directional spillover measures defined previously in equations (2.6) and (2.7). Figure 3 plots the directional spillovers transmitted by each variable to all others in the first column and the spillovers received by each variable from all other variables in the second column. Finally in the third column we plot the net spillover measure, obtained as the difference between the first two measures.

[Figure 3 about here.]

Studying first the average level of spillovers across the various subfigures of Figures 3 we see that, as with the total connectedness index earlier, our mixed-frequency approach typically results in higher estimated levels of spillovers than the common-frequency approach. Note that for the net spillover measures in the third column of each figure, a 'higher' level of spillovers corresponds to values further from zero, either positive or negative, rather than larger values in a conventional sense. The observed differences in the level of spillovers between the mixed-frequency and common-frequency cases are often large and extremely persistent, particularly for spillovers transmitted by the financial variables to others in panels (a) and (d) and those received by industrial production from the financial markets in panel (h).

[Table 1 about here.]

The absolute and relative sizes of these differences are summarised in Table 1, which lists both the differences and ratios between the corresponding mixed-frequency and common-frequency spillover measures that were previously plotted in Figures 3. These are computed by either subtracting or dividing a given mixed-frequency spillover estimate by its corresponding common-frequency equivalent and then computing the mean over the sample period.

It can be seen that the spillovers transmitted from the two financial markets to others are estimated to be between 3 and 4 times as large for the mixed-frequency approach as for the common frequency approach, corresponding to average spillover values of approximately 5 percentage points higher than their common-frequency analogues. The differences in the estimates of spillovers received by industrial production from all others are similar, with the mixed-frequency approach producing average spillovers approximately 3.4 times larger than the common-frequency approach or approximately 6 percentage points higher. For the case of spillovers to the financial markets from all others and from industrial production to the financial markets we observe smaller differences in the average spillover measures and for the latter the values for the common-frequency case are even marginally higher. Moving finally to the net spillover measures, we observe the largest relative differences, with the ratio values indicating that the average levels of net connectedness for the mixed-frequency approach are between 0.2 and 121.4 times larger than those obtained from the common-frequency approach, although the magnitude of the differences in absolute terms are similar to those for the other measures.

A possible explanation for this finding of higher average spillover levels for the mixed-frequency case can be found in the previous literature on the effects of macroeconomic announcements on financial markets. In this literature some studies such as Andersen et al. (2003) and Green (2004) have employed high-frequency intraday financial data to study the effects of these announcements over short time periods and have found significant intraday effects. However, the use of lower frequency daily data prevents these effects from being observed and thus may bias estimates of the response in the financial markets downwards. Intuitively an analogous explanation can be applied in the current analysis, for which shocks to the either the financial or real variables may result in significant within-the-month spillovers that are visible through the use of weekly data for some series in the mixed-frequency case, but either ignored completely or underestimated by the use of purely monthly data in the common-frequency approach.

Having highlighted the differences between the spillover measures obtained from the mixed and common-frequency approaches, we focus from this point onwards on the measures obtained from our mixed-frequency approach to keep discussion concise, occasionally highlighting any notable differences between the two approaches. From the levels of the mixed-frequency spillover measures in Figure 3 it is also clear that spillovers from the equity and bond markets to others are generally large: shocks transmitted from each of these financial markets to other variables comprise approximately 10% of the forecast error variance in the entire system on average over the sample period. Furthermore, from the plots in Figure 3 it can be seen the spillovers transmitted from each financial market to others frequently peak well above these sample average values during extreme market conditions, most notably during the recent crisis. Interestingly however, the relative importance of the equity and bond markets appears to have differed during the sample period, with equities playing a larger role in spillover transmission from 2000 until the present day and the bond market being more influential during periods of high bond market volatility in the 1980's

Shocks to each of the financial markets are thus transmitted strongly to the other financial market and also to the real side of the economy via industrial production. Spillovers received by the two financial markets from each other and IP in panels (b) and (e) are again large in size, but are typically of a smaller magnitude than those transmitted to other variables, resulting in positive net spillover values in panels (c) and (f) and making them net transmitters of spillovers to others. The opposite is true for industrial production, which typically exhibits a low level of spillovers transmitted to other variables, but a high level of spillovers received from others, with sample averages in Table 1 of approximately 10% and a sustained period between 15% and 20% between 2009 and 2014s. This results in industrial production being a net receiver of spillovers for the entire sample period, in contrast to the financial markets. It should be noted that this conclusion concerning industrial production changes substantially if the common-frequency approach is employed instead; in this case net spillovers from industrial production typically fluctuate around zero, but in sub-periods such as 2009 to 2014 actually becomes a strong net transmitter of shocks to the financial markets.

Turning next to the dynamics of the directional spillover measures, we observe increased levels of spillovers transmitted to and received by others during the recent crisis in the majority of panels in Figure 3. For the financial variables in the first and second rows of the figures, the largest visible spike in connectedness to others occurs for the bond market, but for the latter it is the equity markets. Given that these two models are providing estimates of related but distinct aspects of macro-financial linkages, there is of course no reason to expect the same patterns to be observed in each case. Nonetheless, the difference is sufficiently clear to be worth highlighting. It should also be noted that during the recent crisis the increase in spillover level for the two financial markets is not restricted to spillovers transmitted to other variables in panels (a) and (d), but also extends also to spillovers received from others in panels (b) and (e), reflecting a general increase in the total level of macro-financial spillovers during the crisis that is visible clearly in Figure 2.

Moving back through the sample period we observe a short-lived but large spike in spillovers transmitted from the equity market to others in 1987 associated with Black Monday, which is then followed by a period of elevated spillovers from the equity market during the turbulent period of the late 1980's and early 1990's. These increases in spillovers from the equity market to others are much more strongly identified by the mixed-frequency approach than the common-frequency approach; the latter shows no increase in connectedness from the S&P500 to others in 1987 following Black Monday and in fact falls slightly, which seems intuitively inconsistent with the events that occurred.

Considering next the spillover dynamics of industrial production in the final row of Figure 3, it appears that during the recent crisis industrial production was also transmitter of shocks to the equity and bond markets, exhibiting a visible spike in spillovers to others. This result holds irrespective of whether we use mixed-frequency or common-frequency methods, however the magnitude of the change is much larger in the common-frequency case. At the same time, spillovers received by industrial production from the financial variables are consistently larger, resulting in negative net spillover values for the mixed-frequency approach in panels (f) and (i) of Figure 3 and suggesting that spillovers do still flow from the financial markets to the real side of the economy. The same is not true for the common-frequency approach, for which industrial production actually becomes a net transmitter of spillovers to the financial markets during the recent crisis.

To a lesser extent we see similar patterns in the directional spillover measures for industrial production during the late 1980's and early 1990's, with the effects again appearing relevant both for financial return volatility and for the level of returns. Although the estimated transmission of shocks from industrial production to others (in this case others corresponds to the financial markets) is of a smaller magnitude than that from the financial markets to others, it does nonetheless suggest that the non-financial side of the economy is also playing a role in transmitting shocks to the other variables, rather than them originating solely on the financial side. This could be tentatively interpreted as support for the type of macro-financial feedback loops that are expected intuitively and predicted by economics theory during crisis periods. A more detailed analysis of connectedness in the time periods surrounding these events could be performed in future to potentially shed further light on the timing of these effects during crisis periods.

Finally, we decompose the directional spillover measures above once more and examine the pairwise directional spillover measures for each combination of variables. In Figure 4 panels (a), (b), (d), (e), (g) and (h) contain the pairwise spillovers for each of the possible pairwise combinations of variables in each direction and panels (c), (f) and (i) contain the the net pairwise spillovers as defined in equation (2.8). Note that it is only necessary to display net pairwise spillovers in one direction for any given pair of variables, since for example the value of net pairwise spillovers from the S&P500 to industrial production is minus one times the net pairwise spillovers from industrial production to the S&P500.

[Figure 4 about here.]

As was the case for the more aggregated spillover measures discussed above, we again observe substantial differences between levels and dynamics of the pairwise spillover measures obtained from our mixed-frequency and those from the common-frequency approach. In particular, the level of pairwise spillovers implied by our MF approach typically exceed those obtained from the CF approach, with the key exception being that of spillovers transmitted from IP to the two financial markets in panels (e) and (h).

The almost entirely positive values for net pairwise spillovers from the respective financial markets to industrial production for the mixed-frequency approach in panels (f) and (i) imply again that industrial production is almost always a net receiver of shocks from both of the financial markets, or equivalently that the financial variables are net transmitters to industrial production. In panels (e) and (h) we do however see again the previous discussed spike in spillovers from industrial production to the financial markets during the recent crisis, particularly for the equity market. Although the increase is not large enough to make industrial production a net transmitter of spillovers to either financial market, it is clear that shocks to the real side of the economy were transmitted to the financial markets during the recent crisis[11]. At the very least this implies that the relationship is not unidirectional in nature although it cannot be conclusively interpreted as evidence of the type of feedback loops predicted by economic theories such as the financial accelerator.

Panels (a) to (c) provide information about the spillover structure between the two financial markets. Although the levels of net pairwise spillovers between the equity market and bond market in panel (c) are generally lower than net pairwise combinations that include industrial production, it is clear from panels (a) and (b) that there are strong spillovers between the two financial markets, frequently reaching values in the range of 8% to 12%, but that these spillovers offset each other when computing the net measures. From a cursory examination of panel (c) it appears that during turbulent market conditions, such as the period 1999-2002, equity markets are a net transmitter of volatility spillovers to the bond market and yet during other sub-periods, such as the first half of the 1980's, the opposite is true. According to the mixed-frequency connectedness measures, net volatility spillovers from the stock market to the bond market, which was

[11] One exception to this is the large spike in pairwise spillovers from equity markets to industrial production in August and September 2013, although this is short-lived.

positive in early 2000s, increased further to 5% in 2005 and stayed around this level until dropping substantially and sharply in the liquidity crisis of 2007. As the sovereign debt crisis unfolded in Europe in late 2009 and 2010, the bond market's role became more central and it became a net spillover transmitter to equities, before the equity market became the dominant source of spillovers again during the later stages of the crisis.

Crucially these pairwise measures allow us to use our methodology to provide an alternative perspective on an existing question of interest in the finance literature, namely whether different financial markets respond differently to a common real economic shock. The fact that the level and dynamics of the pairwise spillovers in panel (e) differ from that in panel (h) implies that the spillover structure between the equity market and industrial production differs from that between the bond market and industrial production. This finding is in agreement with the earlier work of Brenner et al. (2009), who find the response of bond and equity markets to macroeconomic news and announcements to differ substantially in terms of both timing and magnitude.

Given the bidirectional nature of our methodology we can also examine the parallel question of whether the response of industrial production to financial shocks depends on the financial market in which the shock originates. From panels (d) and (g) it is clear that both the magnitude and dynamics of spillovers received by industrial production do indeed differ substantially depending on whether the shock originates in the bond or equity market.

It is perhaps more informative however to consider net spillovers from the two financial markets to IP growth plotted in panels (f) and (i). Whilst net spillovers transmitted from both equities and bonds to industrial production are positive throughout our sample period, they again show clear differences in both level and dynamics. Net spillovers from equities to IP growth, plotted in panel (f), peak at above 5% in the early 1980s, before falling and fluctuating between 2 and 5% from 1983 to 2003, with a clearly visible peak in 1987 corresponding to Black Monday. From 2003 until the beginning of the global financial crisis, net spillovers from equities to IP growth drop steadily to almost zero, before sharply rising for the duration of the crisis, during which time the series reaches its peak value of over 10%.

Net volatility spillovers from US government bonds to IP growth on the other hand fluctuated around 10% from the beginning of the sample to the mid 1980s, consistently higher than net spillovers from equities during the same period. Following this they registered a significant decline in late 1980s, before fluctuating in the 2-5% range for more than a decade and then falling until the year 2000. During the relatively turbulent period in 2000 and 2001, net spillovers from bond markets to IP growth begin to rise steadily again in the pre-crisis period, before falling in the immediate pre-crisis period and quickly beginning to increase again as the crisis took hold. These dynamics both before and during the global financial crisis clearly differ substantially from those discussed previously for net spillovers from equity markets to IP growth, again suggesting that the two financial markets played distinct roles in the transmission of financial shocks to the real economy.

3.2 Determinants of Macro-Financial Spillovers

In the preceding subsection we showed that temporal variation in the level of macro-financial spillovers is associated primarily with short-run and medium-run fluctuations and that these fluctuations appear to be closely related to known financial and economic events and the current state of the economy.

Motivated by this, we next identify factors that have explanatory power for movements in our macro-financial spillover measures. These factors are drawn from a set of macroeconomic and financial variables identified in the literature as key indicators of economic and financial conditions, allowing us to confirm that our macro-financial spillover measures are linked to economic and financial fundamentals. Whilst the factors we employ have been widely used across the literature, some key previous studies that we view as particularly relevant for the current analysis include Engle and Rangel (2008), Paye (2012) and Engle et al. (2013), who examine the macroeconomic determinants of financial return volatility, Asgharian et al. (2015), who examine macro-financial determinants of the long-run stock-bond correlation, and the studies of Allen et al. (2012), Bali et al. (2014), who study the predictive ability of financial systemic risk for the macroeconomy and the exposure of hedge funds to macroeconomic risk respectively.

By separately considering the spillover measures obtained from the mixed-frequency and common-frequency approaches, together with the difference between them, we analyse whether the incorporation of additional higher frequency information in the MF method results in spillover measures that are more strongly associated with fundamentals, or whether these fundamentals explain the divergence observed between the spillovers measures from the two approaches. Finally, by dividing our set of factors into financial and macroeconomic groups we explore whether, as might be expected, financial fundamentals are more closely linked with spillovers for variables on the financial side of the economy than the real side of the economy and vice versa.

The financial factors we employ are the levels of the TED spread, the term spread and the VIX volatility index, the return on the US Dollar Index (USDX) and the investor sentiment index of Baker and Wurgler (2007). On the macroeconomic side we employ the rate of CPI inflation, the US national unemployment rate and the growth of industrial production[12].

Further details of these data, including sample moments and correlation matrix are presented below in Table 2. With the exception of the investor sentiment data, which are obtained directly from the authors' website, and those for the USDX exchange rate index from Bloomberg, the data are from the Federal Reserve Economic Data (FRED) service of the St Louis Fed. Whilst the raw data for some variables are transformed (for example to compute growth rates), the FRED series identifiers for each variable are given in brackets in Table 2. Finally, due to data availability constraints for the VIX

[12] Although it may seem strange to include IP growth both as a possible explanatory factor and as variable in the VAR from which the spillover measures are obtained, it is (along with GDP growth) a standard indicator of real economic conditions from the literature (see for example Engle et al., 2013, Asgharian et al., 2015). Given the lack of monthly data for the broader measures of GDP growth, we employ IP growth as a proxy.

series, the period of analysis is shortened relative to that used in the previous subsections to 1990-2015.

[Table 2 about here.]

From Panel B of Table 2 it is clear that although the pairwise correlations between these factors are occasionally high (see, for example, term spread and unemployment), they are low for most combinations of variables. This suggests that sets of multiple factors are likely to have greater explanatory power for our spillover measures than single factors in isolation.

The values of the various spillover measures are regressed on one or more of these macro and financial factors and we then examine the values and statistical significance of the estimated coefficients and, perhaps more importantly the R-squared values from the regressions. The latter provide a easily interpretable standard measure of explanatory power and statistical association that permits us to answer questions of the nature outlined above. To conserve space we focus throughout on the most aggregated total spillover index and the most disaggregated pairwise spillover measures, with analogous results for the intermediate spillover measures (to and from all others) reported in Appendix C.3.

[Table 3 about here.]

We begin with a simple regression framework in which we regress the mixed-frequency and common-frequency spillover measures, in addition to the difference between the two measures, on a single one of the factors listed above. The standard R-squared values from this exercise are reported in Table 3. It can be seen that explanatory power of each factor in isolation varies substantially from factor to factor; that of the TED spread, USDX returns, investor sentiment index, inflation and IP growth are typically low, only rarely exceeding 10%. The term spread and VIX on the other hand have more substantial explanatory power in several cases and unemployment in particular has consistently high predictive ability for both the MF and CF spillover measures. We also observe some initial evidence that the difference between the respective MF and CF spillover measures may be associated with these same factors.

Next we examine the explanatory power of subsets of the factors by regressing each of the spillover measures on multiple factors. In addition to regressing each of the spillover measures on the complete set of factors, we also decompose the set of regressors into two subsets; the first contains only financial variables as regressors (TED spread, term spread, VIX, USDX return and investor sentiment) and the second contains only macro variables (inflation, unemployment and industrial production growth). Using this decomposition of the factors, we investigate additional questions, such as whether financial factors have greater explanatory power for spillovers than macro factors and, for the case of pairwise spillovers, if this varies according to whether the spillover measure in question relates to a financial or real variable. Additionally, we perform our analysis not only for the full sample period, but also for two subsamples of 1990 to 2006 and 2007 to 2015, which we refer to pre- and crisis/post-crisis periods. In Table 4 we report adjusted R-squared values for the multiple regression context.

[Table 4 about here.]

Beginning with the full-sample results for the total spillover index, it is interesting to note that the subset of macro variables has higher explanatory power for the common-frequency spillover index than for the corresponding mixed-frequency index (0.721 compared to 0.447), whereas the opposite is true for the financial subset of factors. This is perhaps unsurprising given that the additional information preserved by the mixed-frequency approach is financial in nature and so the resulting spillover indexes are likely to be more closely related to financial fundamentals than those from the common-frequency approach that discard this information.

Moving down the full-sample results to consider the pairwise spillover measures for the mixed-frequency case, we again observe some notable results concerning the decomposition between financial and non-financial factors. Most interestingly, we observe higher adjusted R-squared values for the subset of financial factors than for the macro factors for pairwise spillovers that originate from financial variables. For example, in the case of spillovers transmitted from the bond market to industrial production, the adjusted R-squared for the subset of financial factors is 0.315, whereas that for the subset of macroeconomic factors is just 0.056. For spillovers in the opposite direction, from industrial production to the bond market, the adjusted R-squared for the financial factors is 0.366 compared to 0.601 for the macroeconomic subset of factors.

This implies that, arguably consistent with intuition, conditions on the financial side of the economy are more relevant determinants of spillovers originating in financial markets than conditions on the real side of the economy. The converse is true for pairwise spillovers transmitted from our macro variable, IP growth, to the two financial variables; in this case we observe considerably higher explanatory power in the full sample for the macroeconomic factors than from the financial factors.

In the full-sample results for the common-frequency approach however, the clear dichotomy between the financial and macro subsets of factors previously observed in the mixed-frequency case is no longer so distinct. It is still the case that the macro factors have relatively greater explanatory power for pairwise spillovers transmitted from the real to the financial side of the economy, but the converse is no longer true. It appears in this case that the loss of financial information incurred by aggregating the data serves to decouple the measures of financial spillovers from financial fundamentals.

Finally, comparing results obtained for the two subsamples in the remaining columns of Table 4, we generally observe higher explanatory power for all subsets of factors in the 2007-2015 sub-period than in the earlier 1990-2006 sub-period. The increases in explanatory power in the second 2007-20015 sub-period is often substantial; for example, the adjusted R-squared values for the mixed-frequency and common-frequency total spillover indexes rise from 0.264 and 0.489 respectively in the first sub-period to 0.904 and 0.755 in the second. One interpretation of this finding is that during crisis periods the spillover measures are more closely related to macro and financial fundamentals.

One thing that is not observed during the second 2007-2015 sub-period is a clear difference in the relative explanatory power of the financial and macro subsets of factors; for the total spillover index we observe that the financial and macro sets of factors have very similar explanatory power and although differences are observed for the case of pairwise spillovers, their relative explanatory power are typically broadly similar. This implies that it was a combination of changes in conditions on both the financial and real sides of the economy, rather than from a single side, that were the driving forces behind the recent crisis.

In Table 3 we reported strong explanatory power for a number of factors in a univariate setting including unemployment and the VIX and less importance for others, such as investor sentiment. We now turn to a multivariate framework and the full set of estimated regression coefficients and corresponding sample p-values in Table 5. The timeframe under investigation corresponds to Table 2, from 1990 to 2012. Model coefficients for the full set of factors where the period of analysis is broken into the two previously defined pre and post crises subsamples are given in Tables 6 and 7.

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

In line with the univariate explanatory power for the individual factors, the results of Tables 5 are supportive of certain factors having stronger associations with the spillover indexes. Focusing in on unemployment and the VIX that had high R-squared values, we also report highly significant regression coefficients. Furthermore a 1 percentage point increase in the VIX is associated with a 0.334 percentage point increase in the mixed frequency total spillover index. The effect is stronger for unemployment with the index increasing by 2.556 percentage points from a 1 percentage point shock. The positive associations between the factors and spillovers are in line with relationships that would be predicted a priori, with unemployment and VIX positively associated with connectedness.

It is worth noting that the estimated coefficients on many of the other factors are also statistically significant, for example, IP growth and the term spread, whereas others are not, such as the TED spread. These findings are generally supported for the model coefficients for both pre- and post-crisis periods in Tables 6 and 7. However, some of the factors exhibit inconsistencies in either the sign and/or their significance both for the full sample models in Table 5 and the sub-samples in Tables 6 and 7.

Taking the TED spread as an illustration, it is not significant for either mixed or common frequency spillovers for the full sample, but in contrast it is significant for both connectedness in the post-crises period and for mixed frequency connectedness in the pre-crises period. Based on the signs of the estimated coefficients for the two sub periods, this apparent lack of significance in the full sample context arises because the association between the TED spread and spillovers differs substantially across the pre- and post-crisis periods, being negative in the former and positive in the latter.

Furthermore, one factor whose results are not in line with expectations is investor sentiment. We would expect sentiment would be significantly associated with the level of spillovers, and whilst the model coefficients are positive, they are nonetheless insignificant. We report similar results for the impact of sentiment when we break out the regressions for the pre- and post-crisis periods in Tables 6 and 7.

When we compare the factor coefficients for the mixed and common-frequency approaches there is supporting evidence to that reported in Table 5 to suggest that macro factors (inflation, unemployment and IP growth) are more important for the common frequency approach in comparison to the relative importance of financial factors for the mixed frequency indexes. Beginning with the total spillover measures in Panel A and taking the key variables of the VIX and unemployment identified earlier as examples, we note that both of these variables are highly statistically significant for both the mixed and common-frequency cases. However, the size of the estimated coefficients differs substantially, with that on the VIX being nearly twice as large for the mixed-frequency case (0.334 versus 0.155) and that on unemployment being substantially larger in the common-frequency case (4.103 versus 2.556). Again this provides support for the hypothesis that macro factors are more important for common-frequency spillovers and financial factors more important for the mixed-frequency estimates.

Many of the same conclusions hold when we look more closely at the pairwise spillover measures in Panel B of Table 5. Here we note that both VIX and unemployment are more likely to have strong associations with the connectedness indexes for both common and mixed frequency estimates. Other factors are less influential with, for example, the return on the USDX exchange rate index having a weak association with spillovers, only being significant at the five percent level in 2 of the 6 mixed-frequency regressions and 1 of the common frequency regressions. Table 5 also indicates that the stronger associations for mixed frequency connectedness are with financial factors with 4 of the 5 (TED spread, term spread, VIX, USDX return and sentiment) factors significant at the five percent level, whereas the macro factors tend to have more significance for common frequency connectedness. This finding is also evident for the post-crisis period and holds true for the associations between macro factors and connectedness in pre-crises times.

4 Conclusion

The current work has estimated and analysed the structure of macro-financial spillovers between equities, bonds and industrial production in the US economy from 1975 to 2015. In order to achieve this, we develop a new methodology that combines existing established quantitative measures of financial spillovers with mixed-frequency econometric methods. Our approach thus allows us to directly employ macro-financial datasets with heterogeneous sampling frequencies, whilst avoiding the data aggregation and resulting loss of information that standard common-frequency methods would require. The methodology allows us to compute a range of different macro-financial spillovers measures at various levels of aggregation, taking into account the directionality of spillovers.

In our detailed analysis of macro-financial spillovers in the US economy we find that the magnitude of the spillover measures obtained using our new mixed-frequency approach is substantially greater than for those obtained from an analogous common-frequency approach. This suggests that the loss of high-frequency information incurred by the use of a common-frequency modelling approach results in markets on the financial and real sides of the economy appearing less connected. Furthermore, the preservation of additional high-frequency information by our mixed-frequency approach results in spillover measures that appear more consistent with key events that occurred during our sample period.

The directional nature of our spillover measures allows us to show that financial markets are typically net transmitters of shocks to the real side of the economy, particularly during turbulent market conditions. However, we also find evidence that the bond and equity markets respond heterogeneously to identical macroeconomic shocks and that the response of the real side of the economy to financial shocks depends strongly on the financial market in which the shocks originate.

Motivated by the large short-run and medium-run fluctuations present in our estimated macro-financial spillover measures and their apparent association with market conditions, we identify a set of variables that act as determinants of macro-financial spillovers. These factors are drawn from key macroeconomic and financial variables used in the existing literature as indicators of current economic and financial conditions, with the term spread, VIX and unemployment rate in particular have substantial explanatory power for our spillover measures. The explanatory power of these factors increases dramatically during and following the recent global financial crisis relative to the pre-crisis period, suggesting that macro-financial spillovers are more closely related to economic and financial fundamentals during periods of market stress.

Furthermore, using our mixed-frequency approach we find evidence that financial fundamentals have greater explanatory than macro factors for spillovers originating from financial markets, with the converse true for spillovers originating from the real side of the economy. The same empirical finding is not preserved for the simpler common-frequency approach, suggesting that the loss of high-frequency financial information that occurs through data aggregation results in spillover estimates that are less plausibly linked to underlying financial and real economic conditions.

A Forecast Error Variance Decomposition

A.1 Computation of the Generalised Forecast Error Variance Decomposition

In contrast to alternative orthogonalisation approach employing the Cholesky decomposition for computing the FEVD, the generalised FEVD approach of Pesaran and Shin (1998) that we employ here makes the values of the spillover measures invariant to the ordering of the variables within the VAR and allows directional measures of connectedness to be produced.

More formally, we denote the FEVD values by $\theta_{ij}(H)$, where $\theta_{ij}(H)$ measures the fraction of the H-step-ahead error variance in forecasting variable i attributable to shocks in variable j. Following Pesaran and Shin (1998), the (generalised) forecast error variance decomposition values are computed for any given forecast horizon $H = 1, 2, \dots$ as:

$$\theta_{ij}(H) = \frac{\sigma_{jj} \sum_{h=0}^{H-1} \left(e_i' B_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' B_h \Sigma B_h' e_i\right)} \qquad \text{for } i, j = 1, \dots, K_x \tag{A.1}$$

where Σ is the covariance matrix of the error vector $\underline{\varepsilon}(\tau_L)$, σ_{jj} is the j-th diagonal element of Σ and e_j is the K_x-dimensional selection vector with a 1 in the j-th element and zeros elsewhere. The arrays $B_i, i = 1, \dots$ are the coefficient arrays from the infinite order moving average (MA) representation of the MF-VAR in in equation (2.1):

$$\underline{x}(\tau_L) = \sum_{j=0}^{\infty} B_i \underline{\varepsilon}(\tau_L - j) \tag{A.2}$$

where the first MA coefficient array B_0 is an $(K_x \times K_x)$ identity matrix and the remaining arrays $B_1, B_2, \dots$ are related to those from the original representation in (2.1) via the recursion $B_j = A_1 B_{j-1} + A_2 B_{j-2} + \cdots + A_p B_{j-p}$. Note that we have assumed for simplicity that all elements of A_0 in (2.1) are equal to zero, which can be achieved by simply demeaning each individual series.

In terms of notation employed, equation (A.1) is written assuming that we are dealing with the MF-VAR for the variables of interest. The FEVD arrays for the corresponding common-frequency VAR are however computed in an analogous way from the relevant quantities obtained when estimating the CF-VAR.

A.2 Aggregation of MF-VAR FEVD Arrays

As previously discussed, the $(K_x \times K_x)$ FEVD arrays for a generic MF-VAR model have the form:

$$\begin{bmatrix} \theta_{11}(H) & \cdots & \theta_{1K_x}(H) \\ \vdots & \ddots & \vdots \\ \theta_{K_x 1}(H) & \cdots & \theta_{K_x K_x}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \dots \tag{A.3}$$

and those for the corresponding CF-VAR are $(K \times K)$ arrays of the form:

$$\begin{bmatrix} \phi_{11}(H) & \cdots & \phi_{1K}(H) \\ \vdots & \ddots & \vdots \\ \phi_{K1}(H) & \cdots & \phi_{KK}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \dots \tag{A.4}$$

where we again use ϕ_{kl} instead of θ_{ij} to distinguish the FEVD values for the CF-VAR from those for the MF-VAR. As we previously argued, each element $\phi_{kl}(H)$ in the CF-VAR FEVD array will generally correspond to multiple elements $\theta_{ij}(H)$ in the MF-VAR

FEVD array, due to the fact that the MF-VAR mathematically treats the observations for each high-frequency period within each low-frequency period as distinct variables. The correspondence between the elements of the FEVD arrays for the mixed-frequency and common-frequency cases is the key to understanding the structure of the FEVD aggregation scheme.

This is best illustrated using a simple example, for which we use a bivariate model with one low-frequency monthly series and one high-frequency weekly series, which can be thought of as a macroeconomic and financial variable respectively. We also make the simplifying assumption that there are 4 weeks within every month. For this example we thus have $m = 4, K_L = 1$ and $K_H = 1$, giving a stacked mixed-frequency variable vector of dimensions $K_x = mK_H + K_L = 5$, with the form:

$$\underline{x}(\tau_L) = [x_H(\tau_L, 1), x_H(\tau_L, 2), x_H(\tau_L, 3), x_H(\tau_L, 4), x_L(\tau_L)]'$$

and (5×5) MF-VAR FEVD arrays of the form:

$$\begin{bmatrix} \theta_{11}(H) & \theta_{12}(H) & \theta_{13}(H) & \theta_{14}(H) & \theta_{15}(H) \\ \theta_{21}(H) & \theta_{22}(H) & \theta_{23}(H) & \theta_{24}(H) & \theta_{25}(H) \\ \theta_{31}(H) & \theta_{32}(H) & \theta_{33}(H) & \theta_{34}(H) & \theta_{35}(H) \\ \theta_{41}(H) & \theta_{42}(H) & \theta_{43}(H) & \theta_{44}(H) & \theta_{45}(H) \\ \theta_{51}(H) & \theta_{52}(H) & \theta_{53}(H) & \theta_{54}(H) & \theta_{55}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \ldots \tag{A.5}$$

For the corresponding common-frequency VAR, we have a $K = K_L + K_H = 2$ dimensional vector process $\overline{x}(\tau_L) = [x_{HtL}(\tau_L), x_L(\tau_L)]'$ and (2×2) FEVD arrays of the form:

$$\begin{bmatrix} \phi_{11}(H) & \phi_{12}(H) \\ \phi_{21}(H) & \phi_{22}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \ldots \tag{A.6}$$

We can then group the MF-VAR FEVD elements into sub-arrays as follows:

$$\begin{bmatrix} \Theta_{11}(H) & \Theta_{12}(H) \\ \Theta_{21}(H) & \Theta_{22}(H) \end{bmatrix} \quad \text{for} \quad H = 1, 2, \ldots \tag{A.7}$$

where:

$$\Theta_{11}(H) \equiv \begin{bmatrix} \theta_{11}(H) & \theta_{12}(H) & \theta_{13}(H) & \theta_{14}(H) \\ \theta_{21}(H) & \theta_{22}(H) & \theta_{23}(H) & \theta_{24}(H) \\ \theta_{31}(H) & \theta_{32}(H) & \theta_{33}(H) & \theta_{34}(H) \\ \theta_{41}(H) & \theta_{42}(H) & \theta_{43}(H) & \theta_{44}(H) \end{bmatrix} \qquad \Theta_{12}(H) \equiv \begin{bmatrix} \theta_{15}(H) \\ \theta_{25}(H) \\ \theta_{35}(H) \\ \theta_{45}(H) \end{bmatrix}$$

$$\Theta_{21}(H) \equiv \begin{bmatrix} \theta_{51}(H) & \theta_{52}(H) & \theta_{53}(H) & \theta_{54}(H) \end{bmatrix} \qquad \Theta_{22}(H) \equiv \theta_{55}(H)$$

Each of the sub-arrays $\Theta_{kl}(H)$ in (A.7) can be viewed as a disaggregated analogue of the corresponding scalar element $\phi_{kl}(H)$ from the CF-VAR FEVD array in (A.6). For example, the (4×1) sub-vector $\Theta_{12}(H)$ characterise the effects of shocks to the monthly low-frequency variable (variable 2) on the weekly high-frequency variable (variable 1). Specifically, θ_{i5} for $i = 1, \ldots, 4$ measures the fraction of the H-step-ahead error variance in forecasting the high-frequency variable in week i of the month that is attributable to shocks in the low-frequency variable. The scalar element $\phi_{12}(H)$ for the common-frequency case describes the same directional pairwise relationship for the case where both variables are observed at the lower monthly frequency.

The aim of our aggregation scheme is to produce new arrays from the MF-VAR FEVD array elements with the same structure and dimensions as those for the corresponding CF-VAR. We denote a generic element of the new $(K \times K)$ aggregated FEVD arrays by $\psi_{kl}(H)$ for $k, l = 1, \ldots, K$. Whilst many simple aggregation schemes are possible, the difficulty is to implement aggregation in such a way that the value and interpretation of an individual element $\psi_{kl}(H)$ in the aggregated array is directly comparable with the corresponding element $\phi_{kl}(H)$.

This requires us to take one step back from the final MF-VAR FEVD array elements, $\theta_{ij}(H)$, and return to equation (A.1) in which these elements are defined. For ease of notation, we denote the numerator and denominator of (A.1) more compactly as:

$$\theta_{ij}(H) = \frac{\lambda_{ij}(H)}{\mu_i(H)} \quad \text{for } i, j = 1, \ldots, K_x \tag{A.8}$$

where:

$$\lambda_{ij}(H) \equiv \sigma_{jj} \sum_{h=0}^{H-1} \left(e_i' B_h \Sigma e_j\right)^2 \quad \text{and} \quad \mu_i(H) \equiv \sum_{h=0}^{H-1} \left(e_i' B_h \Sigma B_h' e_i\right)$$

The denominator $\mu_i(H)$ corresponds to the total H-step-ahead forecast error variance for variable i and the numerator is the forecast error variance for variable i due to shocks in variable j (normalised such that the shock is one standard deviation in size), thus giving $\theta_{ij}(H)$ the previously discussed interpretation.

We compute each element $\psi_{kl}(H)$ in the H-step-ahead aggregated FEVD array as:

$$\psi_{kl}(H) = \frac{\displaystyle\sum_{i \in \mathcal{I}_k,\ j \in \mathcal{J}_l} \lambda_{ij}(H)}{\displaystyle\sum_{i \in \mathcal{I}_k} \mu_i(H)} \quad k, l = 1, \ldots K,\ H = 1, 2, \ldots \tag{A.9}$$

where $\mathcal{I}_k$ and $\mathcal{J}_l$ are sets containing the row and column indexes respectively for the elements in the MF-VAR FEVD array (A.3) that correspond to element $\phi_{kl}(H)$ in (A.4). These correspondences and thus the values of the indexing sets $\mathcal{I}_k$ and $\mathcal{J}_l$ are determined entirely by the relative sampling frequencies of the series.

To help fix ideas, we illustrate the aggregation scheme for the previous bivariate example above. We previous argued that the elements in the MF-VAR FEVD array that correspond to $\phi_{kl}(H)$ are those contained in the sub-array $\Theta_{kl}(H)$. For example, for $k = 1, l = 1$, we have $\mathcal{I}_1 = \{1, \ldots, 4\}$, $\mathcal{J}_1 = \{1, \ldots, 4\}$ and:

$$\psi_{11}(H) = \frac{\displaystyle\sum_{i \in \mathcal{I}_1,\ j \in \mathcal{J}_1} \lambda_{ij}(H)}{\displaystyle\sum_{i \in \mathcal{I}_1} \mu_i(H)} = \frac{\displaystyle\sum_{i=1,j=1}^{4} \lambda_{ij}(H)}{\displaystyle\sum_{i=1}^{4} \mu_i(H)} \qquad H = 1, 2, \ldots$$

Likewise, for $k = 2, l = 1$ we find $\mathcal{I}_2 = \{5\}$, $\mathcal{J}_1 = \{1, \ldots, 4\}$ (the elements of $\Theta_{21}(H)$) and thus:

$$\psi_{21}(H) = \frac{\displaystyle\sum_{i \in \mathcal{I}_2,\ j \in \mathcal{J}_1} \lambda_{ij}(H)}{\displaystyle\sum_{i \in \mathcal{I}_2} \mu_i(H)} = \frac{\displaystyle\sum_{j=1}^{4} \lambda_{5j}}{\mu_5(H)} \qquad H = 1, 2, \ldots$$

Finally, as when using the generalised VAR approach for a common frequency VAR, the values of the elements in each row will not sum to unity, which would be advantageous when computing and interpreting the connectedness measures. This is solved by working with arrays of normalised FEVD values, $\tilde{\psi}_{ij}(H)$, obtained as:

$$\tilde{\psi}_{ij}(H) = \frac{\psi_{ij}(H)}{\sum_{j=1}^{K} \psi_{ij}(H)} \tag{A.10}$$

where by construction $\sum_{j=1}^{K} \tilde{\psi}_{ij}(H) = 1$ and $\sum_{i,j=1}^{K} \tilde{\psi}_{ij}(H) = K$.

B Data Appendix

B.1 Construction of Weekly Financial Series

To avoid the complications introduced by deterministic time variation in the number of weeks per month, we work with what we term 'pseudo weeks' rather than standard calendar weeks. These pseudo weeks are constructed by dividing the trading days within each month into exactly 4 sub-periods whose lengths vary, but are as close as possible to being equal. For example, months with 20 trading days are divided into four 5-day sub-periods, those with 19 trading days are divided into three 5-day periods and a 4-day period, those with 22 days are split into two 5-day periods and two 6-day periods and so on. The vast majority of pseudo-weeks contain either 5 or 6 trading days, however Februarys or months with an unusually large number of weekday non-trading days due to holidays may contain one or more weeks with 4 trading days.

Furthermore, to minimise the chance of introducing any systematic artefacts into the data at this pre-processing stage, we change the order in which the splitting is performed within each month. For example, the months with 21 working days can be split into four pseudo-weeks with lengths 5-5-5-6, with lengths 5-5-6-5, with lengths 5-6-5-5 or with lengths 6-5-5-5. The specific split order is chosen randomly for each month, but we ensure that the splitting is consistent and synchronised across the two financial assets so that the pseudo-weeks for both assets correspond to identical periods of calendar time. Finally, while computing pseudo-weekly returns or return volatilities we also adjust the return and volatility values obtained to account for the fact that the length of the return period actually differs slightly from pseudo-week to another.

B.2 Proxy for Return Volatility

The specific range-based estimator of return volatility employed by Diebold and Yılmaz (2012a) and Diebold and Yılmaz (2014) is that of Parkinson (1980), which estimates return volatility from the high and low prices during the chosen return period. Unfortunately the data required to compute the pseudo-weekly high and low prices are not available during the earlier parts of the sample period.

Instead, we approximate this estimator by replacing the pseudo-weekly high and low prices with the highest and lowest daily closing prices observed during each week. For the later parts of the sample period where both estimators can be computed, we confirm that our volatility measure using only close prices is highly correlated with the Parkinson (1980) estimator, with a correlation coefficient of just over 0.9 for the S&P500 and just under 0.9 for the 10-year Treasury Note series.

C Supplementary Empirical Results

C.1 Static Full Sample Results

Table 8 presents the static spillover table for the full sample period of January 1975 to September 2015. Panel A contains results for the case where the two financial variables enter as log return volatilities and those in Panel B are for the case where they enter as returns. In both panels the spillover values for the left half are obtained from the new mixed-frequency DY approach using a combination of weekly and monthly data, whilst those in the right half are obtained from the existing common-frequency DY approach with purely monthly data. To conserve space, we report results only for the intermediate 6-month horizon for the static case, with other results available upon request.

[Table 8 about here.]

The upper left 3 by 3 sub-arrays in each case are the (directional) pairwise connectedness between each pair of variables, with the ij-th element corresponding to the estimated contribution from innovations in variable j to the forecast error variance of variable i. The off-diagonal column and row sums of these elements give the 'from others' and 'to others' values, which correspond to the 'to' and 'from' directional connectedness measures previously defined in equation (2.6). The final table rows labelled 'net' are the relevant 'to others' value minus the 'from others' value, corresponding to the measure in equation (2.7). The single bolded value in the lower right of each sub-table is the value of the total connectedness index, as defined in equation (2.5).

Several points are immediately visible from the empirical results in Table 8. Firstly, in all cases the full-sample connectedness between the three variables is relatively low; recall that values are defined as percentages and so, for example, the values in the first row of panel (a) imply that for the MF-VAR approach using log return volatilities over 90% of the S&P500 forecast error variance at a 6 month horizon is due to innovations or shocks to the S&P500 itself, with only 7.2% and 2.6% being attributable to shocks in the bond market and industrial production respectively (giving a 'from others' value of $7.2\% + 2.6\% = 9.8\%$). Whilst typically small, the magnitude of these values is broadly comparable to those obtained in previous studies applying the common-frequency DY approach to purely financial datasets, such as Diebold and Yılmaz (2012a).

C.2 Empirical Results for Return Levels

During the main body of the text we analysed spillover measures between asset return volatilities and industrial production growth rates. We chose to focus on (logarithmic) return volatilities rather than returns, primarily because of the importance of changes in financial volatility during crisis periods. Logarithmic return volatilities also have the added advantage of being approximately Gaussian, a condition that should be satisfied in order to apply generalised variance decomposition.

However, it is also of interest to see whether the spillovers we obtain from stock returns and bond yields are very different from the ones we obtained using their volatilities. Therefore, the current subsection presents results analogous to those reported previously in Section 3.1, but with financial return volatility series replaced with the corresponding return levels when computing the spillover measures.

[Figure 5 about here.]

In Figure 5 we present the total spillover index using financial returns. A quick comparison of Figures 3 and 5 shows that the most important conclusion of Figure 3 is still valid in the case of return levels; namely, that the mixed-frequency based spillover index is consistently higher than the corresponding common-frequency based index.

The mixed-frequency total spillover index obtained using financial asset returns is in general higher than the corresponding index obtained when using asset return volatilities and tends to be smoother. The latter is expected because return volatilities tend to jump more significantly than returns in times of crises or major economic and political shocks that might affect financial markets. Finally, during the recent financial crisis the jumps observed in the mixed-frequency total spillover indexes obtain from returns and return volatilities were similar in magnitude. However, the post-crisis drop in total spillovers once the crisis episode is dropped out of the rolling window is more pronounced in the case of return volatilities, with the index for return levels remaining higher relative to its pre-crisis level than the index for return volatilities.

[Table 9 about here.]

[Figure 6 about here.]

[Figure 7 about here.]

In Figure 6 and 7 we present the total and pairwise spillover measures obtained from the model with financial asset returns rather than the return volatilities. The total spillovers to others, from others and net spillovers to others present a picture which is somewhat but not necessarily completely different from the one obtained with return volatilities. The most significant differences appear to be in panels (b) and (c) that correspond to total and net spillovers from stock returns to others. The total and net spillovers from stock returns to others appeared to record significant jumps in 1982, during Black Monday in October 1997 and in October 2008, following the collapse of Lehman Brothers.

Analysis of pairwise spillovers with financial asset returns in Figure 7 show that the net mixed-frequency spillovers between stock and bond returns are mostly fluctuating around zero, with positive spillovers from stocks to bonds in late 1990s and early 200s and from the collapse of Lehman Brothers in October 2008 to 2013. The net mixed-frequency spillovers from both financial assets to industrial production growth are always positive; the spillovers from stock returns to industrial production growth rate follows a pattern reflecting the jumps of 1982, Black Monday of October 1987 and during the global financial crisis and the net mixed-frequency spillovers from government bond yields to IP growth is in general similar to the one obtained with yield volatilities.

C.3 Supplementary Results for Second Stage Analysis

[Table 10 about here.]

[Table 11 about here.]

References

Adams, Z., R. Füss, and R. Gropp. 2014. Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk Approach. *Journal of Financial and Quantitative Analysis* 49:575–598.

Adrian, T., and M. K. Brunnermeier. 2016. CoVaR. *American Economic Review* 106:1705–1741.

Allen, L., T. G. Bali, and Y. Tang. 2012. Does Systemic Risk in the Financial Sector Predict Future Economic Downturns? *Review of Financial Studies* 25:3000–3036.

Almeida, H., and M. Campello. 2007. Financial Constraints, Asset Tangibility, and Corporate Investment. *Review of Financial Studies* 20:1429–1460.

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega. 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange, typescript. *American Economic Review* 93:38–62.

Asgharian, H., C. Christiansen, and A. J. Hou. 2015. Macro-Finance Determinants of the Long-Run Stock–Bond Correlation: The DCC-MIDAS Specification. *Journal of Financial Econometrics* p. nbv025.

Baele, L. 2006. Volatility Spillover Effects in European Equity Markets. *Journal of Financial and Quantitative Analysis* 40:373–401.

Baker, M., and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *Journal of Economic Perspectives* 21:129–151.

Bali, T. G., S. J. Brown, and M. O. Caglayan. 2014. Macroeconomic risk and hedge fund returns. *Journal of Financial Economics* 114:1–19.

Baur, D. G. 2012. Financial contagion and the real economy. *Journal of Banking and Finance* 36:2680–2692.

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. Mehl. 2014. The Global Crisis and Equity Market Contagion. *The Journal of Finance* 69:2597–2649.

Bekaert, G., C. R. Harvey, and A. Ng. 2005. Market integration and contagion. *Journal of Business* 78:39–69.

Bernanke, B., M. Gertler, and S. Gilchrist. 1996. The Financial Accelerator and the Flight to Quality. *Review of Economics and Statistics* 78:1–15.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104:535–559.

Braun, M., and B. Larrain. 2005. Finance and the Business Cycle: International, Inter-Industry Evidence. *The Journal of Finance* 60:1097–1128.

Brenner, M., P. Pasquariello, and M. Subrahmanyam. 2009. On the Volatility and Comovement of U.S. Financial Markets around Macroeconomic News Announcements. *Journal of Financial and Quantitative Analysis* 44:1265.

Brown, G. W., and J. E. Hund. 2007. Estimating systemic risk in the international financial system. *Journal of Financial Economics* 86:835–869.

Brownlees, C. T., and R. F. Engle. 2016. SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *forthcoming in Review of Financial Studies* pp. 1–32.

Brunnermeier, M. K., G. Gorton, and A. Krishnamurthy. 2011. Risk topography. *NBER Macroeconomics Annual* 26:149–176.

Chaieb, I., V. Errunza, and R. Gibson Brandon. 2014. Integration of Sovereign Bonds Markets: Time Variation and Maturity Effects. *Swiss Finance Institute Research Paper No. 14-47* .

Chauvet, M., T. B. Götz, and A. Hecq. 2014. Realized Volatility and Business Cycle Fluctuations: A Mixed-Frequency VAR Approach. *Working Paper* .

Chauvet, M., Z. Senyuz, and E. Yoldas. 2015. What does financial volatility tell us about macroeconomic fluctuations? *Journal of Economic Dynamics and Control* 52:340–360.

Chiu, W.-C., J. I. Peña, and C.-W. Wang. 2015. Industry characteristics and financial risk contagion. *Journal of Banking and Finance* 50:411–427.

Claessens, S., M. A. Kose, and M. E. Terrones. 2009. What Happens During Recessions, Crunches and Busts? *Economic Policy* 24:653–700.

Claessens, S., M. A. Kose, and M. E. Terrones. 2012a. How do business and financial cycles interact? *Journal of International Economics* 87:178–190.

Claessens, S., H. Tong, and S.-J. Wei. 2012b. From the financial crisis to the real economy: Using firm-level data to identify transmission channels. *Journal of International Economics* 88:375–387.

Corradi, V., W. Distaso, and M. Fernandes. 2012. International market links and volatility transmission. *Journal of Econometrics* 170:117–141.

De Bruyckere, V., M. Gerhardt, G. Schepens, and R. Vander Vennet. 2013. Bank/sovereign risk spillovers in the European debt crisis. *Journal of Banking and Finance* 37:4793–4809.

Diebold, F. X., and K. Yılmaz. 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal* 119:158–171.

Diebold, F. X., and K. Yılmaz. 2012a. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28:57–66.

Diebold, F. X., and K. Yılmaz. 2012b. Measuring the Dynamics of Global Business Cycle Connectedness. *Working paper* .

Diebold, F. X., and K. Yılmaz. 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182:119–134.

Dungey, M., M. Luciani, and D. Veredas. 2013. Googling SIFIs. *Working Paper* .

Engle, R. F., E. Ghysels, and B. Sohn. 2013. Stock Market Volatility and Macroeconomic Fundamentals. *Review of Economics and Statistics* 95:776–797.

Engle, R. F., E. Jondeau, and M. Rockinger. 2015. Systemic Risk in Europe. *Review of Finance* 19:145–190.

Engle, R. F., and B. Kelly. 2012. Dynamic Equicorrelation. *Journal of Business and Economic Statistics* 30:212–228.

Engle, R. F., and J. G. Rangel. 2008. The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes. *Review of Financial Studies* 21:1187–1222.

Forbes, K. J., and R. Rigobon. 2002. No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance* 57:2223–2261.

Foroni, C., E. Ghysels, and M. Marcellino. 2013. Mixed-Frequency Vector Autoegressive Models. In *Advances in Econometrics*, pp. 247–272. Emerald Group Publishing Limited.

Ghysels, E. 2016. Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics* 193:294–314.

Ghysels, E., J. B. Hill, and K. Motegi. 2015. Simple Granger Causality Tests for Mixed Frequency Data. *Working Paper* .

Ghysels, E., and J. I. Miller. 2015. Testing for Cointegration with Temporally Aggregated and Mixed-Frequency Time Series. *Journal of Time Series Analysis* 36:797–816.

Götz, T. B., A. Hecq, and J.-P. Urbain. 2013. Testing for Common Cycles in Non-Stationary VARs with Varied Frequency Data. In *Advances in Econometrics*, pp. 361–393. Emerald Group Publishing Limited.

Green, T. C. 2004. Economic news and the impact of trading on bond prices. *The Journal of Finance* 59:1201–1233.

Ivashina, V., and D. Scharfstein. 2010. Bank lending during the financial crisis of 2008. *Journal of Financial Economics* 97:319–338.

Jiang, G. J., E. Konstantinidi, and G. Skiadopoulos. 2012. Volatility spillovers and the effect of news announcements. *Journal of Banking and Finance* 36:2260–2273.

Longstaff, F. A. 2010. The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics* 97:436–450.

Mariano, R. S., and Y. Murasawa. 2010. A Coincident Index, Common Factors, and Monthly Real GDP. *Oxford Bulletin of Economics and Statistics* 72:27–46.

Parkinson, M. 1980. The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business* 53:61–65.

Paye, B. S. 2012. 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics* 106:527–546.

Pesaran, M. H., and Y. Shin. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58:17–29.

Ramcharan, R., S. Verani, and S. J. van den Heuvel. 2014. From Wall Street to Main Street: The Impact of the Financial Crisis on Consumer Credit Supply. *The Journal of Finance (forthcoming, doi: 10.1111/jofi.12209)* .

Schorfheide, F., and D. Song. 2015. Real-Time Forecasting with a Mixed-Frequency VAR. *forthcoming in Journal of Business and Economic Statistics* .

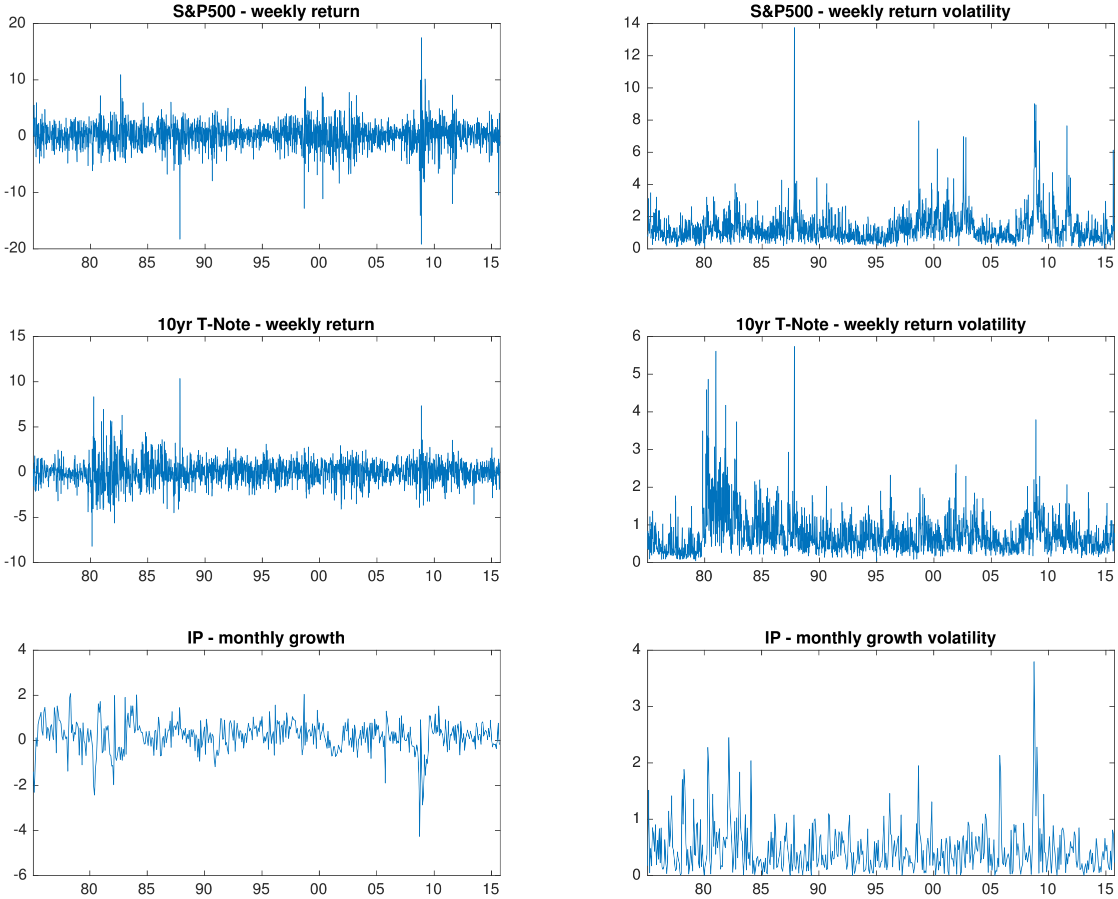

Figure 1: Time series plots of financial and real economy series
The financial (S&P500 and 10-year Treasury Bond) and real economy (industrial production) series are plotted for the full sample period 1975:01 to 2015:09. Returns and return volatilities are expressed in percentage terms for the weekly frequency, with standard deviations plotted for the latter constructed using a range-based approach detailed in Appendix B.2. Industrial production is expressed as a monthly series of month-on-month percentage growth rates and the volatility of IP growth is calculated as in Engle et al. (2013).

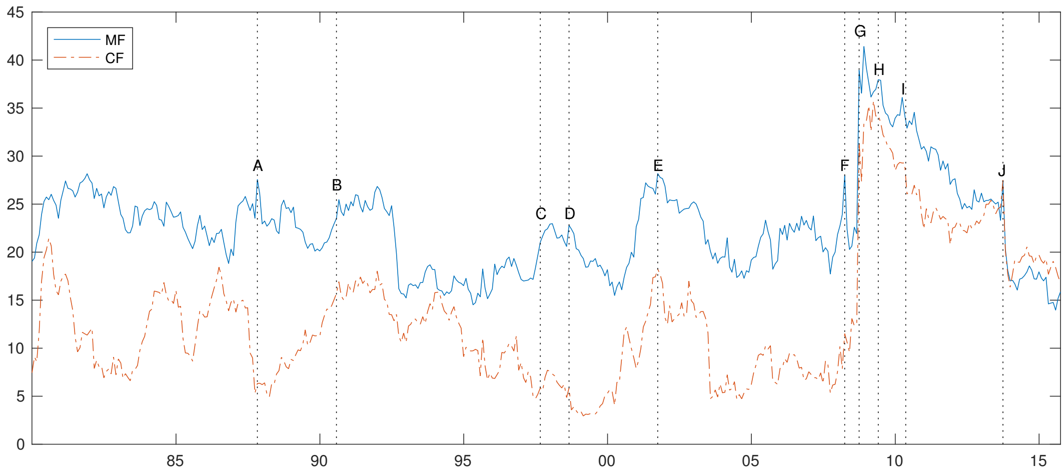

Figure 2: Total spillover index between the financial and real economy series
Total spillover indexes for mixed-frequency (denoted MF) and common-frequency (denoted CF) approaches are presented for the sample period 1980:01-to 2015:09. Logarithmic return volatilities are employed for the financial S&P500 and 10-year Treasury Note series, monthly growth rates for the real economy series industrial production. Values are computed using a 6-month forecast horizon and a 60-month rolling window. Points marked are as follows. A: Black Monday, Oct '87, B: Iraq's invasion of Kuwait, Jul '90, C: Asian financial crisis, Jul '97, D: Russian financial crisis and LTCM collapse, Aug to Sept '98, E: September 11, Sept '01, F: collapse of Bear Stearns, Mar '08, G: Lehman Brothers collapse, AIG bailout and Fannie Mae and Freddie Mac being placed in government conservatorship, Sept '08, H: announcement of results for the SCAP stress tests and announcement of large losses for Fannie Mae and Freddie Mac, May '09, I: start of the EU debt crisis in April '10 and flash crash of May '10, J: US government shutdown, Sept '13.

Figure 3: Directional spillovers to and from the financial and real economy series
The figure plots the spillovers transmitted by each variable to all others (panels (a), (d) and (g)), received by each variable from all others (panels (b), (e) and (h)) and the net spillovers for each variable to/from all others (panels (c), (f) and (i)) for the full sample period 1980:01-2015:09. Logarithmic return volatilities are used for the financial S&P500 and 10-year Treasury Note series and monthly growth rates for the real economy IP series. Values are computed using a 6-month forecast horizon and a 60-month rolling window.

Figure 4: Pairwise spillovers for the financial and real economy series

The first and second plots in each row (panels (a) and (b), panels (d) and (e) and panels (g) and (h)) contain the pairwise spillover in each direction for a given pair of variables, Pairwise spillovers are defined as the total forecast error variance of receiving variable at the chosen forecast horizon that is due to shocks in the transmitting variable. The third plot in each row (panels (c), (f) and (i) gives the net pairwise spillover for the same combination of variables, computed by subtracting the values in the second plot of the row from those in the first plot. The figure only displays net pairwise spillovers in one direction for any given pair of variables, since for example the value of net pairwise spillovers from the S&P500 to industrial production is minus one times the net pairwise spillovers from industrial production to the S&P500. Logarithmic return volatilities are used for the financial S&P500 and 10-year Treasury Note series and monthly growth for the real economy IP series. Values are computed using a 6-month forecast horizon and a 60-month rolling window.

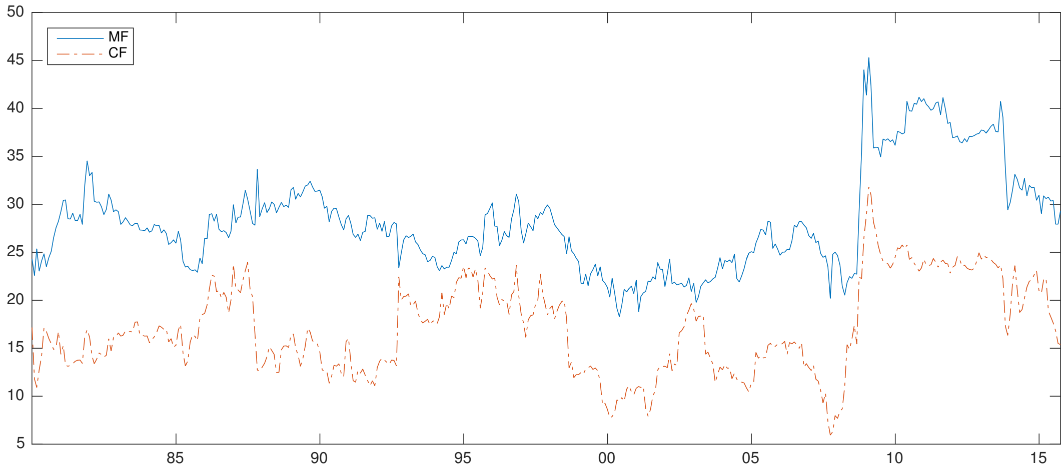

Figure 5: Total spillover index between the financial and real economy series using return levels

Total spillover indexes for mixed-frequency (denoted MF) and common-frequency (denoted CF) approaches are presented for the sample period 1980:01-to 2015:09. Return levels are employed for the financial S&P500 and 10-year Treasury Note series, monthly growth rates for the real economy series industrial production. Values are computed using a 6-month forecast horizon and a 60-month rolling window.

Figure 6: Directional spillovers to and from the financial and real economy series using return levels
The figure plots the spillovers transmitted by each variable to all others (panels (a), (d) and (g)), received by each variable from all others (panels (b), (e) and (h)) and the net spillovers for each variable to/from all others (panels (c), (f) and (i)) for the full sample period 1980:01-2015:09. Return levels are used for the financial S&P500 and 10-year Treasury Note series and monthly growth rates for the real economy IP series. Values are computed using a 6-month forecast horizon and a 60-month rolling window.

Figure 7: Pairwise spillovers for the financial and real economy series using return levels
The first and second plots in each row (panels (a) and (b), panels (d) and (e) and panels (g) and (h)) contain the pairwise spillover in each direction for a given pair of variables, Pairwise spillovers are defined as the total forecast error variance of receiving variable at the chosen forecast horizon that is due to shocks in the transmitting variable. The third plot in each row (panels (c), (f) and (i) gives the net pairwise spillover for the same combination of variables, computed by subtracting the values in the second plot of the row from those in the first plot. The figure only displays net pairwise spillovers in one direction for any given pair of variables, since for example the value of net pairwise spillovers from the S&P500 to industrial production is minus one times the net pairwise spillovers from industrial production to the S&P500. Logarithmic return volatilities are used for the financial S&P500 and 10-year Treasury Note series and monthly growth for the real economy IP series. Values are computed using a 6-month forecast horizon and a 60-month rolling window.

Table 1: Summary details of mixed-frequency and common-frequency spillover measures

Panel A: summary statistics

	To all others		**From all others**		**Net**	
	MF	CF	MF	CF	MF	CF
Mean						
S&P500	9.671	4.477	6.674	5.556	2.997	-1.079
10yr TN	9.198	4.500	6.596	4.933	2.602	-0.434
IP	2.403	4.203	8.002	2.690	-5.599	1.513
Std. Dev.						
S&P500	2.189	2.212	2.711	4.525	2.819	3.282
10yr TN	2.253	2.795	1.821	3.306	2.205	2.860
IP	1.719	4.754	1.925	1.017	2.522	4.747
Minimum						
S&P500	5.274	0.036	1.706	0.085	-4.547	-12.885
10yr TN	3.965	0.598	3.334	0.524	-4.209	-10.555
IP	0.419	0.170	3.623	0.465	-12.809	-4.154
Maximum						
S&P500	19.214	10.199	16.236	18.129	12.916	7.215
10yr TN	17.145	14.365	11.768	14.965	7.126	8.445
IP	9.255	21.700	14.122	7.681	1.332	20.207

Panel B: differences and ratios

	To all others		**From all others**		**Net**	
	MF - CF	MF/CF	MF - CF	MF/CF	MF - CF	MF/CF
S&P500	5.016	3.865	1.631	2.950	3.385	0.237
10yr TN	5.183	2.773	1.791	1.946	3.393	3.874
IP	-0.790	0.961	5.987	3.471	-6.777	121.417

The table presents summary statistics for the mixed frequency and common frequency spillover indexes for the sample period 1975:01 to 2015:09. Logarithmic return volatilities are used for financial variables. Panel A reports the mean, standard deviation, minimum and maximum spillover measures. Panel B reports the differences and ratios between the spillover indexes. Differences (denoted by MF - CF) are computed by subtracting the dynamic common-frequency spillover measure from its mixed-frequency analogue and then taking the sample average and the ratios (denoted by MF/CF) are computed similarly by dividing the mixed-frequency measure by its common-frequency analogue and then taking the mean over the sample period.

Table 2: Summary details of variables associated with spillover indexes

Panel A: Variable definitions

Variable	Definition and construction
TED spread	Difference between 3-month LIBOR rate and the 3-month US Treasury Note yield expressed in percentage points (series TEDRATE from FRED)
Term spread	Difference between 10-year and 3-month US Treasury yields expressed in percentage points (series GS10 minus TB3MS, both obtained from FRED)
VIX	Level of the CBOE Volatility Index expressed as the end of month level (VIXCLS from FRED)
USDX return	Return level of the US Dollar Index (or USDX) as a monthly percentage return. Measures the value of the US Dollar relative to 6 major currencies, with increases corresponding to an appreciation of the Dollar (obtained from Bloomberg)
Investor sentiment	Investor sentiment index of Baker and Wurgler (2007) in units of original index, with higher values corresponding to more positive investor outlook (obtained from authors' website)
Inflation	Level of US CPI inflation expressed as monthly percentage (series CPIAUCSL from FRED)
Unemployment	National US unemployment rate expressed as a percentage (series UNRATE from FRED)
IP growth	Month-on-month percentage growth rate of US industrial production (transformation of series INDPRO from FRED)

Panel B: Sample moments

	TED spr.	Term spr.	VIX	USDX ret.	Sent.	Infl.	Unem.	IP grow.
Mean	0.505	1.929	19.909	0.011	0.128	0.206	6.107	0.168
Std. dev.	0.370	1.109	7.583	2.418	0.619	0.339	1.591	0.638

Panel C: Correlation matrix

	TED spr.	Term spr.	VIX	USDX ret.	Sent.	Infl.	Unem.	IP grow.
TED spr.	1.000							
Term spr.	-0.316	1.000						
VIX	0.462	0.020	1.000					
USDX ret.	0.074	-0.026	0.053	1.000				
Sent.	0.067	-0.295	-0.051	0.061	1.000			
Infl.	-0.146	-0.074	-0.202	-0.093	0.037	1.000		
Unem.	-0.321	0.660	0.071	0.011	-0.451	-0.006	1.000	
IP grow.	-0.265	0.027	-0.242	0.009	-0.009	0.028	-0.010	1.000

Table contains summary details of the independent variables employed for the regression-based analysis of Section 3.2. The variables include both financial (TED spread, term spread, VIX, USDX return and investor sentiment) and real economy (inflation, unemployment and IP growth) series. All variables are at the monthly frequency for the adjusted sample period of 1990:01 to 2015:09. Variable definitions and sources are presented in Panel A, summary statistics in Panel B and their correlation matrix in Panel C.

Table 3: Explanatory power of individual factors for macro-financial spillover indexes

	TED spr.	Term spr.	VIX	USDX ret.	Sentiment	Inflation	Unemp.	IP growth
Panel A: Total spillover index								
MF	0.012	0.077	0.308	0.003	0.067	0.019	0.367	0.072
CF	0.017	0.253	0.083	0.000	0.110	0.026	0.655	0.049
MF minus CF	0.093	0.196	0.027	0.006	0.044	0.008	0.295	0.002
Panel B: Pairwise spillovers								
i) MF								
From equities to bonds	0.001	0.005	0.157	0.002	0.103	0.007	0.213	0.034
From equities to IP	0.018	0.012	0.006	0.016	0.054	0.001	0.027	0.005
From bonds to equities	0.015	0.096	0.304	0.001	0.053	0.024	0.302	0.025
From bonds to IP	0.001	0.057	0.112	0.006	0.077	0.006	0.000	0.060
From IP to equities	0.026	0.053	0.152	0.000	0.126	0.019	0.465	0.035
From IP to bonds	0.000	0.244	0.136	0.000	0.048	0.019	0.546	0.045
ii) CF								
From equities to bonds	0.009	0.175	0.061	0.004	0.103	0.011	0.491	0.060
From equities to IP	0.022	0.052	0.004	0.000	0.075	0.003	0.131	0.000
From bonds to equities	0.097	0.195	0.003	0.001	0.041	0.012	0.249	0.003
From bonds to IP	0.007	0.026	0.188	0.001	0.030	0.006	0.023	0.038
From IP to equities	0.005	0.169	0.135	0.004	0.103	0.027	0.605	0.028
From IP to bonds	0.026	0.036	0.185	0.004	0.055	0.017	0.330	0.061
iii) MF minus CF								
From equities to bonds	0.010	0.250	0.002	0.001	0.017	0.004	0.258	0.025
From equities to IP	0.077	0.102	0.020	0.016	0.000	0.005	0.022	0.004
From bonds to equities	0.172	0.060	0.205	0.000	0.003	0.000	0.018	0.002
From bonds to IP	0.011	0.030	0.005	0.006	0.045	0.002	0.017	0.023
From IP to equities	0.000	0.256	0.093	0.009	0.064	0.028	0.580	0.018
From IP to bonds	0.050	0.015	0.100	0.006	0.025	0.005	0.052	0.033

Table reports the explanatory power of the factors, estimated by regressing the relevant spillover measure on a constant and a single one of the financial or macroeconomic explanatory factors using simple OLS. Values reported are standard (non-adjusted) R-squared values obtained from each regression. Panel A reports results for the total spillover index and Panel B for the pairwise spillover measures. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF). Regressions are estimated for the adjusted sample period of 1990:01 to 2015:09.

Table 4: Explanatory power of subsets of factors for macro-financial spillover indexes

	Full sample			Subsample 1: 1990-2006			Subsample 2: 2007-2015		
	All	Financial	Macro	All	Financial	Macro	All	Financial	Macro
Panel A: Total spillover index									
MF	0.676	0.405	0.447	0.286	0.207	0.060	0.839	0.634	0.651
CF	0.746	0.368	0.721	0.475	0.236	0.365	0.848	0.807	0.763
MF minus CF	0.364	0.245	0.296	0.428	0.333	0.321	0.594	0.372	0.042
Panel B: Pairwise spillovers									
i) MF									
From equities to bonds	0.475	0.294	0.243	0.195	0.172	0.049	0.685	0.385	0.562
From equities to IP	0.160	0.098	0.024	0.241	0.227	0.033	0.568	0.170	0.128
From bonds to equities	0.565	0.400	0.340	0.526	0.445	-0.008	0.706	0.706	0.521
From bonds to IP	0.362	0.315	0.056	0.440	0.399	0.102	0.611	0.588	0.275
From IP to equities	0.712	0.274	0.509	0.161	0.063	-0.001	0.776	0.558	0.609
From IP to bonds	0.691	0.366	0.601	0.466	0.315	0.342	0.764	0.553	0.657
ii) CF									
From equities to bonds	0.571	0.268	0.552	0.322	0.101	0.268	0.678	0.638	0.602
From equities to IP	0.139	0.093	0.125	0.152	0.154	0.022	0.436	0.385	0.438
From bonds to equities	0.301	0.225	0.255	0.590	0.284	0.477	0.624	0.341	0.059
From bonds to IP	0.363	0.345	0.056	0.452	0.386	0.113	0.622	0.603	0.487
From IP to equities	0.766	0.329	0.651	0.324	0.264	0.160	0.874	0.694	0.747
From IP to bonds	0.573	0.236	0.397	0.323	0.286	0.172	0.841	0.662	0.689
iii) MF minus CF									
From equities to bonds	0.364	0.252	0.278	0.472	0.319	0.403	0.523	0.183	0.071
From equities to IP	0.162	0.157	0.022	0.200	0.169	0.159	0.519	0.256	0.006
From bonds to equities	0.296	0.282	0.011	0.521	0.378	0.454	0.601	0.361	0.193
From bonds to IP	0.185	0.132	0.032	0.241	0.231	0.136	0.625	0.581	0.323
From IP to equities	0.685	0.351	0.616	0.368	0.355	0.171	0.843	0.723	0.750
From IP to bonds	0.278	0.145	0.079	0.546	0.388	0.470	0.774	0.630	0.583

Table reports the explanatory power of the factors, estimated by regressing the relevant spillover measure on either all factors (macroeconomic and financial), only financial factors (TED spread, term spread, VIX, USDX return and investor sentiment), or only macro factors (inflation, unemployment and industrial production growth) using simple OLS. Values reported are adjusted R-squared values obtained from each regression. Panel A reports results for the total spillover index and Panel B for the pairwise spillover measures. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF). Regressions are estimated for the complete adjusted sample period of 1990:01 to 2015:09, 1990:01 to 2006:12 (subsample 1) and 2007:01:2015:09 (subsample 2).

Table 5: Regression analysis of macro-financial spillover indexes

	TED spr.	Term spr.	VIX	USDX ret.	Sent.	Infl.	Unem.	IP grow.
Panel A: Total spillover index								
MF	0.473	-0.981	0.334	-0.239	0.371	-0.981	2.556	-1.168
	(0.200)	(0.000)	(0.000)	(0.001)	(0.159)	(0.042)	(0.000)	(0.000)
CF	-0.502	-0.401	0.179	-0.060	0.604	-2.873	4.103	-2.070
	(0.264)	(0.066)	(0.000)	(0.268)	(0.075)	(0.000)	(0.000)	(0.000)
MF minus CF	0.975	-0.580	0.155	-0.179	-0.232	1.892	-1.547	0.902
	(0.094)	(0.022)	(0.000)	(0.032)	(0.280)	(0.005)	(0.000)	(0.003)
Panel B: Pairwise spillovers								
i) MF								
From equities to bonds	-0.891	-0.695	0.094	-0.051	-0.405	-0.275	0.660	-0.322
	(0.000)	(0.000)	(0.000)	(0.034)	(0.001)	(0.110)	(0.000)	(0.001)
From equities to IP	0.734	-0.507	-0.005	-0.091	-0.435	0.067	0.378	-0.051
	(0.002)	(0.000)	(0.329)	(0.004)	(0.002)	(0.391)	(0.000)	(0.344)
From bonds to equities	0.324	-0.113	0.116	-0.008	0.130	-0.295	0.707	-0.052
	(0.144)	(0.085)	(0.000)	(0.403)	(0.093)	(0.093)	(0.000)	(0.325)
From bonds to IP	-0.668	0.618	0.082	-0.063	0.908	-0.053	-0.208	-0.515
	(0.002)	(0.000)	(0.000)	(0.025)	(0.000)	(0.405)	(0.000)	(0.000)
From IP to equities	0.701	-0.311	0.024	-0.015	-0.038	-0.252	0.614	-0.085
	(0.000)	(0.000)	(0.000)	(0.141)	(0.220)	(0.002)	(0.000)	(0.225)
From IP to bonds	0.272	0.028	0.023	-0.010	0.211	-0.172	0.404	-0.143
	(0.007)	(0.173)	(0.000)	(0.189)	(0.000)	(0.007)	(0.000)	(0.028)
ii) CF								
From equities to bonds	-0.025	-0.171	0.045	-0.089	0.018	-0.584	1.165	-0.791
	(0.463)	(0.089)	(0.001)	(0.006)	(0.460)	(0.031)	(0.000)	(0.000)
From equities to IP	-0.071	-0.043	-0.018	-0.004	-0.299	-0.276	0.268	-0.084
	(0.360)	(0.269)	(0.038)	(0.445)	(0.001)	(0.083)	(0.000)	(0.260)
From bonds to equities	-1.317	0.391	-0.022	0.040	0.043	-1.039	0.605	-0.511
	(0.001)	(0.002)	(0.065)	(0.226)	(0.412)	(0.010)	(0.000)	(0.002)
From bonds to IP	-1.008	0.069	0.079	-0.022	0.487	-0.051	0.052	-0.247
	(0.000)	(0.101)	(0.000)	(0.161)	(0.000)	(0.351)	(0.107)	(0.002)
From IP to equities	1.286	-0.271	0.047	0.009	0.231	-0.640	1.279	-0.168
	(0.000)	(0.000)	(0.000)	(0.377)	(0.008)	(0.000)	(0.000)	(0.153)
From IP to bonds	0.633	-0.375	0.048	0.006	0.124	-0.282	0.734	-0.269
	(0.001)	(0.000)	(0.000)	(0.397)	(0.062)	(0.026)	(0.000)	(0.035)
iii) MF minus CF								
From equities to bonds	-0.866	-0.525	0.049	0.037	-0.423	0.310	-0.505	0.468
	(0.000)	(0.000)	(0.000)	(0.115)	(0.002)	(0.109)	(0.000)	(0.000)
From equities to IP	0.805	-0.464	0.013	-0.087	-0.136	0.343	0.111	0.033
	(0.002)	(0.000)	(0.146)	(0.002)	(0.170)	(0.082)	(0.053)	(0.385)
From bonds to equities	1.641	-0.504	0.138	-0.048	0.087	0.744	0.102	0.460
	(0.001)	(0.000)	(0.000)	(0.187)	(0.309)	(0.037)	(0.213)	(0.012)
From bonds to IP	0.340	0.549	0.003	-0.042	0.421	-0.002	-0.259	-0.268
	(0.054)	(0.000)	(0.366)	(0.045)	(0.000)	(0.496)	(0.000)	(0.004)
From IP to equities	-0.584	-0.040	-0.023	-0.024	-0.269	0.387	-0.664	0.083
	(0.000)	(0.194)	(0.000)	(0.092)	(0.000)	(0.000)	(0.000)	(0.130)
From IP to bonds	-0.361	0.404	-0.026	-0.016	0.087	0.110	-0.330	0.126
	(0.012)	(0.000)	(0.000)	(0.240)	(0.114)	(0.194)	(0.000)	(0.099)

Table reports estimated coefficients (without parentheses) and corresponding t-statistics (with parentheses) obtained from OLS regressions of macro-financial spillover values on a constant and the complete set of macroeconomic and financial explanatory factors. Results are obtained for the adjusted sample period of 1990:01 to 2015:09. Panel A reports results for the total spillover index and Panel B for the pairwise spillover measures. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF).

Table 6: Regression analysis of macro-financial spillover indexes for 1990-2006

	TED spr.	Term spr.	VIX	USDX ret.	Sent.	Infl.	Unem.	IP grow.
Panel A: Total spillover index								
MF	-3.069	-0.665	0.277	-0.153	0.374	-1.260	1.090	-1.318
	(0.001)	(0.013)	(0.000)	(0.050)	(0.110)	(0.046)	(0.001)	(0.000)
CF	-0.268	-0.226	0.106	-0.187	1.904	-0.430	2.979	-1.228
	(0.396)	(0.225)	(0.004)	(0.023)	(0.000)	(0.277)	(0.000)	(0.001)
MF minus CF	-2.800	-0.439	0.171	0.034	-1.530	-0.829	-1.888	-0.091
	(0.005)	(0.074)	(0.000)	(0.349)	(0.000)	(0.097)	(0.000)	(0.395)
Panel B: Pairwise spillovers								
i) MF								
From equities to bonds	-1.142	-0.450	0.092	-0.024	-0.408	-0.256	0.199	-0.442
	(0.001)	(0.001)	(0.000)	(0.284)	(0.000)	(0.212)	(0.110)	(0.005)
From equities to IP	-1.720	-0.361	-0.058	-0.042	-0.532	0.387	-0.351	-0.077
	(0.000)	(0.001)	(0.000)	(0.114)	(0.000)	(0.109)	(0.003)	(0.322)
From bonds to equities	2.241	-0.041	0.138	-0.021	0.320	-0.685	0.656	-0.025
	(0.000)	(0.335)	(0.000)	(0.235)	(0.000)	(0.004)	(0.000)	(0.425)
From bonds to IP	-2.529	0.292	0.087	-0.044	0.742	-0.605	0.109	-0.636
	(0.000)	(0.011)	(0.000)	(0.120)	(0.000)	(0.019)	(0.253)	(0.000)
From IP to equities	0.115	-0.176	-0.002	-0.019	0.054	0.046	0.180	0.020
	(0.142)	(0.000)	(0.250)	(0.020)	(0.042)	(0.311)	(0.000)	(0.308)
From IP to bonds	-0.034	0.071	0.020	-0.003	0.197	-0.147	0.298	-0.159
	(0.389)	(0.028)	(0.000)	(0.402)	(0.000)	(0.019)	(0.000)	(0.000)
ii) CF								
From equities to bonds	-0.413	-0.356	0.055	-0.151	0.303	-0.396	1.394	-0.602
	(0.221)	(0.021)	(0.007)	(0.001)	(0.043)	(0.181)	(0.000)	(0.002)
From equities to IP	-0.782	-0.103	-0.066	0.010	-0.249	0.257	0.005	0.228
	(0.008)	(0.173)	(0.000)	(0.389)	(0.004)	(0.198)	(0.484)	(0.077)
From bonds to equities	2.052	0.060	0.052	-0.115	0.533	-0.181	1.651	-0.512
	(0.000)	(0.314)	(0.001)	(0.001)	(0.000)	(0.278)	(0.000)	(0.001)
From bonds to IP	-0.995	0.192	0.083	0.024	0.451	-0.360	-0.170	-0.542
	(0.002)	(0.008)	(0.000)	(0.186)	(0.000)	(0.040)	(0.036)	(0.000)
From IP to equities	0.295	0.064	-0.013	0.020	0.493	-0.054	0.315	0.181
	(0.043)	(0.126)	(0.027)	(0.139)	(0.000)	(0.344)	(0.000)	(0.010)
From IP to bonds	-0.425	-0.083	-0.005	0.026	0.373	0.304	-0.217	0.019
	(0.009)	(0.073)	(0.195)	(0.047)	(0.000)	(0.009)	(0.000)	(0.400)
iii) MF minus CF								
From equities to bonds	-0.729	-0.094	0.037	0.127	-0.711	0.141	-1.195	0.161
	(0.078)	(0.263)	(0.032)	(0.001)	(0.000)	(0.331)	(0.000)	(0.170)
From equities to IP	-0.938	-0.258	0.008	-0.052	-0.283	0.130	-0.356	-0.305
	(0.005)	(0.023)	(0.276)	(0.035)	(0.020)	(0.347)	(0.001)	(0.014)
From bonds to equities	0.190	-0.101	0.085	0.093	-0.213	-0.504	-0.995	0.487
	(0.366)	(0.243)	(0.000)	(0.005)	(0.069)	(0.077)	(0.000)	(0.003)
From bonds to IP	-1.534	0.100	0.004	-0.068	0.291	-0.245	0.279	-0.094
	(0.000)	(0.181)	(0.365)	(0.014)	(0.011)	(0.186)	(0.018)	(0.255)
From IP to equities	-0.180	-0.240	0.011	-0.039	-0.440	0.099	-0.135	-0.161
	(0.149)	(0.000)	(0.053)	(0.006)	(0.000)	(0.248)	(0.014)	(0.008)
From IP to bonds	0.391	0.154	0.025	-0.029	-0.176	-0.450	0.515	-0.178
	(0.014)	(0.006)	(0.000)	(0.040)	(0.003)	(0.001)	(0.000)	(0.020)

Table reports estimated coefficients (without parentheses) and corresponding t-statistics (with parentheses) obtained from OLS regressions of macro-financial spillover values on a constant and the complete set of macroeconomic and financial explanatory factors. Results are obtained for the pre-crisis sample period of 1990:01 to 2006:12. Panel A reports results for the total spillover index and Panel B for the pairwise spillover measures. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF).

Table 7: Regression analysis of macro-financial spillover indexes for 2007-2015

	TED spr.	Term spr.	VIX	USDX ret.	Sent.	Infl.	Unem.	IP grow.
Panel A: Total spillover index								
MF	4.422	-0.663	0.179	-0.248	1.141	-0.122	3.621	-0.995
	(0.000)	(0.105)	(0.001)	(0.006)	(0.247)	(0.433)	(0.000)	(0.013)
CF	-3.010	1.535	0.186	-0.013	-8.516	-2.091	1.288	-1.811
	(0.006)	(0.000)	(0.001)	(0.462)	(0.000)	(0.001)	(0.000)	(0.001)
MF minus CF	7.432	-2.198	-0.007	-0.235	9.658	1.969	2.332	0.815
	(0.000)	(0.000)	(0.456)	(0.050)	(0.000)	(0.008)	(0.000)	(0.074)
Panel B: Pairwise spillovers								
i) MF								
From equities to bonds	-0.023	-0.431	0.047	-0.068	1.961	-0.386	1.038	-0.269
	(0.465)	(0.008)	(0.004)	(0.018)	(0.000)	(0.098)	(0.000)	(0.006)
From equities to IP	2.230	-0.467	-0.010	-0.134	3.423	-0.008	1.245	0.017
	(0.000)	(0.012)	(0.306)	(0.005)	(0.000)	(0.487)	(0.000)	(0.463)
From bonds to equities	-0.147	0.695	0.063	-0.002	-2.326	0.220	0.095	-0.189
	(0.317)	(0.000)	(0.004)	(0.488)	(0.004)	(0.188)	(0.243)	(0.079)
From bonds to IP	0.486	-0.075	0.073	-0.053	-1.485	0.398	-0.016	-0.258
	(0.019)	(0.274)	(0.000)	(0.056)	(0.004)	(0.034)	(0.420)	(0.003)
From IP to equities	1.167	-0.256	0.002	0.009	-0.321	-0.159	0.721	-0.158
	(0.000)	(0.004)	(0.420)	(0.361)	(0.215)	(0.120)	(0.000)	(0.202)
From IP to bonds	0.709	-0.130	0.003	0.000	-0.112	-0.186	0.538	-0.138
	(0.000)	(0.028)	(0.379)	(0.496)	(0.363)	(0.069)	(0.000)	(0.179)
ii) CF								
From equities to bonds	-1.068	0.078	0.089	-0.052	-1.455	-0.237	0.286	-0.517
	(0.001)	(0.320)	(0.000)	(0.094)	(0.007)	(0.203)	(0.007)	(0.000)
From equities to IP	-0.356	0.222	0.018	-0.044	-0.258	-0.286	0.325	-0.387
	(0.077)	(0.093)	(0.129)	(0.135)	(0.350)	(0.081)	(0.002)	(0.001)
From bonds to equities	-4.688	1.484	0.028	0.119	-3.301	-1.649	-1.465	-0.074
	(0.000)	(0.000)	(0.189)	(0.057)	(0.003)	(0.000)	(0.000)	(0.395)
From bonds to IP	-0.028	-0.087	0.023	-0.052	-1.738	0.248	0.105	0.006
	(0.412)	(0.162)	(0.003)	(0.009)	(0.000)	(0.023)	(0.039)	(0.468)
From IP to equities	1.766	-0.143	0.022	0.017	-1.045	-0.217	1.274	-0.395
	(0.000)	(0.174)	(0.098)	(0.329)	(0.045)	(0.145)	(0.000)	(0.048)
From IP to bonds	1.364	-0.020	0.006	-0.001	-0.720	0.050	0.764	-0.443
	(0.000)	(0.421)	(0.325)	(0.491)	(0.060)	(0.371)	(0.000)	(0.011)
iii) MF minus CF								
From equities to bonds	1.045	-0.509	-0.042	-0.016	3.416	-0.149	0.752	0.248
	(0.000)	(0.000)	(0.007)	(0.313)	(0.000)	(0.217)	(0.000)	(0.013)
From equities to IP	2.586	-0.688	-0.027	-0.090	3.680	0.277	0.920	0.404
	(0.000)	(0.001)	(0.088)	(0.040)	(0.000)	(0.191)	(0.000)	(0.014)
From bonds to equities	4.540	-0.789	0.036	-0.121	0.975	1.870	1.561	-0.115
	(0.000)	(0.017)	(0.205)	(0.095)	(0.227)	(0.000)	(0.000)	(0.369)
From bonds to IP	0.514	0.012	0.050	-0.001	0.254	0.150	-0.121	-0.264
	(0.002)	(0.450)	(0.000)	(0.477)	(0.254)	(0.169)	(0.012)	(0.000)
From IP to equities	-0.599	-0.113	-0.020	-0.008	0.724	0.058	-0.553	0.237
	(0.015)	(0.116)	(0.023)	(0.361)	(0.018)	(0.323)	(0.000)	(0.018)
From IP to bonds	-0.655	-0.110	-0.003	0.000	0.608	-0.236	-0.226	0.305
	(0.000)	(0.024)	(0.363)	(0.488)	(0.011)	(0.002)	(0.000)	(0.000)

Table reports estimated coefficients (without parentheses) and corresponding t-statistics (with parentheses) obtained from OLS regressions of macro-financial spillover values on a constant and the complete set of macroeconomic and financial explanatory factors. Results are obtained for the crisis and post-crisis sample period of 2007:01 to 2015:09. Panel A reports results for the total spillover index and Panel B for the pairwise spillover measures. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF).

Table 8: Static spillover indexes between the financial and real economy series

Panel A: Financial variables entering as log return volatilities

	MF				**CF**			
	S&P500	10yr TN	IP	From others	S&P500	10yr TN	IP	From others
S&P500	90.20	7.19	2.61	9.80	91.55	7.31	1.14	8.45
10yr TN	10.52	84.35	5.13	15.65	6.13	90.23	3.63	9.77
IP	1.24	1.37	97.39	2.61	2.71	2.93	94.36	5.64
To others	11.76	8.56	7.74	**Total:**	8.84	10.24	4.77	**Total:**
Net	1.96	-7.09	5.13	**9.35**	0.39	0.48	-0.87	**7.95**

Panel B: Financial variables entering as returns

	MF				**CF**			
	S&P500	10yr TN	IP	From others	S&P500	10yr TN	IP	From others
S&P500	94.57	2.73	2.69	5.43	96.69	1.70	1.61	3.31
10yr TN	3.20	94.45	2.35	5.55	3.40	95.40	1.20	4.60
IP	1.34	1.50	97.16	2.84	0.84	4.52	94.64	5.36
To others	4.54	4.24	5.05	**Total:**	4.24	6.21	2.81	**Total:**
Net	-0.89	-1.32	2.21	**4.61**	0.93	1.62	-2.55	**4.42**

Table reports static spillover measure estimates for financial and real economy series over the full sample period of 1975:01 to 2015:09, with a forecast horizon of 6 months. The upper left 3 by 3 sub-arrays in each case are the (directional) pairwise connectedness between each pair of variables, with the ij-th element corresponding to the estimated contribution from innovations in variable j to the forecast error variance of variable i. The off-diagonal column and row sums of these elements give the 'from others' and 'to others' values, which correspond to the 'to' and 'from' directional connectedness measures previously defined in equations (2.6) and (2.6) respectively. The final table rows labelled 'net' are the relevant 'to others' value minus the 'from others' value, corresponding to the measure in equation (2.7). The single bolded value in the lower right of each sub-table is the value of the total connectedness index, as defined in equation (2.5).

Table 9: Summary details of mixed-frequency and common-frequency spillover measures for return levels

Panel A: summary statistics

	To all others		**From all others**		**Net**	
	MF	CF	MF	CF	MF	CF
Mean						
S&P500	12.530	5.934	8.687	5.919	3.843	0.015
10yr TN	11.470	4.829	8.837	6.209	2.633	-1.380
IP	2.597	3.317	9.073	1.951	-6.476	1.365
Std. Dev.						
S&P500	2.408	2.113	2.101	3.765	2.057	3.412
10yr TN	1.874	2.133	2.055	2.013	1.810	2.236
IP	1.910	4.290	2.111	0.957	2.323	4.199
Minimum						
S&P500	6.895	0.909	3.806	0.407	-1.223	-11.241
10yr TN	6.626	0.420	5.241	1.774	-4.312	-6.935
IP	0.702	0.044	4.308	0.200	-17.122	-2.880
Maximum						
S&P500	24.295	10.158	13.259	15.269	14.984	8.118
10yr TN	15.773	9.440	13.704	9.825	6.078	3.441
IP	10.200	16.076	18.983	4.313	2.715	14.109

Panel B: differences and ratios

	To all others		**From all others**		**Net**	
	MF - CF	MF/CF	MF - CF	MF/CF	MF - CF	MF/CF
S&P500	6.596	2.775	2.768	2.360	3.828	25.043
10yr TN	6.641	3.130	2.628	1.622	4.013	-6.291
IP	-0.719	1.717	7.122	6.271	-7.841	-4.489

The table presents summary statistics for the mixed frequency and common frequency spillover indexes for the sample period 1975:01 to 2015:09. Return levels are used for financial variables. Panel A reports the mean, standard deviation, minimum and maximum spillover measures. Panel B reports the differences and ratios between the spillover indexes. Differences (denoted by MF - CF) are computed by subtracting the dynamic common-frequency spillover measure from its mixed-frequency analogue and then taking the sample average and the ratios (denoted by MF/CF) are computed similarly by dividing the mixed-frequency measure by its common-frequency analogue and then taking the mean over the sample period.

Table 10: Explanatory power of individual factors for macro-financial spillover indexes

	TED spr.	Term spr.	VIX	USDX ret.	Sentiment	Inflation	Unemp.	IP growth
Panel A: Spillovers to all others								
i) MF								
Equities	0.003	0.000	0.091	0.011	0.117	0.001	0.155	0.026
Bonds	0.011	0.129	0.343	0.001	0.000	0.024	0.144	0.066
IP	0.010	0.135	0.163	0.000	0.098	0.022	0.562	0.044
ii) CF								
Equities	0.022	0.210	0.033	0.003	0.157	0.012	0.577	0.047
Bonds	0.098	0.211	0.009	0.000	0.016	0.016	0.259	0.015
IP	0.012	0.111	0.165	0.004	0.088	0.024	0.521	0.043
iii) MF minus CF								
Equities	0.051	0.280	0.012	0.002	0.008	0.007	0.194	0.006
Bonds	0.164	0.020	0.180	0.001	0.018	0.000	0.030	0.012
IP	0.012	0.069	0.129	0.010	0.060	0.021	0.371	0.032
Panel B: Spillovers from all others								
i) MF								
Equities	0.023	0.101	0.310	0.001	0.095	0.028	0.450	0.036
Bonds	0.000	0.050	0.189	0.001	0.105	0.012	0.378	0.047
IP	0.014	0.010	0.093	0.022	0.002	0.002	0.013	0.055
ii) CF								
Equities	0.033	0.285	0.024	0.003	0.100	0.027	0.597	0.017
Bonds	0.000	0.147	0.127	0.000	0.109	0.017	0.559	0.079
IP	0.031	0.084	0.054	0.001	0.012	0.008	0.155	0.019
iii) MF minus CF								
Equities	0.154	0.208	0.084	0.002	0.026	0.006	0.218	0.000
Bonds	0.000	0.145	0.013	0.000	0.035	0.008	0.307	0.050
IP	0.072	0.015	0.021	0.019	0.017	0.001	0.036	0.021
Panel C: Net spillovers to all others								
i) MF								
Equities	0.007	0.099	0.049	0.018	0.003	0.014	0.056	0.000
Bonds	0.019	0.038	0.062	0.000	0.103	0.005	0.025	0.007
IP	0.002	0.032	0.000	0.025	0.075	0.005	0.205	0.005
ii) CF								
Equities	0.014	0.103	0.001	0.028	0.001	0.019	0.118	0.002
Bonds	0.105	0.001	0.103	0.002	0.068	0.000	0.123	0.042
IP	0.047	0.047	0.108	0.008	0.074	0.016	0.353	0.024
iii) MF minus CF								
Equities	0.052	0.003	0.056	0.000	0.010	0.000	0.005	0.005
Bonds	0.157	0.014	0.227	0.001	0.000	0.005	0.041	0.063
IP	0.093	0.011	0.161	0.001	0.007	0.009	0.104	0.066

Table reports the explanatory power of the factors, estimated by regressing the relevant spillover measure on a constant and a single one of the financial or macroeconomic explanatory factors using simple OLS. Values reported are standard (non-adjusted) R-squared values obtained from each regression. Panels A, B and C report results spillovers transmitted to all others, received from all others and net to all others respectively. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF). Regressions are estimated for the adjusted sample period of 1990:01 to 2015:09.

Table 11: Explanatory power of subsets of factors for spillover indexes

	Full sample			Subsample 1: 1990-2006			Subsample 2: 2007-2015		
	All variables	Financial only	Macro only	All variables	Financial only	Macro only	All variables	Financial only	Macro only
Panel A: Spillovers to all others									
i) MF									
Equities	0.400	0.223	0.173	0.228	0.222	0.073	0.678	0.247	0.375
Bonds	0.541	0.484	0.222	0.487	0.422	0.063	0.675	0.666	0.436
IP	0.755	0.321	0.618	0.366	0.124	0.266	0.783	0.564	0.640
ii) CF									
Equities	0.637	0.311	0.627	0.345	0.159	0.312	0.717	0.655	0.667
Bonds	0.358	0.272	0.279	0.504	0.297	0.296	0.632	0.412	0.101
IP	0.724	0.301	0.578	0.307	0.299	-0.012	0.876	0.694	0.736
iii) MF minus CF									
Equities	0.331	0.291	0.197	0.530	0.388	0.456	0.604	0.233	0.033
Bonds	0.252	0.248	0.033	0.250	0.166	0.184	0.621	0.458	0.167
IP	0.534	0.218	0.414	0.320	0.228	0.089	0.878	0.746	0.738
Panel B: Spillovers from all others									
i) MF									
Equities	0.750	0.435	0.504	0.549	0.421	-0.009	0.861	0.800	0.714
Bonds	0.601	0.322	0.426	0.193	0.122	0.044	0.775	0.474	0.676
IP	0.150	0.124	0.060	0.244	0.215	0.040	0.660	0.466	0.239
ii) CF									
Equities	0.633	0.336	0.633	0.654	0.358	0.517	0.678	0.627	0.461
Bonds	0.715	0.305	0.643	0.281	0.088	0.183	0.837	0.734	0.761
IP	0.237	0.176	0.173	0.107	0.099	0.012	0.561	0.532	0.528
iii) MF minus CF									
Equities	0.383	0.312	0.217	0.650	0.518	0.553	0.414	0.245	0.047
Bonds	0.379	0.160	0.355	0.263	0.203	0.130	0.679	0.518	0.318
IP	0.104	0.099	0.049	0.086	0.086	0.005	0.577	0.468	0.056
Panel C: Net spillovers to all others									
i) MF									
Equities	0.190	0.183	0.061	0.379	0.330	0.046	0.526	0.321	0.040
Bonds	0.324	0.265	0.028	0.389	0.381	0.029	0.384	0.149	0.034
IP	0.266	0.103	0.207	0.268	0.207	0.042	0.320	0.320	0.145
ii) CF									
Equities	0.172	0.124	0.131	0.480	0.443	0.078	0.319	0.200	0.077
Bonds	0.426	0.204	0.156	0.505	0.455	0.144	0.696	0.395	0.308
IP	0.570	0.213	0.383	0.201	0.157	0.020	0.555	0.393	0.370
iii) MF minus CF									
Equities	0.091	0.089	0.000	0.105	0.067	0.015	0.287	0.198	0.110
Bonds	0.361	0.303	0.098	0.139	0.130	0.010	0.638	0.548	0.279
IP	0.345	0.196	0.168	0.209	0.189	0.021	0.694	0.490	0.235

Table reports the explanatory power of the factors, estimated by regressing the relevant spillover measure on either all factors (macroeconomic and financial), only financial factors (TED spread, term spread, VIX, USDX return and investor sentiment), or only macro factors (inflation, unemployment and industrial production growth) using simple OLS. Values reported are adjusted R-squared values obtained from each regression. Panels A, B and C report results spillovers transmitted to all others, received from all others and net to all others respectively. In each panel we report regression results for the mixed-frequency (MF) and common-frequency (CF) approaches, in addition to the difference between the two (MF minus CF). Regressions are estimated for the complete adjusted sample period of 1990:01 to 2015:09, 1990:01 to 2006:12 (subsample 1) and 2007:01:2015:09 (subsample 2).