Dynamic Spillovers between REITs and Stock Markets in Global Financial Markets

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Abstract

We study spillovers between REITs and stock markets in a global context. We compute both directional and net spillover indexes in a global and dynamic setting. Our findings indicate that connectedness between these markets has increased importantly over time. On average stock markets are net transmitters and REITs markets are net receivers. Considerable time variation is observed. Spillovers are higher during crises and REITs were net spillover transmitters to stock markets during the Subprime Financial Crisis. Our results have important implications for global investors.

JEL Classification: G01; G15; C32

Keywords: Spillovers; Market connectedness; REITs markets; Stock markets; LASSO methods.

1. Introduction

Financial globalization, the integration of markets and countries with the global financial system, has increased substantially since the 1990s. Stronger cross-border economic and financial integration has implied that macroeconomic shocks in one country are increasingly likely to spill over into other economies. In fact, over the past two decades crises have

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propagated more rapidly than in the past and have proven to be more persistent and disruptive.

Large volatility spillovers, which have been a salient feature of recent financial crises, have motivated motivated the emergence of a large and growing literature on financial contagion and volatility transmission. This literature, which has largely focused on currencies, stocks and more recently hedge funds, has reported solid evidence of financial spillovers and contagion during various crisis periods (e.g., Boyson, et al., 2010; Caccioli et al., 2014; Aït-Sahalia et al., 2015; Gomez-Gonzalez et al., 2020). The literature concerning real estate markets is more limited. However, real estate has become a key asset class for global investors, offering stable income returns, partial protection against inflation and a good diversification with other investments in the portfolio. Moreover, studies on financial contagion involving real estate markets (Fry, et al., 2010; Hoesli and Reka, 2013; Hoesli et al., 2015) confirm the existence of significant spillovers between these and other financial markets.

In this paper we study spillovers between real estate investment trusts (REITs) and the stock market indexes of nine developed countries. A few recent papers have studied spillovers between REITs and financial markets focusing on a single country. Damianov and Elsayed (2018) study spillovers between the U.S. housing, mortgage, REITs and stock markets over the period January 1975 - December 2016. They find that each of the four markets acts as both receiver and transmitter of spillovers during specific subperiods. Similarly, Tiwari et al. (2020) study the strength and time variation of spillovers between returns on residential real estate, REITs, stocks and bonds in the U.S. and find that spillovers reduce the benefits of portfolio diversification, especially in crisis times, when asset returns tend to be more correlated. We extend this strand of the literature by considering the interrelations between REITs and stock markets in a global context. The considerable growth of REITs during the last two decades has been decisive for the consolidation of real estate as a new asset class in international financial markets and has been an important channel of shock transmission between real estate and financial markets globally.

While real estate markets have traditionally been viewed as local markets, there is a growing body of literature that analyzes the importance of various shocks in driving national and global real estate prices. In fact, recent studies have reported evidence supporting the hypothesis of international housing price synchronization (Terrones and Otrok, 2004; Bandt et al., 2010; Cesa-Bianchi, 2011). Some papers suggest that this price synchronization is significantly explained by the development of REITs markets and their interplay with other financial markets (see, for instance, Gomez-Gonzalez et al., 2018). Therefore, studying spillovers between real estate and financial markets becomes relevant for understanding the interplay between these markets and their effects on optimal portfolio composition and risk diversification, especially during times of financial distress. This paper contributes towards that goal. We compute directional and net spillovers between REITs and stock markets, following the approach of Diebold and Yilmaz (2009, 2012, 2014).

We carry out our estimations using the method proposed by Demirer et al. (2018), combining a traditional vector autoregression set up with selection and shrinkage of the parameter space by LASSO (Least Absolute Shrinkage and Selection Operator). By so doing, we construct dynamic spillover statistics that would be unfeasible in a traditional regression framework due to the curse of dimensionality. Our sample includes eighteen markets, which would have been impossible to include without the usage of LASSO methods.

Our results show that connectedness between these markets has increased importantly over the last fifteen years. Importantly, there is no single market in which a unique net position prevails for the whole sample period. All markets play both net receiver and net transmitter positions for different periods. On average, however, the highest transmitter positions are reported for stock markets while the highest receiver positions are for REITs markets. Considerable time variation is observed. Spillovers are higher during crises and REITs were large net spillover transmitters to stock markets during the Subprime Financial Crisis.

Section 2 describes the data used in the empirical analysis. Section 3 presents the methodological framework. Section 4 shows our main results, and the last section concludes.

2. Data

Our data set consists of daily closing prices from nine stock and nine REITs markets from February 28 2003 to November 15 2015. All data on stock market indexes is collected from Bloomberg. Data from REITs is collected from the European Public Real estate Association

(EPRA). The following stock markets indices are included in the study: S&P500 (the USA), S&P/TSX (Canada), DAX (Germany), FTSE100 (the UK), CAC40 (France), FTSEMIB (Italy), NIKKEI 225 (Japan), HANG SENG (Hong Kong), and S&P ASX200 (Australia). REITs markets are represented by nine country indexes computed by the EPRA, one for each of the nine countries mentioned above. These indexes are generically denoted by FTSE EPRA NAREIT, followed by the name of the respective country.

We work with monthly moments (estimated based on daily frequency data) seeking to identify relatively persistent shocks in the market and reduce the noise presented by intraday data. The span period of the data allows us to evaluate the effect of the global financial crisis on the dynamic interactions between different markets.

3. Methodology

The spillover indices are built upon a VAR with N variables that comprises series of stock, FX and commodity markets. These statistics are constructed by means of the associated forecast error variance decomposition (FEVD). The errors are estimated from the moving average representation of the VAR following equations 1 and 2:

$$X_t = \Theta(L)\varepsilon_t, \tag{1}$$

$$X_t = \sum_{t=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2}$$

where X_t is a matriz $T \times N$, $\Theta(L) = (I - \phi(L))^{-1}$, ε_t is a vector of independently and identically distributed disturbances with zero mean, and Σ covariance matrix, $A_i = \phi A_{i-1} + \phi A_{i-2} + \cdots + \phi A_{i-p}$ is the parameters' matrix, p is the number of lags in the estimation, and T is the number of time periods. To estimate the FEVD from the h-step ahead forecast, first we f need to identify the structural perturbations to the VAR system. This can be achieved by imposing restrictions on the MA parameters. Following Diebold and Yilmaz's (2012) suggestion, we use the proposal of Koop et al. (1996) and Pesaran and Shin (1998), namely the generalized VAR for the construction of the FEVD.

The errors in the FEVD can be divided into *own variance* shares and *cross variance* shares. The former are the fractions of the errors that are associated to a shock to x_i on itself, while the latter are the portion of the shocks on x_i related to the rest of the variables in the system. Thus, the h-step ahead FEVD can be defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i{}' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i{}' A_h \Sigma A_h{}' e_i)}, \tag{3}$$

where σ_{jj} is the standard deviation of the *j*-th equation, e_i is a selection vector, with ones in the *i*-th element and zero otherwise, and Σ is the variance matrix of ε_t. To guarantee that the sum of each row is 1, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$, each entry of the variance decomposition must be normalized as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{4}$$

where $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

With the normalized variance decomposition, a total spillover index can be calculated as:

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

This index measures the percentage of the forecasted variance series that can be explained by cross-spillovers. It can be extended to a *directional spillover* index, in which the effect of a shock from all other variables *j* on the variable x_i is given by:

$$C_{i \leftarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100, \tag{6}$$

conversely, the effect of a shock from x_i on all other markets *j* is given by:

$$C_{i \rightarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100, \tag{7}$$

with the two directional spillover indices one constructs a *net spillover* index, given by:

$$C_i(H) = C_{i \rightarrow j}(H) - C_{i \leftarrow j}(H). \tag{8}$$

The net spillover index is a measure of the effect related to a shock in the variable x_i on the rest of the system. Therefore, each variable will act either as a *net receiver* or as a *net transmitter* of shocks in each *t*. It is also possible to construct a *net pairwise spillover* statistic, which accounts for the net spillover effect of variable x_i on x_j, where $i \neq j$. The net pairwise index is defined as follows:

$$C_{ij}(H) = \frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N} \times 100. \tag{9}$$

It is also possible to present the information contained in the variance of the forecasted error by networks. Nodes and edges constitute network graphs. In the results section the placement of nodes in the network is determined by the Force Atlas2 algorithm developed by Jacomy et al. (2014). This algorithm encounters a steady-state balance between forces of transmission and reception. Color intensity represents the degree of connectedness between the corresponding markets. Darker color segments correspond to more connected markets.

To include a large number of markets in our empirical analysis, we use LASSO methods, following the approach of Demirer et al. (2018) in the context of VAR systems for financial connectivity. These authors highlight that in applications that study connectivity across numerous markets or asset classes the VAR system requires estimation on a large dimensional space, without losing excessive degrees of freedom (to the point of making the estimation unfeasible). By using shrinkage or through model comparison and selection (using traditional AIC or BIC criteria) this can be achieved. LASSO blends the two approaches.

Consider an ordinary regression by least squares:

$$\hat{\beta} = \underset{\beta}{\arg min} \sum_{t=1}^{T} (y_t - \sum_{i}^{N} \beta_i x_{it})^2, \tag{10}$$

subject to the restriction

$$\sum_{i=1}^{K} |\beta_i|^q \leq c \text{ ,} \tag{11}$$

which can be also presented as a penalized estimation problem as follows:

$$\hat{\beta} = \underset{\beta}{\arg min} [\sum_{t=1}^{T} (y_t - \sum_{i}^{N} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q], \tag{12}$$

Concave penalty functions non-differentiable at the origin produce selection, whereas smooth convex penalties generate shrinkage. Thus, penalized estimation blend selection and shrinkage. The LASSO solves the penalized regression problem with q = 1. Hence it shrinks and selects. In addition, it requires only one minimization, and it uses the smallest q for which the minimization problem is convex.

The Adaptive elastic net is an extension of LASSO due to Zou and Zhang (2009), which does on top of shrinking and selecting, presents the ‘oracle property’. In the implementation of the adaptive elastic net in this proposal, following Demirer et al. (2018) is necessary to solve

$$\hat{\beta}_{AEnet} = \arg min_{\beta} \left[\sum_{t=1}^{T} (y_t - \sum_{i}^{N} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} w_i \left(\frac{1}{2} |\beta_i| + \frac{1}{2} \beta_i^2 \right) \right], \quad (13)$$

where $w_i = 1/\left|\hat{\beta}_{i,OLS}\right|$ and λ is selected equation-by-equation by 10-fold cross validation. The adaptive elastic net penalty weights the average by the inverse of OLS parameter estimates, and by so doing it shrinks the smallest OLS coefficients toward zero.

4. Results

Table 1 presents average (static) spillover indexes for the whole sample period. The percentage of the variation of the forecast error (1 month ahead) explained by each market in the sample is reported in rows. Each entry of the column “From Others” presents the total spillover received by the respective market from all other markets included in the sample. For example, 96.1% of the U.S. REIT’s forecasted market variation is received from the other markets. In contrast, each entry of the row “To Others” shows the total spillover given by the respective market to all other markets in the sample. The column “Net” contains net spillovers (the difference between “To Others” and “From Others”) generated by each market. Notably, the main average spillover transmitters are the stock markets from Hong Kong and the U.S., while the main spillover receivers are Japan’s REITs and stock markets. The average total connectedness index is 90.5%, showing that the markets included in the sample are highly interconnected.

Figure 1 presents the evolution of the total connectedness indicator over time. It is clear from this figure that connectedness exhibits high time variation. However, a ´positive trend is observed, indicating a secular tendency to higher interconnection between REITs and stock markets. In fact, the maximum value of the indicator is reported at the end of the sample, in November 2015 (94.1%). Of special relevance, this index increased significantly during the Subprime Financial Crisis, indicating that market connectedness increases during times of financial distress (see, for instance, Gamba-Santamaria et al., 2017, 2019). Figure 2 graphically depicts market connectedness using the Force Atlas2 algorithm developed by Jacomy et al. (2014). Color intensity represents the degree of connectedness between the corresponding markets. Darker color segments correspond to more connected markets.

Figure 3 presents net spillovers transmitted by stock markets (Panel A) and REITs markets (Panel B). A feature that is common to all markets included in this study is that net positions are not stable over time. Specifically, none of these markets maintains neither a net transmitter nor a net receiver position during the whole sample period. This result shows that financial market interactions are very dynamic and change over time depending on the occurrence of market innovations and the state of risk aversion. A regularity can be observed, however. Stock markets (except for Japan) are spillover transmitters while REITs markets are spillover receivers, most of the time. An important exception happens during the Subprime Financial Crisis when REITs markets become net spillover transmitters. In fact, spillover transmission during this major financial disruption are higher than during most other periods of time. This result indicates that in times of financial distress diversification opportunities are significantly reduced as market correlations between different asset classes increase.

5. Conclusions

We study spillovers between REITs and stock markets, following the approach of Diebold and Yilmaz (2009, 2012, 2014). We extend findings in this strand of the literature by considering the interrelations between these markets in a global context. Earlier studies focus on a single country. In contrast, our sample includes nine developed countries. Our sample includes a total of eighteen markets. We include this large number of markets by using LASSO methods.

Our findings indicate that connectedness between REITs and stock markets has increased importantly over the last fifteen years. While there is no single market in which a unique net position prevails for the whole sample period, on average the highest transmitter positions are reported for stock markets while the highest receiver positions are for REITs markets. Considerable time variation is observed. Spillovers are higher during crises and REITs were an important source of shock transmission to stock markets during the Subprime Financial Crisis. This result indicates that in times of financial distress diversification opportunities are significantly reduced as market correlations between different asset classes increase.

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Tables and Figures

Table 1: Average Spillovers

	Reits_USA	Reits_Canada	Reits_UK	Reits_France	Reits_Germany	Reits_Italy	Reits_HongKong	Reits_Japan	Reits_Australia	USA	Canada	UK	France	Germany	Italy	Hong Kong	Japan	AUS
Reits_USA		6,49	6,36	5,46	4,20	4,48	6,35	1,44	7,80	7,99	7,39	6,15	4,61	3,44	4,98	9,04	3,59	6,38
Reits_Canada	4,00		6,57	5,44	4,27	4,51	5,09	1,48	7,33	7,00	6,58	6,81	6,11	4,74	6,24	7,32	3,92	6,58
Reits_UK	3,67	5,39		5,15	4,24	4,42	5,32	1,14	6,11	7,16	7,00	7,24	6,89	5,60	6,65	7,82	3,83	5,90
Reits_France	2,61	4,30	6,86		3,89	4,12	7,43	0,36	3,55	8,35	8,49	7,46	7,83	6,81	7,13	10,84	2,76	2,50
Reits_Germany	5,49	5,00	7,98	8,65		7,35	2,86	2,45	5,69	4,00	2,92	5,83	4,70	3,79	4,33	3,71	2,38	5,00
Reits_Italy	4,33	5,40	6,74	9,14	7,20		3,40	1,95	5,24	4,22	3,47	4,69	4,94	3,25	5,61	4,68	2,68	5,52
Reits_HongKong	3,33	5,32	4,63	4,65	4,81	4,15		1,27	6,12	7,44	6,40	6,43	5,05	4,82	4,56	12,40	4,19	5,66
Reits_Japan	4,48	6,96	4,78	4,64	4,73	3,83	2,60		6,10	3,73	1,40	2,95	1,76	0,93	1,43	2,68	8,12	4,43
Reits_Australia	3,89	5,47	6,72	5,25	4,19	4,41	5,45	1,08		7,11	6,83	7,20	6,97	5,70	6,54	8,09	3,64	5,46
USA	3,15	7,53	4,10	4,04	3,01	3,24	4,53	1,46	6,32		10,73	7,01	5,21	4,39	4,30	7,87	4,05	5,60
CANADA	5,04	6,19	7,38	6,20	5,38	5,06	5,12	1,44	7,54	6,22		6,40	5,62	4,32	5,83	7,06	2,76	6,88
UK	2,79	4,21	4,31	3,88	4,14	3,40	3,58	1,09	4,74	6,62	6,70		9,25	8,06	7,42	6,09	4,27	6,75
FRANCE	4,99	8,36	6,35	5,63	4,01	4,24	6,08	1,96	9,92	8,61	7,74	5,05		2,05	3,54	8,41	3,25	6,67
Germany	4,69	7,53	5,34	5,99	7,72	4,63	6,77	2,23	8,85	7,57	6,12	4,51	3,44		3,22	9,36	3,01	5,63
Italy	7,10	8,89	8,73	6,91	5,61	4,62	3,65	2,56	11,10	6,96	6,20	4,75	3,52	2,29		5,09	2,57	5,85
HongKONG	3,01	5,40	4,16	4,05	2,86	3,68	9,13	1,07	6,26	8,05	6,96	6,60	5,15	5,02	4,61		4,48	5,76
Japan	3,99	5,00	6,74	5,83	5,77	5,14	5,83	1,12	6,22	6,00	5,37	6,93	6,35	5,33	6,40	8,24		6,69
AUS	4,20	5,21	5,84	6,09	9,52	5,33	6,02	1,73	6,06	6,10	5,12	6,31	5,06	4,51	4,58	8,78	3,55	
To Others	70,75	102,65	103,61	96,98	85,54	76,60	89,21	25,81	114,95	113,13	105,43	102,33	92,44	75,05	87,36	127,48	63,03	97,26

Figure 1: Total Connectedness Indicator, 2003 -2015

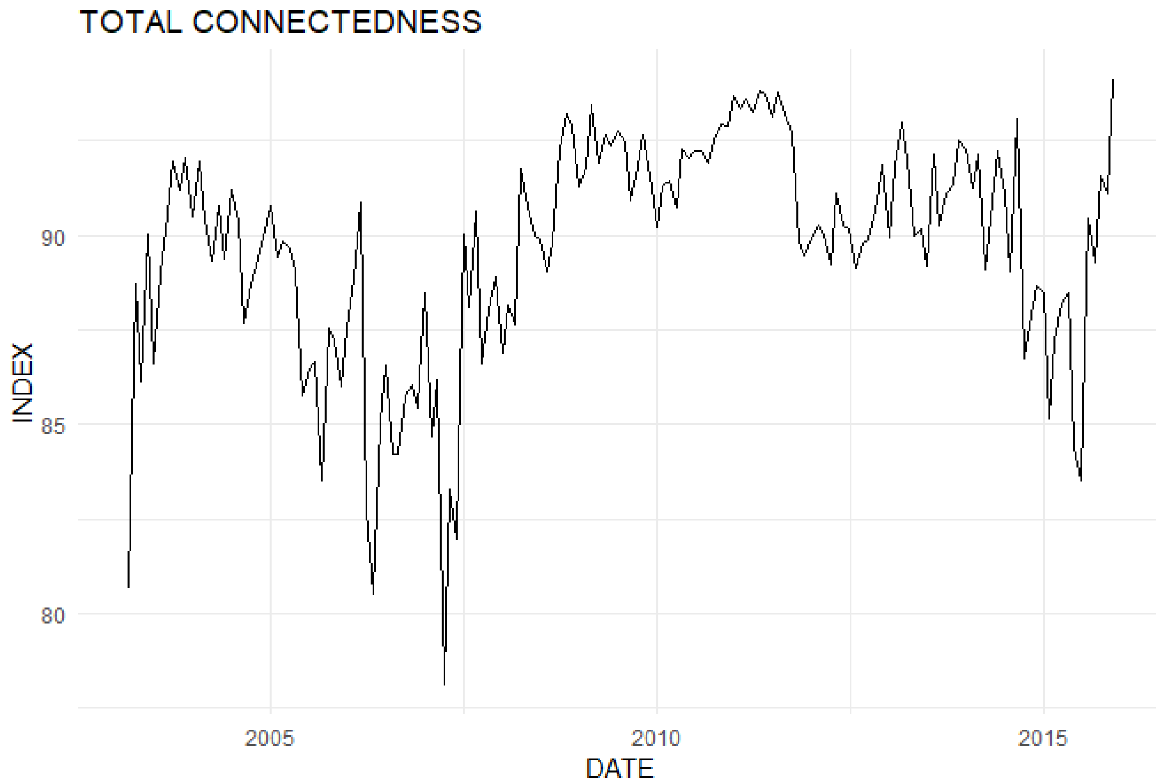


Figure 2: Total Connectedness – Network

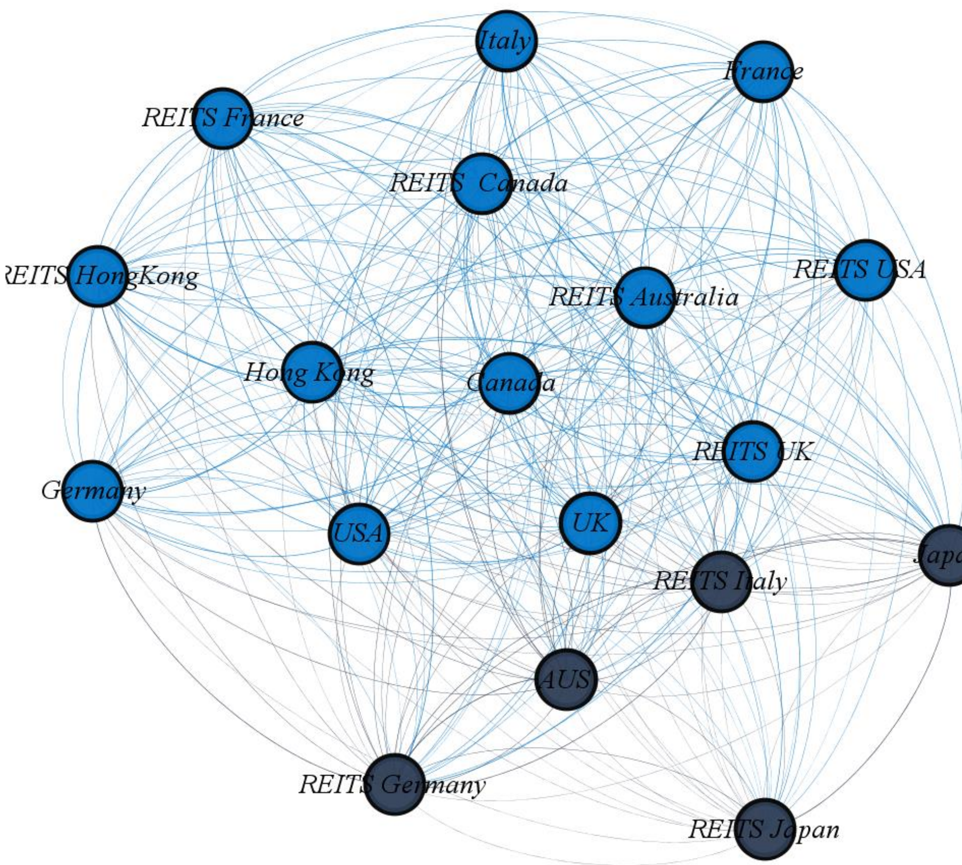
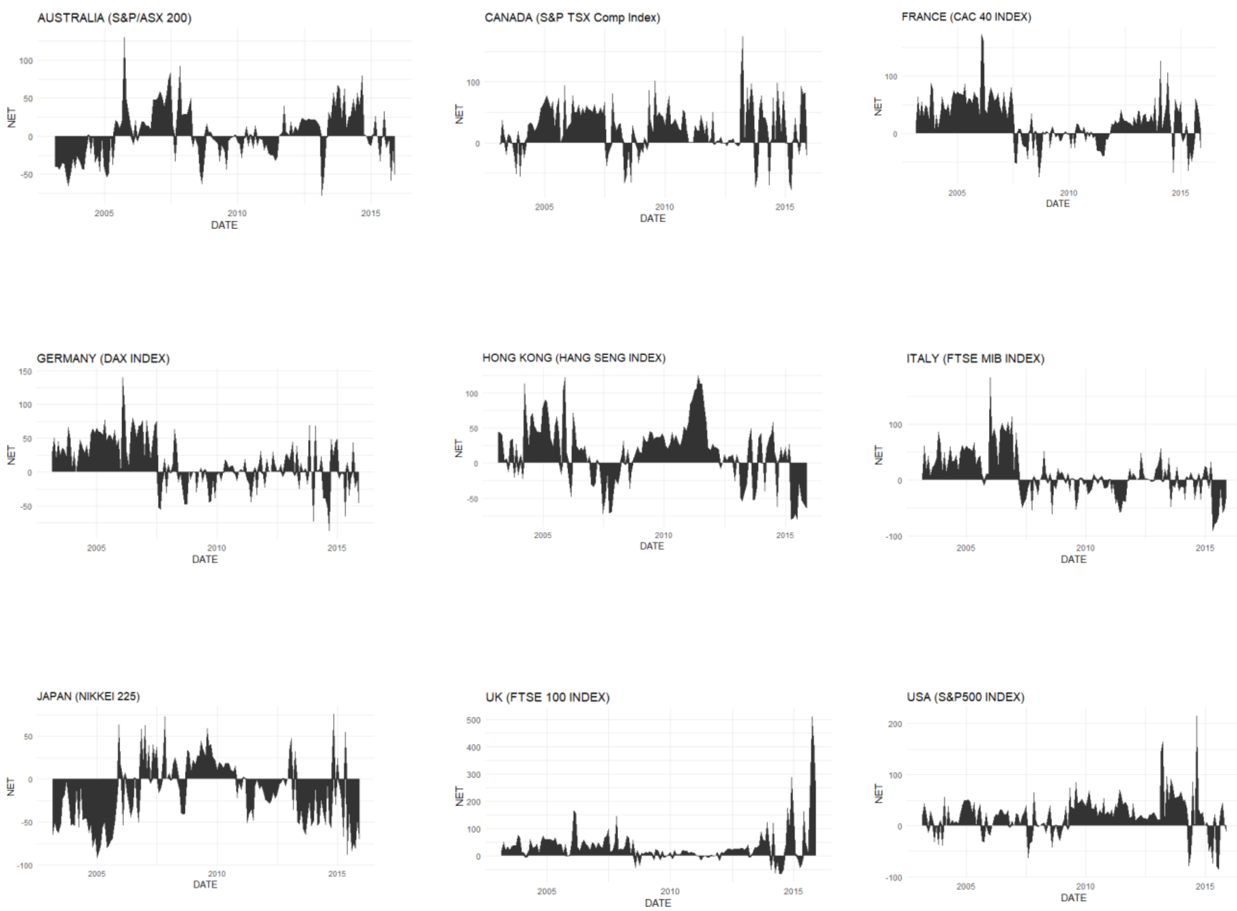


Figure 3: Net Position, 2003 -2015

Panel A: Stock Markets



Panel B: REITS