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Aviral Kumar Tiwari

Montpellier Business School

Christophe André

Organisation for Economic Co-operation and Development

Rangan Gupta

University of Pretoria

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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Spillovers between US Real Estate and Financial Assets in Time and Frequency Domains[#]

Aviral Kumar Tiwari^{*}, Christophe André^{**} and Rangan Gupta^{***}

Abstract

Real estate, either in physical or securitised form, provides valuable diversification opportunities to investors. However, spillovers reduce the benefits of portfolio diversification, especially in times of crisis, when asset returns tend to be more correlated. This paper assesses the strength and time variation of spillovers between returns on residential real estate, real estate investment trusts (REITs), stocks and bonds in the United States, using the Diebold-Yilmaz (DY) (2012) approach in the time domain and the Baruník-Křehlík (BK) (2018) methodology in the frequency domain. On average, spillovers between housing, stock and bond returns are relatively modest and shocks to stock and bond markets affect housing returns more than the other way round, even though net spillovers from housing to other assets spiked in the aftermath of the subprime crisis. Spillovers in both directions are much stronger between REITs and stocks than between REITs and housing. The analysis in the frequency domain highlights the persistence of effects from shocks originating in the housing market, particularly in the aftermath of the subprime crisis.

Keywords: Real estate, Stocks, Bonds, Spillovers, Portfolio management

JEL classification: C32, G10, G11, R30

1. Introduction

Understanding the interconnections between different markets is crucial for investors in both real and financial assets. Markets with relatively low interconnections offer opportunities for diversification and reducing the sensitivity of portfolios to spikes in the returns of specific assets. Importantly, recent crises and in particular the global financial crisis (GFC) sparked by the subprime mortgage market meltdown in 2007, have shown that correlations between asset returns vary over time and can increase spectacularly during exceptionally severe financial crises (IMF, 2015; Adrian and Brunnermeier, 2016). Hence, being able to assess the strength of spillovers between different types of assets and their variation over time is essential. In this paper, we analyse the spillovers between returns on residential real estate, real estate investment trusts (REITs), stocks and bonds in the United States.

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

^{*} Montpellier Business School, 2300, Avenue des Moulins, 34185, Montpellier Cedex 4 0002, France. Email: a.tiwari@montpellier-bs.com.

^{**} Corresponding author. Economics Department, Organisation for Economic Co-operation and Development (OECD), 75775 Paris, Cedex 16, France. Email: christophe.andre@oecd.org.

^{***} Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.

An appealing methodology for studying spillovers has been developed by Diebold and Yilmaz (DY) (2012). Based on a generalized VAR framework (Koop, Pesaran, and Potter, 1996; Pesaran and Shin, 1998), it provides a forecast error variance decomposition invariant to the ordering of the variables, from which a spillover index is derived. In this approach, shocks are not orthogonalized, but the historical co-variance structure of the variables is used to account for correlations between shocks. This removes the need for theoretical restrictions on the parameters of the model, which is particularly convenient in the investigation of financial markets dynamics, where establishing structural relations is challenging. The VAR structure allows capturing spillovers occurring at different speeds across variables.

The methodology has been used extensively since Diebold and Yilmaz's (2012) seminal paper, which looked at volatility spillovers between US stocks, bonds, foreign exchange and commodities daily returns. Most relevant in the context of this paper, the methodology has been applied to spillovers between housing prices and macroeconomic variables and between real estate and financial asset returns. Antonakakis et al. (2016) investigate dynamic spillovers between stocks, housing, uncertainty and the macroeconomy in the United States from 1987M1 to 2014M11. They find that various types of shocks contribute significantly to economic fluctuations, that spillovers vary widely over time and that in the wake of the GFC, spillovers have been exceptionally high. Antonakakis and Floros (2016) find similar results for the United Kingdom over the period 1997M1-2015M2.

Tsai (2015a) studies dynamic spillovers between US housing and stock market returns using monthly data covering the period 1991M1-2014M8. He finds that over the whole sample spillovers account for a mere 3.4% of the variance of the system, although some spikes reach nearly 10% when a rolling window is used. Net spillovers from housing to stock returns are positive over most of the estimation period. They only turn negative at the time the dot-com bubble bursts in 2000-01, when Lehman Brothers' collapses in 2008 and in 2013-14. There is some evidence that quantitative easing in the aftermath of the GFC contributes to explaining the net influence of stock returns on the housing market in 2013-14, a period which does not correspond to a stock market collapse, contrary to the other episodes of net spillover from stocks to housing. Net spillovers vary widely over time and peak in early 2009, at a level about three times higher than previous peaks.

Chiang et al. (2017) estimate spillovers between US equity and mortgage REITs, stocks and bonds, using monthly data covering the period 1972M1-2014M9. Commercial real estate (CRE) returns are added on a shorter period (1998M2-2014M9). The authors find that spillovers account for nearly a third of the variance of the system in the whole sample and about 28% in the sample including CRE. Equity REITs and stocks are found to be net transmitters of shocks to other assets. Bonds and CRE returns appear relatively insulated from spillovers from other assets. The direction and intensity of net spillovers varies substantially over time. The authors subsequently incorporate the estimated spillovers into the Fama-French (2015) five factor asset pricing model and find that net spillovers impact REIT returns negatively, but bond returns positively. CRE returns are found not to be affected by spillovers from other markets.

Damianov and Elsayed (2018) analyse spillovers between housing, mortgage and equity REIT and stock market returns using monthly data covering the period 1975-2016. They find that spillovers account for about 30% of the system's forecast error variance and that the housing market is a net receiver of spillovers, while other markets are net transmitters of spillovers over the whole sample, albeit with substantial variation over time. The housing market generally becomes a net transmitter of spillovers during recessions and housing busts, although not during the subprime crisis.

A number of studies investigate spillovers between housing returns within countries. Zheng and Osmer (2019) analyse spillovers between housing returns (derived from the S&P/Case-Shiller Home Price Index) across 19 US Metropolitan areas using monthly data covering the period 1991-2014. They find that spillovers account for more than two-thirds of the system's forecast error variance. Adding the S&P500 stock market returns to the system only affects the results marginally, as spillovers between stock and housing market returns are found to be relatively limited, as in Tsai (2015a). Spillovers between metropolitan markets have been on a rising trend since the early 2000s, accounting for over 80% of the forecast error variance towards then end of the sample.

Tsai (2015b) estimates spillovers between ten UK regional housing markets and the national market, using monthly data from 1995 to 2011. Ten VAR models are estimated, each of them including housing returns in one region and at the national level. The spillover index ranges from 24% to 45% across regions. Spillovers vary over time and peak during the GFC. Other interesting findings include a relatively weak connection between the London and the national housing market, a leading role of the South East region and an asymmetry in spillovers between the Northern regions and the national market over the cycle. Specifically, Northern markets disconnected from the national market in the recovery following the GFC, suggesting that financial crises may lead to divergence between regional housing prices. Antonakakis et al. (2018) examine housing return spillovers between 13 UK regions over the period 1973Q4-2014Q4. They find strong spillovers, accounting for nearly 84% of the forecast error variance of UK regional housing returns. Spillovers vary over time and are particularly strong in the early 1990s and in the wake of the GFC. The strongest net spillovers originate from the South West and the Outer South East, with the North, Yorkshire & Humberside and Scotland as the main receivers. Net spillovers from Northern Ireland were also sizeable following the GFC. The influence of London on other regional markets varies over time and housing returns in the capital are also affected by spillovers from other regions.

Lee and Lee (2016) and Hwang and Sue (2018) examine spillovers between monthly regional housing market returns in Korea, over respectively 1986-2014 and 2003-2017. They find relatively similar results, with spillovers accounting for about two-thirds of the system's forecast error variance over the full samples and Seoul having the strongest influence on other markets. The second study also investigates spillovers between Seoul districts, among which spillovers explain more than 90% of the forecast error variance. Spillovers are found to vary significantly over time, whether measured using a rolling window as in the first paper or a time-varying parameter VAR (TVP-VAR) as in the second.

Other studies estimate connectedness between property-related returns between countries. Liow (2013) examines spillovers between seven European real estate securities markets (France, Germany, Italy, Netherlands, Sweden, Switzerland and United Kingdom) using daily data from 1990 to 2011. Spillovers account for nearly half of the system's forecast error variance and increase both around the period of the introduction of the euro (1999-2002) and around the GFC. Liow and Schindler (2017) study spillovers between 16 European office markets between 2003 and 2013 using quarterly data. The office markets are strongly interconnected, with spillovers accounting for more than 75% of the system's forecast error variance and London the main source of net spillovers to other markets. Liow (2014) investigates spillovers between public property markets (securitised real estate) in "Greater China" (Mainland China, Hong Kong and Taiwan), three Asian emerging markets (Malaysia, the Philippines and Thailand) and two advanced economies (Japan and the United States) from 1999 to 2013, using weekly data. The total spillover index is close to 40% over the whole sample, but exceeds 70% during the GFC (July 2007 to December 2009). China is the main net volatility transmitter, while the United States is the main receiver. The three "Greater China" markets are mostly net volatility transmitters to the emerging and advanced economies. However, spillovers are bi-directional, time varying and state dependent, and the "Greater China" markets have become more influenced by other markets during the GFC.

Lee and Lee (2018) find that spillovers account for only about 10% of the forecast error variance of G7 countries real housing quarterly returns over the period 1970-2014. However, spillovers vary over time and account for about 40% of the system's forecast error variance around the GFC, with strong net spillovers from the United States. Italy also generates strong spillovers to other countries during the European sovereign debt crisis in 2011-12.

Liow et al. (2018) estimate volatility spillovers between weekly returns on stocks, securitized real estate, bonds and foreign exchange in six advanced economies (G7 excluding Italy) and China from February 1997 to August 2015. Spillovers account for 72% of the system's forecast error variance, with substantial variation over time and in particular peaks during the GFC and the European sovereign debt crisis in 2011-12. The United States is the main transmitter of volatility, while Canada and Japan are the main receivers. China moves from mostly a net receiver before 2008 to mostly a net transmitter afterwards. The authors also study spillovers between economic policy uncertainty (EPU) indices across countries and find that spillovers account for nearly half of the system's forecast error variance, with the United States the main source of net spillovers. EPU spillovers tend to lead financial market risk spillovers and seem to affect securitized real estate spillovers less than stock market spillovers.

Liow and Newell (2016) estimate real estate global beta spillovers over the period 1995-2015, based on weekly overall stock and real estate stock indices from 16 countries covering an Asian (advanced and emerging) and a non-Asian group (United and European countries). Spillovers account for nearly three-fourths of the system's forecast error variance over the whole sample and more than 82% during the GFC (August 2007-November 2011). The Netherlands, France and Germany are the largest net transmitters of shocks, while Hong Kong, Italy and Japan are

the main receivers over the full sample. Spillovers vary over time and in particular increase during the Asian financial crisis (AFC) in 1997-98 and during the GFC and the subsequent European sovereign debt crisis (EDC). Beta spillovers spike in the Asian group during the AFC, while spillovers to the non-Asian group during this episode are limited. During the GFC/EDC, spillovers are high in both groups, pointing to stronger global integration of securitized real estate markets.

Baruník-Křehlík (BK) (2018) propose a methodology to analyse connectedness in the frequency domain, mirroring the Diebold and Yilmaz (2012) approach in the time domain. It allows decomposing spillovers by frequency, and hence assessing the persistence of spillover effects. This is particularly relevant when analysing a set of variables exhibiting different degrees of persistence, as housing and stock market returns. Baruník and Křehlík's (2018) seminal paper studies daily stock price volatility connectedness between 11 major US financial institutions from 2000 to 2016. Total connectedness measured using a one-year window varies from 55% to 85% over the sample period, with spikes in the aftermath of the dot-com bubble burst (2001-03), during the GFC (2007-10) and at the climax of the euro crisis (2012). Interestingly, the frequency decomposition shows that spikes are driven by low-frequency components (over a month). Hence, the volatility spillovers generated during major crises are more persistent than those generated during more normal times. Tiwari et al. (2018) estimate spillovers between global stocks, sovereign bonds, credit default swaps (CDS) and foreign exchange on daily data from September 2009 to September 2016, using both the DY and the BK methodologies. They find weak spillovers, accounting for only about 5% of the variance of the system's forecast error variance, with stocks and CDS being net transmitters of volatility, while bonds and foreign exchange are net receivers. The BK estimates shows that spillovers are stronger at higher frequencies. We are not aware of any paper applying the BK methodology to real estate price spillovers.

Our paper contributes to the literature in two ways. First, it provides an analysis of spillovers between returns on residential real estate, real estate investment trusts (REITs), stocks and bonds in the United States since the mid-1980s, using the Diebold-Yilmaz (2012) approach in the time domain. This complements the studies mentioned above, by covering a different set of asset and time period. Second, we perform an analysis of spillovers in the frequency domain, applying the recent Baruník-Křehlík (2018) methodology. This brings further insights on the time horizons at which different spillovers play. In particular, we show that while spillovers between stocks and REITs are strongest at a frequency corresponding to one to four months, the impact of shocks originating in the housing market is mainly observed at frequencies corresponding to over a year. This result is consistent with the well-documented inertia in housing prices and protracted effect of housing crises on the economy.

More precisely, our main findings are: i) over the period 1985M1-2019M3, spillovers account for nearly a fifth of the forecast error variance within a system comprising returns on residential real estate, real estate investment trusts (REITs), stocks and bonds in the United States; ii) the greatest part results from spillovers between stocks and REITs, of similar magnitude in both directions; iii) connectedness between housing and financial asset (including REITs) returns is

limited, suggesting hedging opportunities from investment in physical real estate; iv) spillovers vary greatly in direction and magnitude over time, with spillovers from housing spiking during the GFC; v) the analysis in the frequency domain shows that spillovers between housing and other asset returns are more persistent than spillovers between financial assets.

The remainder of the paper is organized as follows: Section 2 presents the data and methodology, while Section 3 discusses the results, with Section 4 concluding the paper.

2. Methodology and Data

This section is divided into three parts. The first discusses the time-domain spillover approach of Diebold and Yilmaz (2012), the second describes the frequency domain spillover approach of Baruník and Křehlík (2018) and the third presents the data.

2.1. The Diebold and Yilmaz (DY) spillover index approach

The DY methodological framework is based on a generalized vector autoregressive process in which a forecast error variance decomposition (FEVD) is utilized to estimate the magnitude of connectedness between variables in the time domain. The starting point of the DY approach is a VAR process from which a forecast error variance decomposition is computed. Thus, we describe the n -variate process $x_t = (x_{t,1}, \dots, x_{t,n})$ by the structural VAR(p) at $t = 1, \dots, T$ as:

$$x_t = \Phi(L)x_t + \epsilon_t, \quad (1)$$

where x_t represents a vector of $n \times 1$ endogenous variables, $\Phi(L) = \sum_h \Phi_h L^h$ is a $n \times n$ p -th order lag-polynomial and ϵ_t is a white noise with a possibly non-diagonal covariance matrix Σ . Assuming covariance stationarity, the VAR process has the following MA (∞) representation:

$$x_t = \Psi(L)\epsilon_t = \sum_{i=1}^{\infty} \Psi_i \epsilon_{t-i} + \epsilon_t, \quad (2)$$

where $\Psi(L)$ is a $n \times n$ infinite lag polynomial matrix of coefficients that can be calculated recursively. Pesaran and Shin (1998) show that the generalized forecast error variance decomposition (GFEVD) of a variable can be computed from components attributable to shocks to the different variables in the system for a given forecast horizon H as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^H ((\Psi_h \Sigma)_{ij})^2}{\sum_{h=0}^H (\Psi_h \Sigma \Psi_h')_{ii}}, \quad (3)$$

where Ψ_h is a $n \times n$ matrix of coefficients corresponding to lag h , and $\sigma_{jj} = (\Sigma)_{jj}$, with $\theta_{ij}(H)$ denoting the contribution of the j^{th} variable of the system to the variance of the forecast error of variable i at the forecast horizon H . Given that own- and cross-variable variance contributions do not necessarily add up to one, we standardize the effect attributable to each variable as

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^n \theta_{ij}(H)}, \quad (4)$$

where $\sum_{j=1}^n \theta_{ij}(H) = 1$ and $\sum_{i,j=1}^n \theta_{ij}(H) = N$

$\tilde{\theta}_{ij}(H)$ provide estimates of the pairwise connectedness from j^{th} variable to i^{th} variable at horizon H in the time domain.

2.2. The Barunik and Křehlík (BK) frequency-domain approach

The BK approach proposes an analysis of connectedness in the frequency domain mirroring the DY approach in the time domain. Following the idea of Dew-Becker and Giglio (2016), BK propose a frequency response function that can be obtained as the Fourier transform of the coefficients Ψ_h , with $i = \sqrt{-1}$ and defined as:

$$\Psi(e^{-ih\omega}) = \sum_{h=0}^{\infty} e^{-ih\omega} \Psi_h, \quad (5)$$

where ω denotes the frequency. The associated power spectrum, $S_X(\omega)$, shows the distribution of X_t over the frequency components ω , and is expressed as:

$$S_X(\omega) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ih\omega} = \Psi(e^{-ih\omega}) \Sigma \Psi(e^{-ih\omega}) \quad (6)$$

BK show that the general variance decompositions in the frequency domain can be derived using the frequency response functions from the spectral representation. Essentially, the generalized forecast error variance decompositions at a particular frequency ω is computed using the expression:

$$(\Theta(\omega))_{ij} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-ih\omega}) \Sigma)^2_{ij}}{\sum_{h=0}^{\infty} (\Psi(e^{-ih\omega}) \Sigma \Psi(e^{-ih\omega}))_{it}}, \quad (7)$$

where $(\Theta(\omega))_{ij}$ is the portion of the spectrum of the i^{th} variable at a given frequency ω that can be attributed to shocks in the j^{th} variable. It is worth noting that the forecast horizon H plays no role in the expression above.

Normalizing the frequency domain analysis, we obtain:

$$(\tilde{\Theta}(\omega))_{ij} = \frac{(\Theta(\omega))_{ij}}{\sum_{j=1}^n (\Theta(\omega))_{ij}}, \quad (8)$$

$$\text{where } \sum_{j=1}^n (\tilde{\Theta}(\omega))_{ij} = 1 \text{ and } \sum_{i,j=1}^n (\tilde{\Theta}(\omega))_{ij} = N \quad (7)$$

Hence, $(\tilde{\Theta}(\omega))_{ij}$ measures pairwise connectedness from j to i at a given frequency ω and thus can be interpreted as a within-frequency causality indicator. Conversely, $\tilde{\theta}_{ij}(H)$ indicates the pairwise connectedness from j to i at a particular horizon H, so it is an indicator of the strength of causality in the time domain. When DY quantify the connectedness relationships

using $\tilde{\theta}_{ij}(H)$, they focus on the information aggregated through frequencies, ignoring possible heterogeneous frequency responses to shocks.

In economic and financial analysis, it is important to assess the short, medium, or long-term connectedness, as focusing on causal interactions at a single frequency would ignore market adjustments occurring at various horizons. Frequency bands are introduced to account for this feature in the analysis of connectedness. The cumulative connectedness in a random frequency band $c = (a, b)$ is obtained as:

$$(\tilde{\theta}_c)_{ij} = \int_a^b (\tilde{\theta}(\omega))_{ij} c\omega, \quad (9)$$

and allows us to define a variety of connectedness measures in the frequency domain. The overall connectedness within the frequency band c is then obtained as

$$D^c = \frac{\sum_{i=1, i \neq j}^n (\tilde{\theta}_c)_{ij}}{\sum_{ij} (\tilde{\theta}_c)_{ij}} = 1 - \frac{\sum_{i=1}^n (\tilde{\theta}_c)_{ii}}{\sum_{ij} (\tilde{\theta}_c)_{ij}}. \quad (10)$$

The last phase of our analysis identifies the direction of spillovers using the BK framework. In the frequency band c , the contribution to the variance of the forecast error of variable i from all other variables ($i \neq j$) is called *Within From* connectedness and is computed as:

$$D_{i,From}^c = \sum_{j=1, i \neq j}^n (\tilde{\theta}_c)_{i,j}. \quad (11)$$

In a similar vein, the contribution of variables i to the forecast error variances of all other variables is called *Within To* connectedness which in the frequency band c is computed as:

$$D_{i,To}^c = \sum_{j=1, i \neq j}^n (\tilde{\theta}_c)_{j,i}. \quad (12)$$

Having described the expressions for connectedness measures in both directions, one can compute the net connectedness in frequency band c as $D_{i,Net}^c = D_{i,To}^c - D_{j,From}^c$, where a positive value of $D_{i,Net}^c$ indicates that variable i transmits more information than it receives from all other variables in the system. The net pairwise connectedness between i and j can be calculated as:

$$D_{ij}^c = (\tilde{\theta}_c)_{j,i} - (\tilde{\theta}_c)_{i,j}. \quad (13)$$

Finally, BK show that the contribution of the frequency band c to the entire system connectedness can be obtained using:

$$\tilde{D}^c = D^c \cdot \Gamma(c), \quad (14)$$

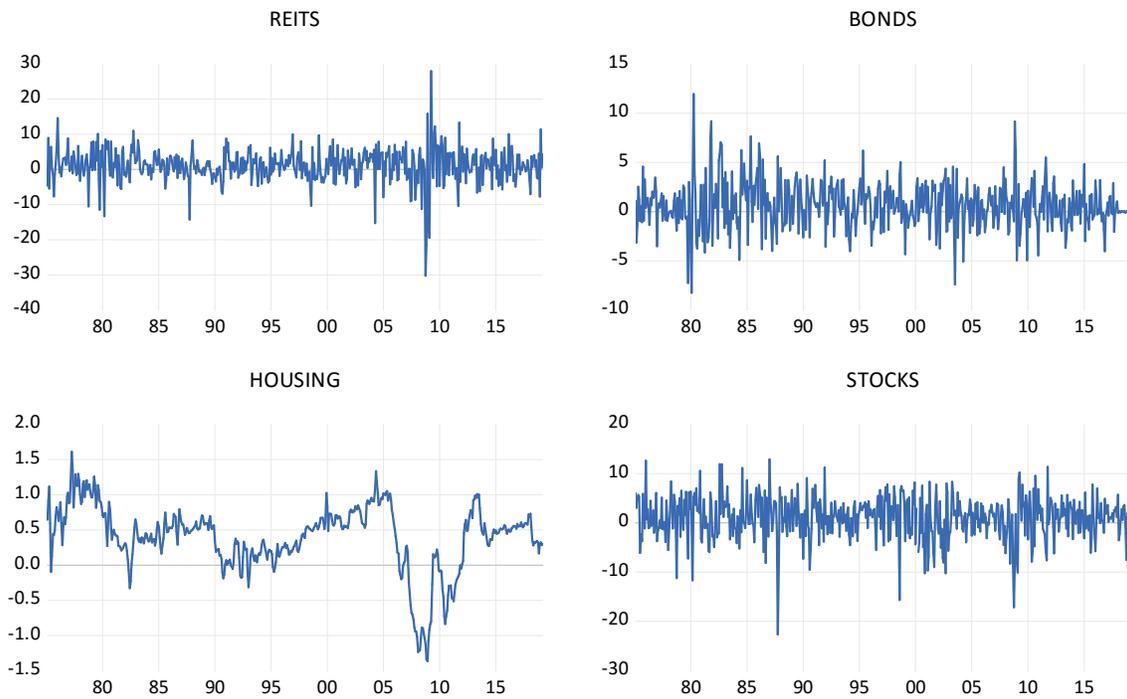
where $\Gamma(c)$ is the spectral weight, defined as $\sum_{i,j=1}^n \frac{(\tilde{\theta}_c)_{ij}}{\sum_{i,j=1}^n (\tilde{\theta})_{ij}} = \frac{\sum_{i,j=1}^n (\tilde{\theta}_c)_{ij}}{n}$, which represents the contribution of the frequency band c to the entire system connectedness. They

also note that the sum of all frequency connectedness measures over disjointed intervals is equal to the original total connectedness measure proposed by DY.

2.3. Data

We use monthly data covering the period 1975M2 to 2019M3. Returns are log-differences of the following series: Freddie Mac house price index (FMHPI)¹, value-weighted Center for Research in Security Prices (CRSP) index², 10-year government bond total return index from Global Financial Database³, and FTSE Nareit U.S. Real Estate Index Series for all REITs⁴. Figure 1 charts the returns (log-differences) of the four series under consideration, while Table 1 displays descriptive statistics. We observe that REIT returns have the highest mean (nearly equal to the mean of stock returns), and highest volatility, while the housing market has the lowest returns on average, as well as the lowest standard deviation. All returns are strongly non-normal, as shown by the overwhelming rejection of the null of normality under the Jarque-Bera test.

Figure 1. Monthly returns (%)



Source: FTSE Nareit, Global Financial Database, Freddie Mac and Center for Research in Security Prices.

¹ Available at: <http://www.freddiemac.com/research/indices/house-price-index.page>.

² Available from website of Professor Kenneth R. French at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

³ Available at: <http://www.globalfinancialdata.com/>.

⁴ Available at: <https://www.reit.com/data-research/reit-indexes/real-time-index-returns/fnar-ftx>.

Table 1. Summary Statistics

Statistic	Monthly returns (Log-differences)			
	REITs	Bonds	Housing	Stocks
Mean	1.03	0.60	0.39	1.03
Median	1.14	0.46	0.48	1.37
Maximum	27.97	11.94	1.61	12.89
Minimum	-30.23	-8.24	-1.37	-22.64
Std. Dev.	4.73	2.35	0.47	4.37
Skewness	-0.74	0.28	-1.08	-0.69
Kurtosis	10.11	4.99	5.05	5.23
Jarque-Bera	1164.12	94.22	194.97	151.92
<i>p</i> -value	0.0000	0.0000	0.0000	0.0000
Observations	529			

Note: Std. Dev: stands for standard deviation; *p*-value corresponds to the Jarque-Bera test with the null of normality.

3. Empirical results

3.1 Time-domain spillovers

We begin by analysing spillovers between housing and financial assets⁵ in the time domain, using the DY approach, with a forecast horizon of 100 months.⁶ The results are displayed in Table 2. The *ji*-th element of each matrix presents the estimated contribution to the forecast error variance of the series in row *j* generated by innovations to the series in column *i*, derived from Equation (4). Consequently, the off-diagonal sum of elements in each row represents the directional spillovers from other series to the series in row *j*, and the off-diagonal sum of elements in each column represents the directional spillovers to other series. The total spillover index (TSI) is about 18%, implying that spillovers between assets account for slightly less than a fifth of the total forecast error variance of the system.

⁵ In this paper, financial assets refer to stocks, bonds and REITs.

⁶ This forecast horizon is chosen because the BK methodology does not allow a shorter horizon. For consistency, we use the same horizon in the application of the DY methodology.

Table 2. Spillovers based on the DY methodology

	Housing	Stocks	Bonds	REITs	From others
Housing	93.44	2.72	0.05	3.79	6.56
Stocks	0.42	72.54	1.03	26.01	27.46
Bonds	0.93	3.06	92.18	3.83	7.82
REITs	0.50	25.73	4.18	69.59	30.41
To others	1.85	31.51	5.26	33.63	
Net	-4.71	4.05	-2.56	3.22	TSI: 18.06

Note: The values of spillovers are standardised so that rows sum to 100. The total spillover index (TSI) is expressed as a percentage of the total forecast error variance of the system.

Own shocks to each asset's forecast error variance account for a large share of the system's variance. The largest spillovers involve REITs and stocks. In fact, bilateral spillovers are largely between these two assets, which explain about a quarter of each other's forecast errors variance. This is consistent with the general literature finding that REIT and stock returns tend to be closely connected (Liu et al., 1990; Glascock et al., 2000; Yang et al., 2012). Conversely, the spillovers from REIT to housing returns are fairly small at less than 4% and spillovers from housing to REIT returns are even smaller. When looking at net spillovers (which are computed as the difference between the directional spillovers transmitted *to others* and the directional spillovers received *from others*), REITs and stocks are the biggest shock transmitters, while housing is the largest receiver of shocks from the system.

In Table 3, we present the results of net pairwise spillovers, which measure how much each asset's variance contributes to that of another. Net spillovers from stocks to REITs are close to zero, as spillovers in both directions are of similar magnitude. Housing receives net spillovers from stocks and REITs. It is not surprising that the strongest net spillover to housing returns comes from REITs, which have property as underlying assets. Stock price shocks also affects housing, through a number of channels. Stock prices are a leading indicator of economic activity, which in turn is a well-known driver of housing prices, especially through household income (Meen, 2002; Miles and Pillonca, 2008; Geng, 2018). Moreover, volatility in stock prices may reflect heightened uncertainty, which has also been shown to affect housing returns (Antonakakis et al., 2015; André et al., 2017). Net spillovers from housing to bonds are positive, but relatively small.

Table 3. Net pairwise spillovers based on the DY methodology

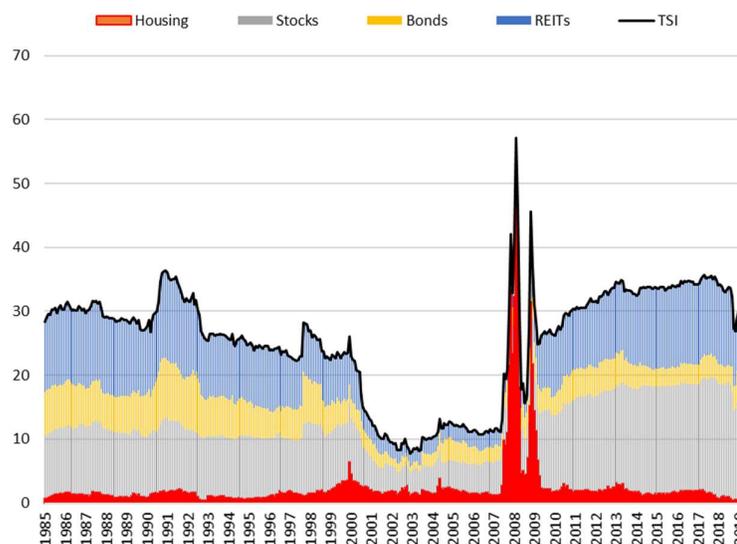
Housing-Stocks	Housing-Bonds	Housing-REITs	Stocks-Bonds	Stocks-REITs	Bonds-REITs
-0.58	0.22	-0.82	0.51	-0.07	0.09

Note: The values are standardised so that the total forecast error variance of the system is 100.

Overall, the static time-domain spillovers between housing, REITs, stocks and bonds explain about a fifth of the forecast error variance of the system formed by these variables. This is largely due to bilateral spillovers between REITs and stocks in both directions, which reflect the well-documented link between these two asset classes. Bilateral spillovers between other pairs of assets are relatively modest, pointing to benefits of portfolio. Housing returns have little impact on financial assets, including REITs. Reverse effects are somewhat stronger, especially from REITs and stocks, but still account for a small share of housing return variance.

As static analysis can mask large variations in spillovers over time, we perform a dynamic spillover analysis, using estimations over a 120-month rolling window. Figure 2 displays the evolution of the overall spillover index over time, as well as its decomposition into the share of spillovers generated by each variable. The total spillover index (TSI) declines, with some fluctuations, from the early 1990s to the beginning of the GFC, when it spikes. In 2009, spillovers stabilise and are on a very mild upward trend thereafter. The decline in spillovers before the GFC is driven by reduced spillovers from bonds, REITs and stocks, with an acceleration after the 2001 recession, which was followed by a period of benign monetary and financial conditions. The spillover index spikes during the GFC are almost entirely generated by spikes in housing returns, which was expected given the role of the subprime crisis in the GFC. The post-GFC period is characterised by larger spillovers from stocks and REITs than in the immediate pre-crisis period.

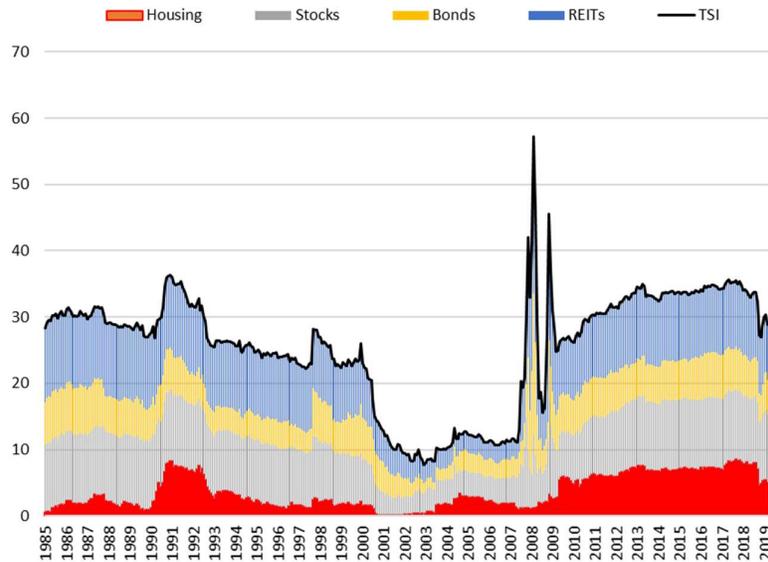
Figure 2: DY Spillover index broken down into spillovers to other assets



Note: The time varying spillover index is computed using a 120-month rolling window.

Regarding the receiving side of spillovers (Figure 3), a few features are worth noting. First, spillovers to housing returns are relatively high during the early 1990s recession and in the wake of the GFC. This is consistent with the general pattern of synchronisation between housing price and business cycle developments, with the 2000-01 downturn being an exception (Leamer, 2007). Second, the spillovers spike during the GFC mainly affected bonds and REITs. Third, post-GFC spillovers to all asset classes are higher than in the immediate pre-crisis period.

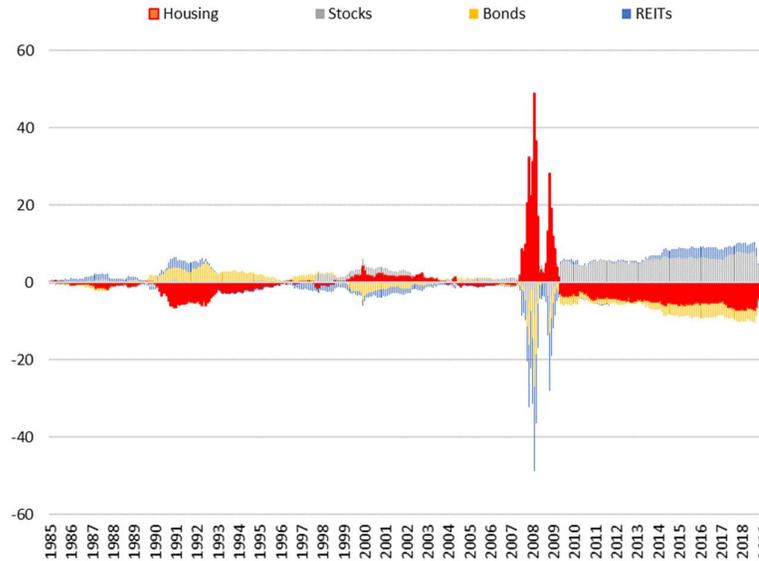
Figure 3: DY Spillover index broken down into spillovers from other assets



Note: The time varying spillover index is computed using a 120-month rolling window.

Net spillovers change significantly over time (Figure 4). In the late 1980s and the early 1990s, housing was a net receiver of spillovers, while bonds were the main source of spillovers. The pattern reversed around the turn of the century, but the magnitude of net spillovers also declined markedly until the GFC. The latter saw a spike in net spillovers from housing, mirrored by large net spillovers to bonds and REITs. While, as the static analysis above has shown, housing returns are generally at the receiving end of spillovers, during the GFC they become a major source of instability, particularly for the bond and REIT markets. Interestingly, we find mostly positive net spillovers from housing between the early 2000s and 2012, as in Tsai (2015). However, in other periods, net spillovers from housing are mostly negative. Hence, Tsai's findings do not extend beyond his sample period.

Figure 4: Net spillovers to other assets (DY methodology)



Note: The time varying spillover index is computed using a 120-month rolling window.

4.2 Frequency-domain inflation spillovers

The method recently developed by Baruník and Křehlík (2016) allows enriching the analysis by distinguishing spillovers at different frequencies and hence distinguishing between spillovers which generate only short-lived volatility from those which have a more persistent effect. The technique provides spectral representations of local variance decomposition into different time-frequency bands. We choose to decompose the total spillover index into four frequency bands: (1) $\left(\pi, \frac{\pi}{1}\right)$ or 3.14 to 3.14 (one month); (2) $\left(\frac{\pi}{1}, \frac{\pi}{4}\right)$ or 3.14 to 0.79 (one to four months); (3) $\left(\frac{\pi}{4}, \frac{\pi}{12}\right)$ or 0.79 to 0.26 (four to 12 months); and (4) $\left(\frac{\pi}{12}, 0\right)$ or 0.26 to 0.00 (more than 12 month). Table 4 displays the results.

Spillovers at a one-month frequency are small between financial assets and almost absent for housing returns. Spillovers between stocks and REITs, in both directions, peak at the one to four month frequency, when they account for nearly a fifth of the forecast error variance of the system at all frequencies. Spillovers between bonds and other financial assets are also generally strongest at this frequency, but are of much smaller magnitude. The total spillover index also peaks in this frequency band. It is also worth noting that own shocks contributions to each asset's forecast error variance is highest in the same frequency band, pointing to dependence over a few months. Own shocks affect housing returns at much lower frequency, which is in line with the well-documented long duration of housing price cycles (Igan and Loungani, 2012; André and Chaux, 2018). Spillovers from financial variables to housing are also increasing at lower frequencies (greater durations), with the strongest effects from REITs, followed by stocks. Hence, financial asset spillovers to housing are relatively small, but relatively persistent.

Table 4. Volatility spillovers based on the BK methodology

Band 3.14 to 3.14 (corresponding to 1 month)					
	Housing	Stocks	Bonds	REITs	From others
Housing	0.03	0.00	0.00	0.00	0.00
Stocks	0.00	1.28	0.00	0.40	0.40
Bonds	0.00	0.07	1.42	0.11	0.18
REITs	0.00	0.28	0.00	1.15	0.28
To others	0.00	0.35	0.00	0.51	
Net	0.00	-0.05	-0.18	0.23	TSI: 0.22
Band 3.14 to 0.79 (corresponding to 1 to 4 months)					
	Housing	Stocks	Bonds	REITs	From others
Housing	2.63	0.04	0.01	0.08	0.13
Stocks	0.05	51.85	0.49	18.08	18.62
Bonds	0.03	2.42	64.54	3.45	5.90
REITs	0.02	17.32	2.10	49.69	19.44
To others	0.10	19.78	2.60	21.61	
Net	-0.03	1.16	-3.30	2.17	TSI: 11.02
Band 0.79 to 0.26 (corresponding to 4 to 12 months)					
	Housing	Stocks	Bonds	REITs	From others
Housing	5.04	0.14	0.01	0.20	0.35
Stocks	0.03	12.30	0.34	4.71	5.08
Bonds	0.05	0.34	16.79	0.18	0.57
REITs	0.03	5.12	1.29	11.87	6.44
To others	0.11	5.60	1.64	5.09	
Net	-0.24	0.52	1.07	-1.35	TSI: 3.11
Band 0.26 to 0.00 (corresponding to more than 12 months)					
	Housing	Stocks	Bonds	REITs	From others
Housing	85.73	2.54	0.03	3.51	6.08
Stocks	0.34	7.12	0.20	2.82	3.36
Bonds	0.84	0.23	9.44	0.09	1.16
REITs	0.45	3.01	0.78	6.88	4.24
To others	1.63	5.78	1.01	6.42	
Net	-4.45	2.42	-0.15	2.18	TSI: 3.71

Note: The values of spillovers are standardised so that the sum of each row at all frequencies sums to 100. The total spillover index (TSI) is expressed as a percentage of the total forecast error variance of the system.

Table 5 presents net pairwise spillovers. At frequencies shorter than 12 months, net spillovers occur mainly between financial assets and are relatively small. At frequencies exceeding 12 months, spillovers from REITs and stocks to housing clearly dominate. Even so, they account for a relatively small portion of the system’s forecast error variance.

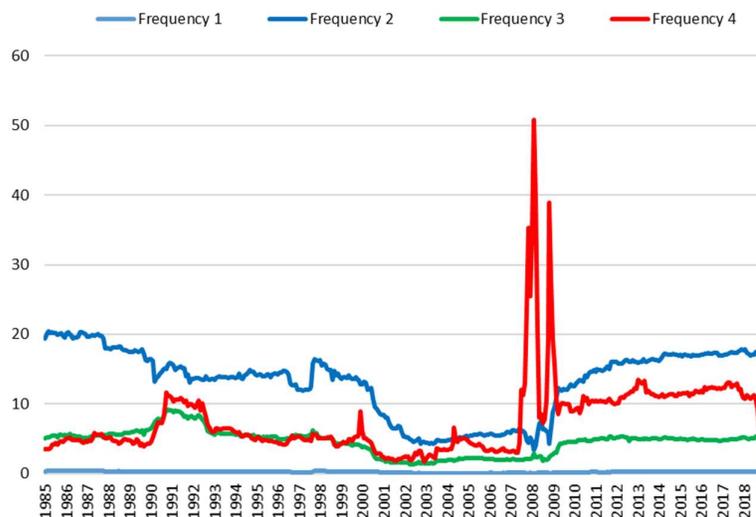
Table 5. Net pairwise spillovers based on the BK methodology

Housing- Stocks	Housing- Bonds	Housing- REITs	Stocks- Bonds	Stocks- REITs	Bonds- REITs
Band 3.14 to 3.14 (corresponding to 1 month)					
0.00	0.00	0.00	0.02	-0.03	-0.03
Band 3.14 to 0.79 (corresponding to 1 to 4 months)					
0.00	0.01	-0.01	0.48	-0.19	-0.34
Band 0.79 to 0.26 (corresponding to 4 to 12 months)					
-0.03	0.01	-0.04	0.00	0.10	0.28
Band 0.26 to 0.00 (corresponding to more than 12 months)					
-0.55	0.20	-0.76	0.01	0.05	0.17

Note: The values are standardised so that the total forecast error variance of the system is 100.

As with the Diebold-Yilmaz index, we perform a dynamic spillover analysis, using a 120-month rolling window estimation, to uncover variations in the spillover pattern over time. Figure 5 displays the Baruník-Křehlík spillover index in the four frequency bands defined above. Spillovers at a one-month frequency are negligible. Over most of the sample period, spillovers are strongest at the one-to-four month frequency, hovering in the 10% to 20% range. However, as the DY index, the BK index at the one-to-four month frequency drops significantly between the early 2000s and the GFC. Spillovers at the four-to-twelve month frequency are modest overall, with their highest levels in the early 1990s and their lowest values in the mid-2000s. Spillovers at the over 12 month frequency are generally moderate, but spike to as high as 50% at the time of the GFC. Beside this event, the strongest spillovers at this frequency occur in the wake of the early 1990s crisis and in the post-GFC period.

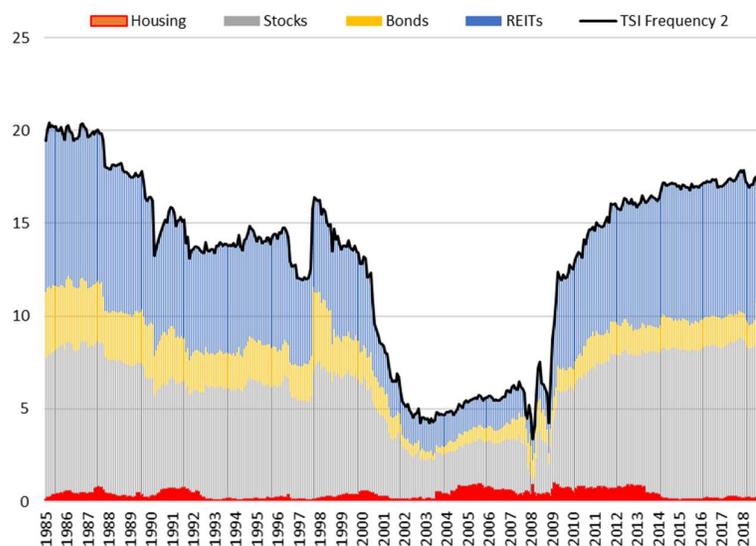
Figure 5: BK Spillover index



Note: Frequencies 1,2,3,4 refer to one, one to four, four to 12, and over 12 months, respectively. The time varying spillover index is computed using a 120-month rolling window.

We now decompose spillovers at the one-to-four month and over 12 month frequencies by spillover source and destination.⁷ At the shorter frequency, spillovers between the financial variables, and especially stocks and REITs, are prevalent over the whole sample period (Figure 6 and 7). They decline between the early 1990s and the GFC, with an acceleration in the fall in the early 2000s. The pattern of spillovers in both directions is similar, implying modest net spillovers (not shown). Spillovers from and to housing are small compared to spillovers between the financial variables.

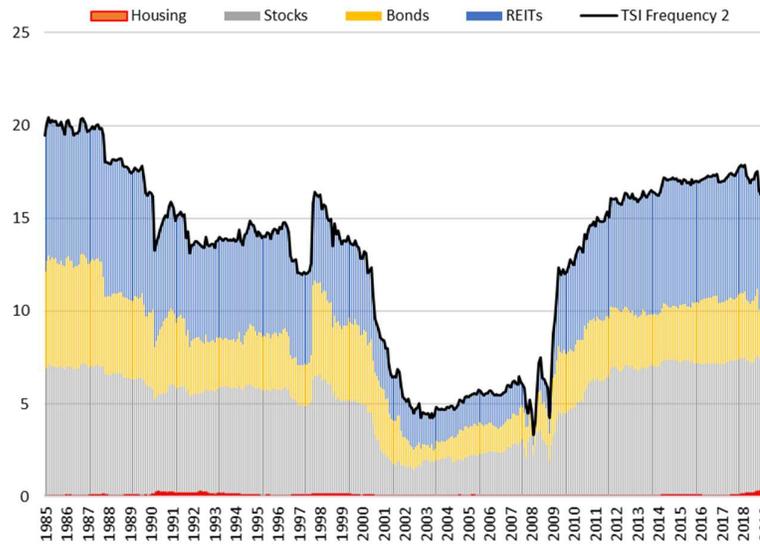
Figure 6: Spillover index at one-to-four month frequency broken down into spillovers to other assets



Note: The time varying spillover index is computed using a 120-month rolling window.

⁷ The decomposition at other frequencies is not shown, since spillovers are smaller. Results are available on request from the authors.

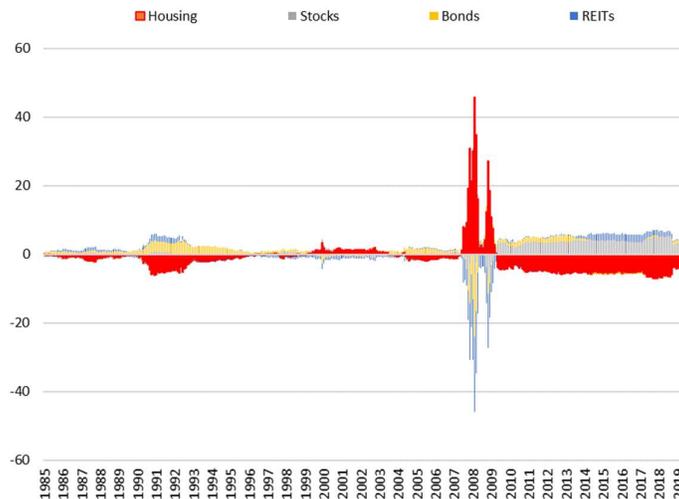
Figure 7: Spillover index at one-to-four month frequency broken down into spillovers from other assets



Note: The time varying spillover index is computed using a 120-month rolling window.

At the over 12 month frequency, spillovers are muted over most of the sample, but spillovers from housing to other assets spike at the time of the GFC. As shown in Figure 8, net spillovers from housing during this period affect bonds and REITs, and to a lesser extent stock returns. Hence, the subprime crisis had a relatively persistent impact on REIT and bond returns. This is consistent with a protracted impact of real estate crises on the economy and the uncertainty surrounding recoveries in property markets (Reinhart and Rogoff, 2013; Jordà et al., 2016), as well as with a strong impact of the housing crisis on bond yields through lower economic growth prospects and accommodative monetary policy, including quantitative easing. Negative spillovers from financial assets also affect housing returns for protracted periods following the early 1990s recession and the GFC, partly reflecting the inertia in housing prices.

Figure 8: Net spillovers to other assets at the over 12 month frequency



Note: The time varying spillover index is computed using a 120-month rolling window.

4. Conclusion

In this paper, we have investigated spillovers between US real estate, REITs, stocks and bonds, using the Diebold-Yilmaz (2012) approach in the time domain and the Baruník-Křehlík (2018) methodology in the frequency domain. We found relatively modest spillovers between these asset classes, accounting for slightly less than a fifth of the system's forecast error variance over the period 1985M1-2019M3. The strongest gross bilateral spillovers are between REITs and stocks, accounting for about a quarter of each other's forecast error variance. However, given that spillovers between these two asset categories are of similar magnitude in both directions, net spillovers are small. Housing is only loosely connected to stocks and REITs and hence provides a hedge against volatility in these markets. However, spillovers vary markedly in direction and intensity over time. While housing is a receiver of spillovers over most of the sample period, it becomes a strong source of spillovers during the GFC. Moreover, the frequency decomposition of spillovers shows that shocks arising from housing have more persistent effects than those originating in financial markets. Overall, hedging strategies involving housing need to take into account potential tail events like the GFC and the investment horizon. Given its capacity to decompose spillovers into different frequencies, the BK methodology is very useful to study connectedness between series characterised by different degrees of inertia, such as housing and financial asset returns. Applying the BK methodology to other countries, especially those which have experienced high housing price volatility, would forward our understanding of interactions between housing and financial market dynamics.

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