Ahmed, Rashad, Hasan, Mohammad S. and Sultan, Jahangir (2020) *Meteor shower and global asset allocation.* European Journal of Finance, 26 (17). pp. 1703-1724. ISSN 1351-847X.

Meteor Showers and Global Asset Allocation

Rashad Ahmed*
University of Southern California

Mohammad S. Hasan**
University of Kent

Jahangir Sultan***
Bentley University

FINAL SUBMISSION

5/5/2020

We thank ThomsonReuters for making their proprietary data on investable equity indices available to us. We are also grateful to Elyas Elyasianiand Ray Murphy for valuable comments on an earlier draft. Special thanks to David Simon, who is no longer with us, for his suggestions. Many thanks to anonymous referees, the associate editor, and the editor for making helpful suggestions. We remain responsible for all remaining errors. Xuxi Guo provided excellent research assistance.

*Doctoral candidate in economics, rashadah@usc.edu.
**Senior lecturer in finance, m.s.hasan@kent.ac.uk.
***Professor of finance, jsultan@bentley.edu.

Keywords: Volatility, spillover, VIX, GARCH, financial crisis, portfolio optimization.JEL Code: F36, F65, G01, G11, G15.

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ABSTRACT

Cross-market linkages allow transmission of shocks among markets. Previous measures of such spillovers are based on broader stock market indexes, which cannot identify the industries that are the principal drivers of spillovers and the industries that are most exposed to the spillovers. Using investable equity indexes, we show that basic materials, financials, industrials, technologies, and telecommunication equity sectors were the primary exporters of volatility from the U.S. and that the magnitude of the spillovers increased primarily during andpost-2008 financial crisis. There is evidence that Canada was most vulnerable to spillovers, while China's exposure was the lowest among the countries in the sample. Based on the minimum variance portfolio optimization, we find that investing in foreign industries with low exposure to spillovers from the U.S. generates high Sharpe ratios for U.S. portfolio managers, especially during the financial crisis.

Keywords: Volatility, spillover, meteor shower, VIX, investable equity indexes, financial crisis, portfolio optimization.JEL Code: F36, F65, G01, G11, G15.

I. Introduction

An unintended consequence of capital market connectedness is that systemic risk is transmitted across borders, affecting economic growth, investor confidence, and capital flows. As evidenced during the 2008 financial crisis, the global equity market experienced significant declines,[1] and according to Batram and Bodnar (2009), falling from an all-time high of $51 trillion in October 2007 to $22 trillion by the end of February 2009. Such catastrophic declines show the extent to which the global equity market is vulnerable to the transmission of systemic shocks. From a policymaker's viewpoint, it is essential to identify whether volatility is homegrown (heat waves) or imported (meteor showers)[2], so that appropriate policy is designed and implemented to safeguard the domestic capital market (see Elaysiani et al. (2015)).Investors care about the linkage because financial spillovers can increase the correlation between markets and reduce diversification benefits.

In this paper, we examine U.S. equity market return spillovers to several of its trading partners. Return spillovers (from hereafter, spillover) are estimated as variance decompositions using the Diebold

[1]The major stock market indices, on average, have declined by more than 10%, while emerging stock market indices have fallen by close to 30%.

[2]Engle et al. (1990) were first to introduce these terms to describe whether market volatility is driven by its own innovations or affected by innovations from a foreign market.

and Yilmaz (2009 and 2012) procedure (from hereafter, DY method). The DY method decomposes the forecast error variance of a given market's returns into components attributable to its own innovations and innovations of other markets. Using the DY method, we identify spillovers from the major U.S. investable [3]equity sectors, including basic materials, consumer staples, financials, health care, industrials, oil and gas, technology, telecommunications, and utilities to identical equity sectors in selected trading partners. The foreign trading partners are Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Korea, Spain, Russia, and the United Kingdom. According to the U.S. Treasury, stock markets in these foreign countries attract significant U.S. investments. We believe that through international portfolio investment from the U.S., volatility in these U.S. sectors eventually spills over to their foreign counterparts. Our objective in this paper is to estimate the magnitude of this spillover and show the extent to which the U.S. portfolio managers can use the spillover measures to guide international investments.

At the country level, we find that Canada was most exposed to the U.S. volatility during the full sample, while China was least exposed. During the pre-financial crisis[4] (January 2, 2002 – February 14, 2007), Canada was again most exposed while China was least exposed in all nine equity sectors. The results are similar during the financial crisis (February 15, 2007 – April 30, 2009). The fact that Canada has high exposure to the U.S. market is consistent with Canada's proximity to the U.S. and trade between these two neighbors. What is interesting is that China was least exposed to the U.S.-specific volatility despite an increasing level of trade and investment between them[5]. Finally, spillovers during the post-financial crisis(May 1, 2009 – September 21, 2015)are similar to the previous results. Canada was most exposed, while China was the least vulnerable country.

At the industry level, we identify the specific foreign equity sectors that are exposed to spillovers from their U.S. equity sector counterparts. For the full sample, basic materials and oil and gas, contributed most to spillover from the U.S, while the utilities sector contributed the least. During the pre-financial

[3] Investable equity indices are typically custom-tailored and are constructed, considering several factors, including liquidity, market capitalization, float, and trading volume. These indices are proprietary in nature.
[4] The dating of the samples is arbitrary though it generally matches the full timeline of the crisis as reported by the St. Louis Fed (https://www.stlouisfed.org/financial-crisis/full-timeline).
[5]We find this result interesting, and it perhaps supports our anecdotal claim that China has been able to keep its capital market insulated through restrictions on foreign capital flows.

crisis, the oil and gas sector (utilities) was the highest (lowest) contributor to spillover. During the financial crisis, the U.S. technology sector was a larger contributor to spillovers than the financial sector. The utilities sector was the lowest contributor to spillovers. Finally, post-financial crisis, the oil and gas (utilities) was the largest (smallest) transmitter of volatility, possibly due to the highly volatile crude oil market. Between 2014 and 2016, the Brent crude oil price fell from $110 to about $30 per barrel.

These results are important for both regulatory purposes and global asset allocation. If volatility transmissions encourage a knee-jerk reaction among regulators to insulate the home country's capital market, it can affect international capital flows. For asset allocation, high spillovers lead to high equity market correlation and exposure. As a result, diversification benefits from investing in countries exposed to spillovers would be lower, and subsequently, capital flow to these countries may decline. Minimum variance portfolio optimization using the spillover magnitude as a criterion confirms that investing in foreign countries and their industries with low exposure to the U.S. volatility generates high Sharpe ratios for the U.S. portfolio managers.

We make several contributions to the literature. First, the results suggest that the use of broader stock indexes can offer only a limited view of the spillovers for the countries in the sample. Instead, a sectoral analysis identifies the major sources of spillovers[6]. Second, in contrast to the existing literature, we find a slight time variation in the magnitude of the spillovers. Third, we also identify the countries and the equity sectors that can offer more significant international diversification benefits to the U.S. portfolio managers. Finally, we show that at times, the spillover measure is distinctly different than the correlation between aforeign country's returns with that of the U.S. In fact, there are instances where the spillover measure deviates from the return correlation. Even though both are based on the covariance structure of returns, correlations are purely contemporaneous while spillover measures incorporate dynamics. We, therefore, believe that the information content of these two measures of connectedness have vastly

[6]The study by Kouki et al. (2011) is the only study that offers a similar approach to studying volatility transmission from the U.S. banking sectors to the banking, financial services, industrial, real estate, and oil sectors in selected developed and emerging markets. We consider ten investable U.S. equity indices for transmitting volatility to the corresponding investable equity sectors in the developed and developing countries. As discussed in later sections, our volatility transmission model is based on important trade and portfolio linkages between the U.S. and its selected trading partners. Furthermore, our study differs in terms of the methodological treatment of volatility transmission.

different implications for international portfolio diversification. In other words, diversification benefits differ whether one is using the correlation or the spillover measure as a criterion.

The paper is organized as follows: Section II reviews the relevant literature on the volatility transmission framework. Section III provides empirical analysis. The final section concludes.

II. Volatility Transmission Mechanism

A World Bank study identifies several volatility transmission channels based on trade, capital flows, commodity, and investor confidence[7]. Trade channels include imbalances in external trade as a result of currency volatility and technological innovation induced productivity changes. The financial transmission channel considers the flow of foreign direct investment and portfolio investment as a result of either an arbitrage mechanism or international diversification. Linkages among banks can magnify spillovers because of interconnectedness in risk exposure. Remittances are also vital to the transmission of shocks from one country to another. The commodity channel points to the effects of instability in the commodities market in light of imbalances in supply and demand. According to the study, investor sentiment is an important catalyst for the transmission of shocks across borders.

Spillover captures volatility transmission where a foreign market affects the conditional variances of returns in another market (see Hamao et al. (1990)). Econometric studies on volatility transmission can be divided into two strands. The first strand examines whether volatility is homegrown or imported. Engle et al. (1990) examine the intra-daily behavior of the Yen/Dollar exchange rate with reference to the hypotheses of a heat wave (homegrown volatility) and meteor showers (imported volatility). The authors find evidence of meteor shower, as opposed to a heat wave type spillover. Another article by Susmel and Engle (1994) investigates the timing of volatility spillover between the New York and London equity markets. The study reports that the evidence of volatility spillover between these markets is minimal, and the impact lasting for an hour or so. The article by Melvin and Melvin (2003) examines the volatility spillover of Mark/Dollar and Yen/Dollar exchange rates across global markets. They find statistically

[7] Global Economic Prospects: Spillovers amid Weak Growth 2016, World Bank. Available at https://www.worldbank.org/content/dam/Worldbank/GEP/GEP2016a/Global-Economic-Prospects-January-2016-Spillovers-amid-weak-growth.pdf.

significant effects for both own-region and inter-regional spillovers. They also suggest that heat waves are more critical than meteor showers. Clements et al. (2015) use high-frequency (10-minute) futures data on the dollar index, Treasury bond, and S&P500 equity index during 2003-2013 and find that meteor shower and heat wave effects are equally significant. Golosnoy et al. (2012),using intra-day data of the Dow Jones and DAX, find evidence of significant short-term volatility spillover within both markets, as well as across the two markets (meteor shower effect). They find that the spillover effects between the U.S. and the German stock markets are of significantly longer duration and increased after the subprime crisis, which indicates substantial contagion effects. Beale (2005) investigates volatility spillover from the U.S. markets to 13 European equity markets using weekly data from January 1980 to August 2001. The study finds that spillover intensities increased in the second half of the 1980s and the first half of the 1990s. Beale contends that increased trade integration, equity market development, and low inflation have contributed to the increase in the intensity of the volatility spillover in the European Union.

There is also evidence that volatility spillover is time-varying, intensifying in times of stress. For example, see Elyasiani *et al.* (2015), Hamao *et al.* (1990), and Theodossiou and Lee (1993). Elyasiani *et al.* (2015) examine the return and volatility interdependence among the U.S., the UK, the EU, and Japanese banks and insurers for the period 2003 to 2009. The study reports strong returns and volatility transmission within and across the banking and insurance sectors. The relationship exhibited contagion-like symptoms during the crisis period of 2007 to 2009, with the U.S. financial institutions acting as information providers in global markets. Kanas (1998) investigates the return and volatility spillovers across three major European markets, namely, London, Frankfurt, and Paris, from January 1984 to December 1993. The study reports bi-directional spillovers between London and Paris and Frankfurt and Paris, with unidirectional spillover from London to Frankfurt. The study finds that the magnitude and intensity of the spillover increased during the post-crash period. Beirne *et al.* (2008) explore the issue of volatility spillover and contagion from mature markets to 41 emerging stock markets. They suggest that the spillover from established markets influences the conditional variance of return in many local and emerging markets -furthermore, the spillover parameter changes during turbulent periods in developed countries.

The second strand of the literature looks at volatility transmission using the generalized spillover index, developed in Diebold and Yilmaz (2009 and 2012). Broadly speaking, the DY method, applied in this paper, combines the notion of meteor showers and heat waves (Engle et al. (1990)), generalized forecast error variance decompositions (FEVDs) (Sims (1980a and 1980b)), and generalized impulse response functions (IRF)(Koop, Pesaran, and Potter (1996), and Pesaran and Shin (1998) (hereafter KPPS)). The FEVDs[8], in percentage terms, decompose the forecast error variance of a dependent variable into components attributable to own innovations and that of other explanatory variables. The p^{th} order, N-variable vector autoregressive (VAR) model is estimated as follows:

$$Z_t = \sum_{i=1}^{p} B_i Z_{t-i} + \varepsilon_t \qquad (1)$$

where $Z_t = (Z_{1t}, Z_{2t,}, ..., Z_{Nt})$ is a vector of N endogenous variables, B_i are i = 1,…, p are NXN autoregressive coefficients matrices, and $\varepsilon_t(0,\sum)$is a vector of i.i.d. error terms that are serially uncorrelated; t = 1, …, T.. The moving average representation of the system (1) may be written as

$$Z_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \qquad (2)$$

where the NXN coefficients matrices Ai follow the recursion $A_i = B_1 A_{i-1} + B_2 A_{i-2} + ... + B_p A_{j-p}$ with A_0 being an NXN identity matrix and $A_i = 0$ for i < 0.[9] The total and directional spillovers are produced by the generalized forecast-error variance decompositions of the moving average representation of the system (1). The FEVDs define the '*own variance shares*' as a fraction of H-step-ahead variance for forecasting Z_i, for i = 1, 2, …N and '*cross variance share or spillover*', as the fraction of H-step-ahead error

[8] For expository convenience, this section is heavily drawn from Diebold and Yilmaz (2012).
[9]Interested readers are referred to Judge, Hill, Griffiths, Lutkepohl, and Lee (1988), and Sims (1980b) for a detailed derivation of the moving average representation and the calculation of FEVDs, and Koop et al. (1996) for a discussion of generalized impulse response functions.

variances for forecasting Z_j, for $i, j = 1, 2, \ldots N$, such that $i \neq j$, for each i.Using the notion of H-step-ahead generalized forecast error variance decomposition of KPPS, the FEVDs can be written as

$$\theta_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i^{/} A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i^{/} A \sum A_h^{/} e_i)} \tag{3}$$

where $\sum$ is variance matrix for the error vector ε, σ_{ii} is the standard deviation of the error term for the i^{th} equation, and e_i is the selection vector with the i^{th} element as one and zeros otherwise. The own variance and cross variance shares are listed in the main diagonal and off-diagonal elements of $\theta(H)$ matrix, respectively. Its row sum normalizes each entry of the FEVD matrix:

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

With $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij} = N$ (see Diebold and Yilmaz 2012, p. 5).Using (3) and (4), the total spillover index can be calculated as:

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

The total spillover (TS) captures the contribution of risks from all sectors to the total forecast error variance. The authors also define directional spillovers from all other markets j to market i as

$$S_{i.}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)} .100 \tag{6}$$

and spillover from market i to all other markets j as

$$S_{\cdot i}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}(H)}.100 \qquad (7)$$

Both spillover measures are utilized to create the total spillover index.[10] Diebold and Yilmaz (2012) examine both total and directional volatility spillover across U.S. stock, bond, foreign exchange, and commodity markets using daily data and a framework of generalized vector autoregressive model for January 1999 to January 2010. The study finds evidence of minimal spillover before the global financial crisis period of 2007. However, volatility spillovers intensified from the stock market to other markets after the collapse of the Lehman Brothers in September 2008.

Since the publication of the DY method, many scholars have examined volatility spillover between financial assets and countries (see Demirer *et al.* (2018) and references therein). Kouki *et al.* (2011) consider key industry sectors such as banking, financial services, industrial, real estate, and oil, of selected developed and emerging markets over the period January 2002 to October 2009. They find that both shocks and the volatility of the U.S. banking sector are transmitted to developed and emerging markets, confirming the hypothesis that the U.S. plays a dominant role in the diffusion of information. Barunik *et al.* (2016) investigate asymmetries in volatility spillovers using 21 most liquid U.S. stocks from seven sectors (financials, information technology, energy, consumer discretionary, consumer staples, telecommunication services, and health care). The study finds that from August 2004 to December 2011, there was evidence of asymmetric connectedness among stocks at the sectoral level. Also, the spillover of bad and good volatility was transmitted at varying magnitudes across sectors over time. The study also reports that intra-

[10]As an anonymous referee pointed out, the spillover measure of Diebold and Yilmaz (2012) is not an index in true sense since the sum of a row in the variance decomposition matrix can be greater than one. Our interpretation is that the DY model has its roots in the unrestricted VAR model of Sims (1980a, 1980b), which is based on orthogonal innovations. While the row sum is equal to one, the variance decomposition results are sensitive to the ordering of the variables. Criticisms associated with the orthogonal identification scheme of unrestricted VAR contributed to the subsequent development of structural VAR, triangularization, and the generalized IRF. Under this scheme, the variance decomposition results are invariant to the ordering of the variables. Also, the row sum may not be equal to one. The variance decomposition or variance allocation from the IRF and VDCs, in percentage term, demonstrates what fraction of variability of one market is contributed by innovations of another market. While VDC is not an index, some researchers have coined the term as an index.

market spillover increased substantially during the financial crisis. The sector-level heterogeneity in the transmission mechanism of volatility spillovers was attributed to the activity of informed traders (which reduces volatility) and uninformed traders (which increases volatility).

The DY model has also contributed to the development of network [11] analysis to study connectedness among countries. Diebold and Yilmaz (2014) suggest several connected measures (total, directional connectedness from and to, bidirectional pairwise directional connectedness, and net directional connectedness) constructed from components of variance decompositions. They demonstrated the time-varying nature of connectedness across thirteen major US financial institutions during May 1999 through April 2010 with a particular emphasis on the 2007-2008 global financial crisis. Demirer *et al.* (2018) estimate the high-dimensional network among the world's top 150 publicly traded banks during 2003-2014. Results from both static and rolling window methods show that global bank connectedness has a strong geographic element while the sovereign bond markets are weakly connected. They find that network movement mostly stems from cross-country rather than within-country bank linkages. Finally, the authors document time variation in global connectedness, with stronger ties emerging during a crisis period.

Along a similar line of research, the paper by Wang et al. (2018) examines volatility connectedness in the Chinese banking system using fourteen publicly traded commercial banks over the period 2008 to 2016. The study demonstrates that joint-stock and city commercial banks emit greater volatility connectedness than state-owned commercial banks. Yarovaya *et al.* (2016) investigate the problem of intra- and inter-regional return and volatility spillovers across ten developed and eleven emerging markets in Asia, America, Europe, and Africa for the period 2005 through 2014. They show that markets are more exposed to domestic and region-specific volatility shocks than to inter-regional volatility shocks. The study also reports that the emerging Asian markets exhibit a lower level of spillover within the region compared to Europe and the Americas. Their results suggest that Asian markets are a more attractive destination for portfolio investment. In another study, Wang *et al.* (2017) note that the US market is highly correlated with

[11] The recent network literature emanates from the mathematical graph theory. See Acemoglu et al. (2015) and a list of references therein for additional details.

other G7 countries (except Japan) and Brazil during the pre-crisis period and that the US market is less correlated with the markets of China, India, and Russia. During the financial crisis period, the correlation between the US market and all other countries increase significantly; but the correlation with China remains low. Finally, Yi *et al.* (2018) use the spillover index and network analysis, suggested by Diebold and Yilmaz (2014) and Demirier *et al.* (2017), to investigate the volatility connectedness in the cryptocurrency market. They show fifty-two cryptocurrencies are highly interconnected and that larger coins such as Bitcoin and Litecoin are major contributors to spillover.

Overall, the DY model has become popular for analyzing return and volatility spillovers and connectedness among countries and financial assets. Yet, the practical use of the connectedness measure based on the stock market spillover measure has not been adequately explored. This is a major shortcoming because it is important for the regulatory agencies to identify the home country industries' exposure to shocks from foreign industries to design policies. Furthermore, the degree to which a capital market is exposed to external shocks can also be used as a screening device for constructing internationally diversified portfolios. For example, investing in countries and industries with low exposure to spillovers could allow the U.S. portfolio managers to hedge the U.S.-specific systemic risk. Surprisingly, this line of research where the magnitude of meteor showers is used as a screening device to guide international diversification is missing.

III. Empirical Analysis

We use daily data for the period from January 2, 2002 to September 21, 2015. The sample is split into four separate regimes to examine the dynamic nature of spillover: Full Sample (January 2, 2002 – September 21, 2015), Pre-Financial Crisis (January 2, 2002 – February 14, 2007), Financial Crisis (February 15, 2007 – April 30, 2009), and Post-financial Crisis (May 1, 2009 – September 21, 2015). These subsamples are expected to capture structural breaks due to significant economic and political events, including the financial crisis and the European debt crisis during this period. There are two ways we can identify the structural breaks for creating the subsamples. The first approach is to use an econometric model that includes exogenous variables that represent financial and economic news events and timelines (see Baur (2012), and Dimitriou and Kenourgios (2013), the Federal Reserve Bank (the Fed) of St. Louis (2009), and the Bank for International Settlements (BIS), (2009)). Alternatively, the subsamples can be derived from econometric models. For example, Boyer *et al.* (2006), Fry *et al.* (2010), and Rodriquez (2007) employed regime-switching models to determine the existence of two regimes (stable and volatile) where the 'volatile' regime defines the crisis period. We chose the first approach to create the subsamples using the timelines reported by the Fed and the BIS.

Data on sectoral investable equity indices are collected from the Datastream[12]. Returns (log-relatives) are based on end-of-day closing prices. To avoid nonsynchronous trading and time zone differences, European and North American financial data are matched on a daily basis. Asian market data were lagged one day to account for the fact that the U.S. still remains as the leading source of market volatility[13].

As noted earlier, our choice of countries and equity sectors is based on data on capital flows from the U.S. According to the U.S. Treasury, at the end of 2013, the U.S. equity portfolio managers held \$5.7 trillion in foreign stocks out of \$6.47 trillion investments in foreign securities (Table 1)[14]. The United Kingdom, Japan, Canada, France, Germany, Korea, Australia, Brazil, Italy[15], and China are among the leading countries receiving the bulk of equity investments from the U.S. In addition, Russia[16] and India were added based on recent data on foreign direct investment from the U.S.[17].

To identify the sources of volatility in the primary equity sectors in the U.S., we first examined the flow of funds from the U.S. to the foreign countries by industry, as reported by the U.S. Treasury(Table 2). We selected all equity sectors listed in the table, except for a few instances where the composition of a particular U.S. equity sector did not precisely match the foreign equity sector. Our universe includes the

[12]The sample period is based upon data availability. We thank ThomsonReuters for the data.
[13]We perform robustness tests later to show that our results are not sensitive to nonsynchronous trading data.
[14]The total holding of foreign securities by the end of 2018 is \$11.3 trillion.
[15]Italy is and remains as a major destination for investment flow from the U.S. For example, the flow data for Italy were as follows: \$66b (2010), \$91b (2016), and \$115b (2018). We are unsure why the data for Italy was not reported in the 2013 report.
[16]Direct investment position of the United States in Russia from 2000 to 2014 (in billion U.S. dollars, on a historical-cost basis). http://www.statista.com/statistics/188637/united-states-direct-investments-in-russia-since-2000/ (accessed March 4, 2016).
[17]India West, Thursday, March 3, 2016.

following ten investable equity sectors from each country: the broad market index (MSCI Investable Index), basic materials, consumer staples, financials, health care, industrials, oil and gas, technology, telecommunications, and utilities). We then matched these foreign equity sectors in Table 2 with their identical (or close) counterparts in the U.S., noting that a perfect match in some cases was not possible.

To make sure that volatility in the preceding U.S. equity sectors reflects investor sentiment and contributes to the spillovers to identical sectors in international trading partners, we estimate the Pearson correlation between the VIX index and the U.S. equity returns. The VIX[18] index, which is a measure of the expected uncertainty in the broad U.S. equity market, is also known as the 'fear index'. Table 3 (Panel A) shows that the returns on the VIX and the USMSCI are negatively correlated, supporting the view that the VIX is a conveyor of uncertainty in the U.S. market. Panel A, Table 3 also shows that during the financial crisis, the correlation fell to -.76, and post-financial crisis correlation drops to -.80, suggesting that uncertainty in the equity market is associated with declining stock returns. The U.S. sectoral equity returns are also negatively correlated with the VIX returns. For the full sample, the lowest negative correlation (-.71) is observed for the industrial sector returns while the highest correlation is observed for the telecommunication and the utilities sectors. During the crisis period, consumer staples, industrials, and technology sectors experienced a stronger negative correlation with VIX returns. Post-financial crisis correlations show an increase in the negative correlation between returns on industrial sectors and the VIX. Overall, these sectors are assumed to be reasonable conveyors of the uncertainty in the U.S. market.

Panel B, Table 3, shows that the broad market returns from the countries in the sample are negatively correlated with VIX returns[19]. The smallest correlation is observed for India. The largest negative correlation is observed for Canada, which is consistent with the close economic ties between Canada and the U.S. For sectoral equity indices, the results are similar. All correlation coefficients are negative, with the largest negative value observed for the industrial sector for Germany. The telecommunication sector returns in China have the lowest correlation. Overall, the correlation

[18]VIX is based on the implied volatility of the tout-of-the-money front and second-month expiration call and put options on S&P500.
[19]To conserve space, we only report the correlation coefficients for the full sample.

coefficients indicate that the VIX, U.S. sectoral indices and aggregate indices across countries share information content regarding stock market uncertainty.

We conducted several diagnostic tests (results not reported to save space) to examine the data. First, KPSS and the Augmented Dickey-Fuller (ADF) tests indicate returns are stationary. Next, in the majority of the cases, stock returns are negatively skewed, suggesting that the equity markets experienced relatively large declines over the sample period. The Bera-Jarque test indicates a departure from normality. The Lagrange Multiplier test (R^2 test) detects autocorrelation in the squared residuals. These test statistics confirm that equity returns are stationary and that the second moment is time-varying.

Broad Market Spillover

Table 4 reports broad stock market spillovers (first row) and sectoral spillovers in the rows below. The VAR[20] model (equation 1) contains fourteen variables (stock returns from all 14 countries, i.e., N = 14). Our analysis concentrates on four distinct regimes, as listed earlier. The foreign countries are arranged in alphabetical order in the table. In Panel A of Table 4, 13% (highest spillover) of the broad market volatility of Canada during the sample period can be attributed to the U.S. market. In contrast, only 3.6% of Indian equity market volatility was attributed to spillovers from the U.S. There is also evidence that spillover from the U.S. market during the period has affected the remaining countries in the sample. These are (in order of low to high spillover) Russia, Korea, China, Italy, Spain, Japan, France, Germany, the UK, Australia, and Brazil.

We believe that investor sentiment and portfolio diversification are critical elements of this spillover. As reported earlier, the U.S. portfolio managers held over $5.7 trillion worth of foreign equities from these high spillover countries. It is logical to assume that the U.S. portfolio managers would not be investing in high spillover countries because high spillovers could also lead to a high correlation between the countries. Naturally, such investments would be counter-productive for diversifying the portfolio.

[20]The VAR system in this study sets P equal to one, and forecast horizon H is equal to 10 days.

Sectoral Spillover

The broader stock market index-based spillover analysis in the previous section is limited in scope because it assumes that all constituent sectors of the stock index would be equally affecting their counterparts in foreign countries. In this section, we explore spillovers at the sectoral level to provide more insights on the degree of connectedness among the equity sectors.

Panel A, Table 4 shows that the spillover from the U.S basic metals industry contributed to 15.1% of the volatility in Canada, while China was least affected (1.9%) among the countries in the sample. For the consumer staples industry, Canada was most exposed (15.3%), while China was least sensitive (.9%) tothe U.S. volatility. The U.S. financial sector was responsible for 16% spillover in the Canadian financial sector, the largest spillover among the countries in the sample. Again, China was the least sensitive. Exposure for the remaining countries to the U.S. financial sector is (from low to high spillover): India, Russia, Italy, Korea, Spain, France, Japan, Germany, the UK, Brazil, and Australia. The average magnitude of spillover in these countries was 6.9%. This is hardly surprising given that the U.S. portfolio managers held almost $6 trillion of equities from these countries.

For the health care sector, Germany, Canada, the UK, France, Japan, Australia, Italy, Spain, India, China, Korea, Canada, and Italy were most affected by the spillover from the U.S. health care industry[21]. In contrast, Korea, China, and India were the least exposed. For the industrial sector, the order of spillover (from low to high) is as follows: China, India, Korea, Italy, Spain, Brazil, France, the UK, Japan, Australia, Germany, and Canada. In the oil and gas sector, 19.1% of the spillover in Canada was contributed by the U.S., which is consistent with the fact that Canada is the major provider of energy to the U.S.(averaging about 3.3 million barrels of crude oil per day in 2016).India, China, and Korea were the countries least affected by the spillovers from the U.S. In the technologies sector, China, India, Italy, Australia, Korea, and Spain were the least affected countries. In contrast, 14.7% of the spillover in the Canadian technology sector returns is contributed by shocks to the U.S technology sector. For the

[21]Health care equity index data were not available for Russia and Brazil.

telecommunication sector, Brazil was most affected while China was least exposed. Finally, Canada was most affected (11.1%) in the utilities sector, while China again was least affected.

Overall, spillovers during the full sample period suggest that China experienced the least spillover from the U.S. in 7 out of 9 equity sectors while Canada was the highest recipient of spillover in 7 out of 9 equity sectors. Brazil experienced the second-highest spillovers during the same period, which is surprising given that in 2013, the U.S. holdings of Brazilian equities were valued at less than $130 billion. A fundamental assumption in our paper is that high spillover indicates the degree of connectedness of the markets through international diversification of U.S. equity portfolios. It could, however, also reflect the flow of information across international borders.

Spillover: Pre, During, and Post-Financial Crisis

Spillover results over the three regimes, pre, during, and post-financial crisis, are reported in Panels B, C, and D of Table 4, respectively[22]. During the pre-crisis period, at the broad market level, Canada was affected most by the U.S. market, to the tune of 13.6%, while India was affected the least (2.6%). In essence, most developed countries were exposed to the U.S., with developing countries relatively less. At the sectoral level, vulnerable foreign countries are Germany, France, Italy, the UK, Spain, and Australia. In contrast, China, India, and Russia were least sensitive to the U.S. Surprisingly, Japan appears to experience low spillovers despite the fact that during 2013, the U.S. portfolio managers held over $600 billion of Japanese equity.

During the financial crisis, at the broad market level, India again was least exposed while Canada was the largest recipient of spillovers from the U.S. The level of spillovers is slightly higher than the pre-crisis level: The median spillover is 6.9%, and Japan, France, the UK, Australia, Brazil, and Canada have higher than the median spillover. Except for Brazil, all countries in the high spillover category are

[22]Given the sheer volume of information across countries and sectors, this section offers a high-level summary of the results reported in Panels A-D, Table 4.

developed countries with mature capital markets free of investment restrictions. Among the lowest spillover countries are India, Russia, Korea, and China.

In the post-crisis era, we expected a lower level of spillovers for the countries that were most exposed during the financial crisis. The rationale is that these countries would implement appropriate policies to reduce their U.S.-specific exposure. However, the results do not support this conjecture. At the broad market level, India was again the lowest recipient, while Canada was the largest recipient of spillovers from the U.S. Somewhat surprisingly, the level of spillovers is slightly higher than it was during the financial crisis. All countries, except India, remained significantly exposed to the U.S.

To summarize, Table 4 reports the countries and the industrial sectors that were most and least exposed to the U.S. broad market and sectoral spillovers. This unique perspective has been long overdue. We are a bit surprised to see that the country-specific average exposure (average across all industries by country and by regimes) to the U.S. remains quite similar across all four regimes. We expected a significant time variation post-crisis, possibly due to the regulatory response to limit exposure to the U.S. market. Our results show that the foreign markets' response to the spillover was not overly dramatic as one would have expected given the significance of the economic shocks to the U.S.

Vulnerability to the U.S. Originated Spillovers

Table 5 summarizes the spillover results by sorting these countries in order of high to low spillover. The country with the highest spillover is noted as 'Most Exposed,' and the country with the lowest spillover is identified as 'Least Exposed'. For the full sample period, at the broad market level, Canada remains as most vulnerable to the U.S. As we have noted earlier, this is consistent, given the geographical proximity and international trade flows between these neighbors. In comparison, India was the least exposed to the U.S. equity market volatility. While India remains as an important trade partner to the U.S., capital market restrictions that still exist in that country for two-way investment flows may be responsible for its low exposure to meteor showers from the U.S.

Table 5 also presents the most exposed and least exposed in all 4 samples at the sectoral level. During the full sample, Canada received the highest spillovers in 7 out of 9 sectors while China scored the lowest rank in 7 sectors. During the pre-financial crisis, Canada scored the highest spillovers in 8 sectors, while China was ranked as the country with the lowest spillovers in 8 sectors. During the financial crisis, Canada was ranked again as the most exposed country in terms of spillovers in 7 out of 9 equity sectors. In contrast, China was least exposed in 7 out of 9 equity sectors. Finally, during the post-financial crisis period, Canada was most exposed in 8 out of 9 sectors, while China received the lowest spillovers in 6 out of 9 equity sectors.

These results may have policy implications. From a regulatory standpoint, countries on the receiving end can design policies to curb the extent of meteor shower effects and insulate their equity sectors. As markets become less subject to external volatility, it promotes a sense of stability and resilience, which may be attractive to global investors.

Non-synchronous Trading

Previously, to eliminate the nonsynchronous effect, we lagged data from markets that are ahead of the U.S .market. To make sure the results are not sensitive to the alignment of data from different time zones[23], we now use the two-day rolling average returns, as suggested by Forbes and Rigobon (2002), and re-estimate the spillover models. Although the results are not reported[24], they are almost identical to the previous results. For instance, the U.S. broad market and sectoral spillovers to China's broad market and the sectors barely change whether we use lagged returns or 2-day rolling returns. The correlation coefficients between these two spillover measures for China is 0.997, and for almost all other countries, hovers in the mid to high 0.90's, with the lowest being 0.88 (Spain). This suggests that the results are robust to non-synchronous markets. In fact, the markets we would be most concerned with, China, Japan,

[23]We thank the anonymous referees for suggesting this.

[24] The results of this robustness test are available upon request.

Russia, Korea, and India, have spillover estimates that change very little when implementing 2-day rolling returns.

Dynamic Spillovers

We also performed an additional exercise to identify spillovers from the U.S. using a dynamic approach. It involves selecting a window of trading days over which dynamic spillover is measured. It seems there is no consistency in the literature regarding the ideal length of the window. Diebold et al. (2014) present 100-day rolling spillover estimates, while Diebold and Yilmaz (2012) present 200-day rolling estimates, and Demirer *et al.* (2018) present 150-day estimates. We chose the 200-day rolling estimates of spillovers. For any sector, there are two plots: Total spillover and Total U.S. sectoral spillover to Others (see Figure 1). As noted earlier, the metric of 'Spillovers to Others" is defined in Diebold and Yilmaz (2009 and 2012) and is computed by identifying all separate forecast error variance components for a given country coming from shocks to other countries and the country itself. 'Spillover to Others' can be computed by taking the sum of the contributions to the forecast error variance of other countries *due* to U.S. innovations. It is also important to note that each country's 'Spillover to Others' (i.e., contribution *to* other's forecast error variances) is not constrained to 100%, while 'Spillovers *from* Others' necessarily is (Diebold and Yilmaz (2014)). Hence, the y-axis across the figures vary in scale, and for some industries, can exceed 100%.

A few selected details and trends in the data are worthy of emphasis. At the broad market level, total cross-country stock market spillovers were relatively low, between 60% and 65% in 2005, but rose sharply to 80% by 2007, and remained high through the Lehman bankruptcy and Global Financial Crisis. Total spillovers remained elevated until 2011 but shooting up (to over 85%) once more in 2012 on the back of the unfolding European Debt Crisis coupled with uncertainty surrounding the U.S. credit downgrade. Total spillovers subsequently fell until a brief spike in 2013, seen as largely driven by U.S. spillovers to Others, possibly associated with the Taper Tantrum resulting from the announcement of the Federal Reserve's tapering of unconventional monetary policies. Finally, a sharp spike in Total but *not* U.S.

spillovers at the end of the sample aligns well with uncertainty over global demand growth, specifically China, which occurred in 2015.

Next, we highlight a few selected sectors to show some of the stylized facts on the extent of spillovers from the U.S.:

Oil & Gas: Total spillovers have steadily risen since 2003 from below 40% to above 70% in 2009, peaking during the financial crisis. Much of this spillover is attributed to the U.S. shale revolution, as the U.S. spillovers to Others rose sharply through the 2000s, roughly doubling from 50% to 100%. Total spillovers subsequently declined to spike again in 2011 due to political instability in the Middle East (Egypt, Libya, Yemen, and Bahrain). Over this period, Brent crude, the U.K. based benchmark oil grade, spiked relative to the U.S. West Texas Intermediate (WTI) crude oil, with the Brent trading at record levels of nearly $30/bbl above the WTI. The rise in total spillovers did not propagate from the U.S., as U.S. spillovers to Others remained stable, consistent with the shifting focus to Euro and Middle Eastern geographies as the sources of the 2011 shocks. Finally, total spillovers steadily declined once more until the end of 2014 and rose sharply into 2015 on the back of the largest oil price collapse since the financial crisis.

Utilities: The dynamic spillovers across the utilities sectors in different countries form an inverted "U" shape over the sample history – rising steadily in the early 2000's, then sharply falling during the financial crisis. The episodes of rising spillovers, however, share a common theme: they appear associated with bond market volatility – a pattern that's consistent with the notion of utilities acting as a close equity substitute to debt. Spillovers peaked over the financial crisis and steadily declined afterward, but with periodic spikes. Total spillovers sharply rose again in 2010, the same year when the 10-year Treasury yield rose by about 100 basis points in a matter of two months (from 2.40% in October to about 3.5% in December). Another major spike in total spillovers occurred in 2011 during the European Debt Crisis. Specific to U.S. spillovers to Others, we observe a sharp rise in 2013 around the Fed Taper Tantrum episode.

Financials: Rolling spillover plots for Financials look strikingly similar to the broad market spillovers across countries. The financial sector, being one of the most economically integrated, would, therefore unsurprisingly, bear this pattern. Total spillover across the financial sectors rose sharply over the pre-crisis period and peaked during the height of the crisis and the Lehman bankruptcy. Total spillovers remained elevated through 2011 and spiked again during the European Debt Crisis, which followed. Financial spillovers have since been on a downward trend, reaching pre-crisis levels of about 55% by 2013, but then rose sharply to 65% amidst the Fed Taper Tantrum. Total spillovers across financial sectors continued to decline into 2015, falling below 55%, a level not seen since 2006.

Portfolio Asset Allocation using Spillover as a Criterion

An issue is whether the desire to diversify or hedge home country risk is an important factor for capital flows from the U.S. We believe that spillovers and asset allocation decisions are correlated. Countries that ex-ante see more significant capital flows from the U.S. are subsequently more exposed to higher spillovers. Consequently, this would lead toa higher correlation with the U.S. This could, ex-post, make them less attractive investments in terms of diversification, ultimately leading to future capital flows being diverted from these countries to those with low spillovers (i.e., low correlation).

In this section, we conduct the minimum variance optimization (MVP)[25] to build globally diversified portfolios by allowing a representative U.S. portfolio manager to use the spillover measure as a screening tool. We assume that portfolio managers would prefer to invest in low spillover countries for diversification benefits. Table 6 (Panels A-L) reports the Sharpe ratios for the portfolios. The benchmark return is the U.S. equity return (USMCI). The risk-free rate is based on the 10-yr U.S. Treasury bond.

Full-Sample Criteria

We adopt three different allocation strategies based on cross-country and cross-sector spillovers. Strategy one: No-screening (minimum variance optimization across the full set of assets), Strategy two: invest only in low spillover (low spillover is defined as spillover less than the median spillover) countries, and Strategy three: invest only in high spillover(high spillover is defined as spillover greater than the

[25]We do not allow short sell, and maximum weight on a single country or sector is capped at 25%.

median spillover) countries. For Strategies two and three, the country indexes(broad market and sectors) are selected, and subsequently, the optimum weights are determined based on the MVP optimization. We consider performance under two sets of assets: Broad market country-level and the sector indexes. The main indicator of profitability is the Sharpe ratio. At the ***broad market*** level (Panel A), the Sharpe ratios from Strategy 1 are: .08 (full sample), .59 (pre-financial crisis), -1.72 (financial crisis), and .22 (post-financial crisis). For Strategy two, the Sharpe ratios are: .17 (full sample), .59 (pre-financial crisis), -1.02 (financial crisis), and .58 (post-financial crisis). Finally, for Strategy three, the Sharpe ratios are: -.04 (full sample), .37 (pre-financial crisis), -1.01 (financial crisis), .25 (post-financial crisis). At the broad market level, Strategy twohas the best Sharpe ratios, even during the financial crisis.

At the ***sectoral*** level (Panel B), similar investment strategies were applied. With Strategy one, the Sharpe ratio is .33, which is higher than the Sharpe ratio from a broad market index-based investment strategy (Panel A). During the pre-financial crisis, the strategy has a Sharpe ratio of .88. During the financial crisis, the performance of this strategy (-1.89) is worse than the Strategy one applied to the broad market indices (-1.72). The post-financial crisis performance of the strategy is better than the results based on broad market indices. The Sharpe ratio is .68, which shows a 209% improvement over the results based on broad market indices. When the universe included only low spillover sectors (sectors with less than the median level of spillover), the Sharpe ratios are as follows: .38 (full sample), .98 (pre-financial crisis), -.88 (financial crisis), and .93 (post-financial crisis). Finally, when the universe included sectors scoring higher than the median spillover (Strategy three), the Sharpe ratios are as follows: .18 (full sample), .53 (pre-financial crisis), -1.57 (financial crisis), and .54 (post-financial crisis).

Sector Diversification

We also experimented with a single sector(Panels C-K) diversification strategy. Our rationale is to allow for the possibility that a U.S. portfolio manager may seek international diversification within a particular industry. For the basic materials sector, Strategy two generated the highest Sharpe ratio of 1.32 during the pre-financial crisis period. Strategy one would have produced a Sharpe ratio of -1.27 during the financial crisis. In the consumer staples sector, Strategy three produced the highest Sharpe ratio of 1.11 for the post-financial crisis period, which is surprising. We believe that taking an aggressive investment strategy on a bull market (recovery period) produces this result. Strategy one has a Sharpe ratio of -1.91 during the financial crisis period. For the financial sector, Strategy two would have a Sharpe ratio of 1.03 during the pre-financial crisis. The same strategy would have been ideal during the financial crisis as the portfolio would have lost the least. The healthcare industry offers the best Sharpe ratio during the post-financial crisis. The Sharpe ratio is 1.66 for Strategy two. The lowest Sharpe ratio for this sector is observed for Strategy one during the financial crisis. For the remaining sectors, the highest Sharpe ratios for the sample periods are as follows: 1.0 (industrial; pre-financial crisis; low spillover strategy), .94 (oil and gas; pre-financial crisis; low spillover strategy), .84 (technology; post-financial crisis; low spillover strategy), .33 (telecommunications; post-financial crisis; low spillover strategy), and .82 (utilities; pre-financial crisis; no screening).

Robustness Test

We apply the statistical tests of Ledoit and Wolfe (2008) to test whether the baseline strategies generate Sharpe ratios statistically different from investing in the broad market index[26]. The results are reported in Table 6, Panel L. Two bootstrapping methods are implemented, one where returns are considered i.i.d, and a second where they are allowed to be serially correlated. Consistent with their high absolute Sharpe ratios, the low-spillover sector-level strategies generate statistically significant Sharpe ratios, while none of the broad market level strategies appear to be statistically significant. These results highlight the potential value of international asset allocation at the sectoral level.

Out-of-Sample Rolling Criteria

While useful for ex-post analysis, the strategy performance under the Full Sample criteria suffers from a look-ahead bias. For this reason, we also estimate a fully out-of-sample, 200-day rolling strategy. As

[26]We thank the editor for suggesting this critical test.

before, no shorting is permitted, and the maximum allocation for any particular asset is limited to 25% of the total portfolio. Again, we consider two sets of assets: Broad market and sector indexes. We specifically focus on the strategy that selects low (below-median) spillover countries and sectors, and we assume daily rebalancing. The dynamic strategy is based on 1-day ahead out-of-sample performance. Each period, indices are sorted based on the spillover from the U.S., which is estimated on a 200-day rolling basis. Below-median spillover cases are selected, and MVP optimization is conducted to derive the portfolio weights (covariance matrix is estimated on the same 200-day rolling period). With a one-day holding period, spillovers are updated, and portfolio weights are rebalanced.

The broad market index-based strategy performs rather poorly out-of-sample (Table 7).The average return is 4.88% (annualized), compared to the 6.73% return on USMSCI. In comparison, the country-sector strategy does well. The annualized mean return is 7.18% with a Sharpe ratio of .41, which is surprisingly higher than the Sharpe ratio for the full-sample static low-spillover strategy (0.38). The Sharpe ratios, however, are not statistically different from that of investing in the USMSCI (based on the method described in Ledoit and Wolf (2008)).The sector-country low-spillover strategy seems to have a cyclical pattern (Figure 2, Panel A). There are extended periods where it outperforms the U.S. broad market investment, and other periods where it under-performs. It performed very well on a relative basis from 2005, pre-financial crisis, and has been lagging from 2010 to about 2015, when it starts to outperform once again.

Finally, the charts(Figure 2, Panel B) plot the dynamic allocation weights of the broad market (country-level) strategy[27]. Interestingly, Canada (notice the flat line) is never selected by the low-spillover screen, and Australia rarely. One possible explanation is that these commodity-dependent advanced economies import considerable spillovers from the U.S. Moreover, this is consistent with the close trade relationship between Canada and the U.S., driving high spillovers between the two countries. Brazil starts to bear positive weight towards the end of the sample period, while several countries see their portfolio

[27]There would simply be too many charts to display the dynamic weights at the country-sectoral level.

allocation vary widely over the entire sample (U.K., Germany, and Japan). Italy received persistent positive, near-maximal weight up through 2010, which abruptly fell to near zero in the post-financial crisis period.

In Figure 3, we plot (standardized) broad market spillovers from the U.S. against the rolling contemporaneous correlation between broad market returns of the U.S. and a foreign country. These plots address whether spillovers are just correlations or something else. First, it is important to note that there is a mechanical relationship between the two given that spillovers are measured as Generalized FEVDs, which are a function of the contemporaneous correlation between two variables (among several other things). So, it would be interesting to explore if the contemporaneous correlation dominates the spillover estimates over time and across countries and by how much. The data suggest that the two are, in fact, correlated, and spillovers from the U.S. tend to track correlation rather closely. However, the two measures do diverge episodically, which suggests that spillovers, at times, contain information that is different from the correlation. Several countries, including the U.K., France, Germany, Italy, Spain, South Korea, and India, all have spillover measures that periodically diverge (sometimes to a great extent) from the return correlation. In contrast, for some countries, spillovers seem to be driven by the contemporaneous correlation almost always (Japan, Brazil, and Russia). From the perspective of a global investor's asset allocation decisions, the distinction between spillovers and correlation is crucial. If they tracked each other identically, screening investment candidates based on exposure to the U.S. spillovers would not add any value over screening candidates based on their correlation with the U.S. market.

IV. Conclusions

The literature suggests that volatility is both homegrown (heat wave) and imported (meteor showers). Previous attempts to capture the spillovers have relied on broad market indexes, which is not very reliable for identifying the equity sectors that are most susceptible to spillovers (meteor showers) from the U.S. Additionally, to our knowledge, there have not been many attempts to use the response to meteor showers to guide international asset allocation. Our paper addresses these two shortcomings. We identify the extent of spillovers from the major U.S. equity sectors (basic materials, consumer staples, financials, health care, industrials, oil and gas, technology, telecommunications, and utilities) to their corresponding equity sectors in 13 trading and investment partners of the U.S. The trading partners are Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Korea, Spain, Russia, and the United Kingdom. Subsequently, we use the spillover measures at the industry level to guide international investments. During the full sample period (January 2, 2002 – September 21, 2015), two industries, basic materials and oil and gas, contributed most to spillovers from the U.S. During the same period, utilities sector was the least contributor to the spillover. During the pre-financial crisis (January 2, 2002 – February 14, 2007), oil and gas sector (utilities) was the highest (lowest) contributor to the spillover. During the financial crisis (February 15, 2007 – April 30, 2009), we find that the financial sector was not the most significant contributor to the spillover. Instead, the technologies sector contributed to most spillovers. The utilities sector was the lowest contributor to spillovers. Finally, during the post-financial crisis period (May 1, 2009 – September 21, 2015), oil and gas industry (utilities) was the largest (smallest) transmitters of volatility.

The main takeaway from this analysis is that high spillovers lead to high equity market correlation, and as a result, reduces diversification benefits from investing in countries receiving high spillovers. Our minimum variance portfolio optimization using spillover measure as a filter confirms this hypothesis. The U.S. portfolio managers can earn high Sharpe ratios by investing in low spillover countries.

The policy implication of our study is that as the extent of global connectedness rises, policymakers need to identify the principal sources of volatility in the domestic capital market and design appropriate policy responses to deal with disparate sources of shocks. Reinhart and Rogoff (2012) recommend the IMF and other institutions to play a greater role with early warning and implementation of market disciplines. To this extent, the results in this study offer a framework for identifying the sectoral sources of volatility propagation and the need to adopt sound regulatory policies that promote bilateral capital flows but limit excessive spillover.

Table 1: Market value of the U.S. holdings of foreign equity, by country, and type of equity, for the countries attracting the most U.S. investment (as of December 31, 2013)

Billions of dollars

Country or region	Total	Common stock	Fund shares	Others*
United Kingdom	978	898	27	54
Cayman Islands	677	277	277	124
Japan	604	597	6	0
Switzerland	430	427	1	1
Canada	405	387	12	6
France	343	335	5	4
Germany	302	279	1	22
Netherlands	230	216	7	7
Ireland	228	209	12	7
Bermuda	179	160	10	9
Korea, South	147	141	0	6
Australia	144	131	12	2
Hong Kong	135	129	5	1
Brazil	129	98	1	30
China, mainland	101	98	3	0
Taiwan	98	98	0	0
Rest of world	1343	1238	50	56
Total	**6473**	**5715**	**429**	**329**

*Source: U.S. Treasury. Includes preferred stock, interests in limited partnerships, and other types of equity. Excludes Hong Kong and Macau, which are reported separately.

Table 2: Market value of the U.S. holdings of foreign securities, by industry, as of December 31, 2013
Billions of dollars

GICS Code*	Industry	Total	Equity	Debt	
				Long-Term	Short-term
1010	Total Energy	789	614	174	1
1510	Total Materials	596	456	138	2
2000	Total Industrial	741	658	82	1
2500	Total Consumer Discretionary	789	739	49	1
3000	Total Consumer Staples	586	530	53	3
3500	Total Health Care	582	548	32	2
4000	Total Financial	2977	1853	851	272
4500	Total Informational Technology	653	621	32	0
5010	Total Telecommunications Services	363	283	79	1
5510	Total Utilities	192	127	63	2
	Government**	759	1	695	63
	Industry Classification Unknown	103	41	57	5
	Total all industries	**9130**	**6473**	**2305**	**353**

Source: U.S. Treasury.
*Stands for Global Classification Industry Standard Code.
**Government includes central, local, and provincial governments, and government-sponsored or guaranteed corporations. Debt issued by international and regional organizations is classified as private.

Table 3: Panel A: Correlation between the U.S. broad market and sectoral stock returns with VIX returns

	Broad Market	Basic Materials	Consumer Staples	Financials	Health Care	Industrials	Oil and Gas	Technology	Telecommunication	Utilities
Full Sample	-0.75	-0.66	-0.68	-0.63	-0.68	-0.71	-0.61	-0.65	-0.55	-0.55
Pre-financial Crisis	-0.73	-0.66	-0.62	-0.66	-0.61	-0.66	-0.52	-0.59	-0.49	-0.46
Financial Crisis	-0.76	-0.67	-0.73	-0.66	-0.69	-0.73	-0.65	-0.72	-0.67	-0.67
Post-financial crisis	-0.80	-0.71	-0.77	-0.71	-0.74	-0.76	-0.69	-0.74	-0.60	-0.57

Note: The U.S. broad market index is the U.S. MSCI Investable Index.

Table 3: Panel B: Correlation between foreign broad market and sectoral stock returns with VIX returns

	Broad Market	**Basic Materials**	**Consumer Staples**	**Financials**	**Health Care**	**Industrials**	**Oil and Gas**	**Technology**	**Telecommunication**	**Utilities**
Australia	-0.43	-0.39	-0.22	-0.36	-0.27	-0.39	-0.37	-0.24	-0.16	-0.26
Brazil	-0.5	-0.45	-0.28	-0.44	-	-0.37	-0.38	-	-0.38	-0.36
Canada	-0.56	-0.39	-0.45	-0.48	-0.32	-0.49	-0.44	-0.35	-0.29	-0.38
China	-0.32	-0.12	-0.09	-0.09	-0.08	-0.1	-0.11	-0.09	-0.06	-0.09
France	-0.48	-0.41	-0.43	-0.44	-0.36	-0.44	-0.4	-0.38	-0.32	-0.31
Germany	-0.47	-0.48	-0.35	-0.49	-0.37	-0.49	-	-0.4	-0.36	-0.37
India	-0.21	-0.18	-0.14	-0.18	-0.14	-0.19	-0.13	-0.18	-0.11	-0.11
Italy	-0.46	-0.32	-0.4	-0.43	-0.29	-0.44	-0.37	-0.21	-0.31	-0.38
Japan	-0.39	-0.36	-0.38	-0.34	-0.32	-0.38	-0.32	-0.37	-0.27	-0.16
Korea	-0.29	-0.26	-0.19	-0.26	-0.08	-0.25	-0.21	-0.2	-0.14	-0.15
Russia	-0.28	-0.17	-	-0.22	-	-	-0.22	-	-0.2	-0.17
Spain	-0.45	-0.4	-0.28	-0.42	-0.31	-0.41	-0.38	-0.31	-0.38	-0.39
The UK	-0.46	-0.38	-0.36	-0.41	-0.3	-0.42	-0.35	-0.35	-0.32	-0.3

Correlation for the full sample period (January 2002- September 15, 2015) only. Missing indices are noted as -.

Table4: Spillover Analysis

Panel A: Full Sample

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Korea	Russia	Spain	UK
Broad Market	8.9%	10.0%	13.0%	5.8%	7.3%	7.7%	3.6%	6.3%	7.2%	5.3%	4.9%	6.4%	7.7%
Basic Materials	10.3%	11.9%	15.1%	1.9%	8.2%	9.1%	2.8%	8.0%	7.7%	6.6%	5.5%	7.0%	9.6%
Consumer Staples	5.6%	5.9%	15.3%	0.9%	10.3%	8.4%	2.2%	7.7%	8.7%	3.8%	--	5.0%	9.5%
Financials	9.9%	8.2%	16.0%	1.5%	6.9%	7.8%	3.5%	5.5%	7.0%	5.6%	3.6%	5.7%	8.0%
Health Care	6.9%	--	10.3%	0.7%	9.8%	10.3%	2.0%	6.7%	9.4%	0.5%	--	6.5%	9.9%
Industrials	9.3%	8.1%	14.4%	1.2%	8.3%	9.6%	2.7%	7.1%	8.4%	5.1%	--	7.1%	8.3%
Oil and Gas	10.8%	11.6%	19.1%	1.4%	8.9%	--	0.7%	8.1%	9.0%	4.0%	5.8%	6.6%	10.0%
Technologies	5.1%	--	14.7%	0.8%	11.0%	11.5%	4.3%	4.9%	10.5%	5.1%	--	6.8%	9.6%
Telecommunication	2.2%	8.9%	8.0%	0.3%	4.5%	5.9%	0.7%	4.9%	5.9%	2.4%	2.2%	5.8%	6.9%
Utilities	3.8%	8.5%	11.1%	0.3%	5.1%	5.6%	0.6%	4.4%	1.9%	2.2%	2.0%	5.1%	5.6%

Panel B: Pre-financial Crisis

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Korea	Russia	Spain	UK
Broad Market	9.5%	8.5%	13.6%	5.3%	7.7%	8.6%	2.6%	6.4%	5.5%	5.3%	3.8%	6.6%	7.3%
Basic Materials	8.3%	8.3%	17.2%	0.7%	8.2%	9.7%	1.5%	5.6%	5.5%	6.1%	3.6%	5.4%	7.9%
Consumer Staples	4.1%	3.4%	18.0%	0.1%	10.2%	11.1%	1.3%	7.9%	6.1%	4.0%	--	3.6%	8.8%
Financials	8.5%	4.7%	16.1%	0.1%	8.3%	8.8%	1.0%	6.6%	3.4%	4.8%	2.0%	6.3%	6.9%
Health Care	4.4%	--	13.0%	0.2%	8.7%	8.9%	1.2%	4.8%	4.4%	0.6%	--	1.8%	9.6%
Industrials	6.5%	4.2%	10.9%	0.1%	7.8%	9.4%	1.4%	7.4%	7.2%	5.3%	--	4.9%	8.0%
Oil and Gas	10.7%	11.8%	21.2%	0.2%	8.2%	--	0.1%	7.1%	6.4%	2.1%	4.9%	6.9%	9.8%
Technologies	2.4%	--	15.6%	0.0%	10.9%	11.2%	3.5%	7.4%	8.2%	3.2%	--	7.0%	8.8%
Telecommunication	1.4%	6.4%	8.0%	0.1%	4.7%	5.8%	0.1%	4.8%	5.0%	3.3%	1.0%	5.2%	6.0%
Utilities	1.8%	5.8%	4.8%	0.1%	3.2%	2.3%	0.6%	2.9%	0.6%	0.9%	0.4%	3.8%	2.6%

Table 4: Spillover Analysis (contd.)

Panel C: Financial Crisis

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Korea	Russia	Spain	UK
Broad Market	8.4%	9.9%	12.5%	5.1%	7.2%	6.9%	3.7%	6.9%	7.1%	4.7%	4.4%	6.9%	7.3%
Basic Materials	10.8%	13.0%	14.6%	1.8%	8.2%	8.6%	2.5%	9.1%	7.7%	6.3%	6.6%	6.8%	10.1%
Consumer Staples	8.6%	5.8%	13.4%	2.2%	11.4%	6.5%	3.8%	6.8%	10.2%	3.9%	--	6.9%	11.4%
Financials	9.2%	8.3%	14.8%	2.8%	6.6%	7.1%	4.6%	6.4%	7.0%	5.5%	3.4%	6.8%	7.1%
Health Care	8.0%	--	9.6%	2.3%	11.2%	12.1%	3.4%	6.4%	10.8%	0.7%	--	6.7%	9.8%
Industrials	9.2%	9.3%	15.8%	1.7%	8.3%	8.9%	2.9%	6.4%	8.0%	4.2%	--	7.0%	7.7%
Oil and Gas	10.7%	13.2%	17.4%	1.7%	9.6%	--	0.9%	9.8%	9.0%	3.2%	5.6%	6.8%	10.2%
Technologies	8.8%	--	15.2%	1.5%	10.1%	11.0%	5.1%	6.1%	11.7%	7.3%	--	7.2%	10.3%
Telecommunication	3.2%	12.8%	6.9%	0.5%	4.9%	5.6%	3.1%	7.3%	8.5%	3.8%	4.0%	7.4%	7.2%
Utilities	3.8%	12.5%	14.5%	0.3%	6.8%	8.0%	0.3%	6.6%	5.6%	4.4%	4.5%	6.5%	6.9%

Panel D: Post-Financial Crisis

	Australia	Brazil	Canada	China	France	Germany	India	Italy	Japan	Korea	Russia	Spain	UK
Broad Market	8.2%	9.8%	12.7%	6.4%	7.2%	7.5%	4.2%	6.3%	7.4%	5.8%	5.8%	6.2%	7.8%
Basic Materials	9.8%	11.3%	14.0%	2.5%	7.9%	9.3%	4.1%	7.9%	8.1%	7.0%	5.5%	7.4%	9.1%
Consumer Staples	5.0%	9.0%	12.6%	1.0%	8.3%	9.3%	2.8%	7.6%	8.7%	3.2%	--	6.2%	8.6%
Financials	8.7%	8.9%	13.9%	1.2%	7.3%	8.8%	3.1%	5.8%	7.6%	7.3%	4.8%	5.5%	8.5%
Health Care	7.1%	--	10.8%	0.7%	9.5%	10.0%	2.0%	8.3%	9.6%	0.5%	--	8.5%	9.9%
Industrials	9.5%	9.1%	15.5%	2.0%	8.4%	9.9%	3.4%	7.4%	8.6%	6.2%	--	7.4%	8.6%
Oil and Gas	10.2%	9.4%	18.0%	3.0%	8.6%	--	2.0%	7.7%	9.2%	6.8%	7.3%	7.2%	9.7%
Technologies	5.0%	--	10.2%	1.4%	10.7%	11.6%	4.9%	2.6%	10.2%	6.7%	--	6.7%	9.4%
Telecommunication	3.2%	6.2%	7.4%	0.9%	4.6%	6.3%	0.8%	4.8%	3.7%	1.1%	3.2%	6.0%	7.1%
Utilities	4.3%	7.4%	11.2%	0.6%	4.9%	5.4%	1.3%	3.6%	1.0%	1.7%	3.0%	4.7%	5.7%

Spillover measures the contribution to the forecast error variance of a country's returns, coming from the U.S. The DY method (Diebold-Yilmaz (2012))is used for the variance decomposition to identify the extent of spillovers from one market to the other.

Table 5: Winners and Losers based on vulnerability to the U.S. originated spillovers

Sample	Degree of vulnerability to spillover	Broad Market	Basic Materials	Consumer Staples	Financials	Health Care	Industrials	Oil and Gas	Technologies	Telecommunication	Utilities
		Equity Sectors									
Full Sample	Highest	Canada	Canada	Canada	Canada	Germany	Canada	Canada	Canada	Brazil	Canada
	Lowest	India	China	China	China	Korea	China	India	China	China	China
Pre-financial Crisis	Highest	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Brazil
	Lowest	India	China	China	China	China	China	India	China	China	China
Financial Crisis	Highest	Canada	Canada	Canada	Canada	Germany	Canada	Canada	Canada	Brazil	Canada
	Lowest	India	China	China	China	Korea	China	India	China	China	China
Post-financial Crisis	Highest	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Germany	Canada	Canada
	Lowest	India	China	China	China	Korea	China	India	China	India	China

Note: In this table, we sort the 13 countries in order of spillovers from the U.S. to identify the highest and lowest spillover countries. Spillover is measured using the Diebold and Yilmaz (2012) methodology. Highest represents the country that was most exposed to the spillover while lowest represents the country least exposed.

Table 6: Portfolio construction using spillover as a screening tool

Panel A: Broad market

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	5.51%	7.10%	3.78%	12.44%	14.04%	10.63%	-19.17%	-19.94%	-19.82%	7.33%	10.21%	5.62%
Annual Std.	13.70%	15.75%	14.50%	9.42%	11.76%	9.55%	22.41%	23.42%	23.55%	11.48%	13.07%	12.38%
Sharpe Ratio	0.08	0.17	-0.04	0.59	0.59	0.37	-1.72	-1.02	-1.01	0.22	0.58	0.25

Panel B: All Sectors

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	7.18%	7.97%	6.20%	11.71%	13.89%	11.03%	-11.49%	-7.98%	-16.46%	10.10%	10.24%	7.51%
Annual Std.	8.38%	9.36%	10.02%	6.05%	6.89%	7.42%	11.40%	13.54%	12.98%	7.07%	8.22%	9.19%
Sharpe Ratio	0.33	0.38	0.18	0.88	0.98	0.53	-1.89	-0.88	-1.57	0.68	0.93	0.54

Panel C: Basic Materials

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	6.22%	6.35%	6.29%	22.12%	22.04%	20.27%	-15.96%	-20.27%	-12.32%	3.53%	3.53%	3.53%
Annual Std.	16.04%	16.53%	19.39%	10.71%	11.36%	13.02%	24.56%	25.19%	30.35%	14.80%	15.46%	17.18%
Sharpe Ratio	0.12	0.12	0.10	1.11	1.32	1.01	-1.27	-0.96	-0.53	-0.05	0.06	0.06

Panel D: Consumer Goods

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	10.07%	9.94%	7.26%	15.32%	16.67%	8.66%	-15.72%	-8.53%	-19.44%	12.15%	10.67%	15.36%
Annual Std.	10.51%	10.81%	13.89%	9.89%	10.56%	12.76%	12.78%	17.46%	13.61%	8.61%	8.78%	11.49%
Sharpe Ratio	0.54	0.51	0.21	1.04	0.91	0.12	-1.91	-0.71	-1.72	0.74	0.92	1.11

Panel E: Financials

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	4.88%	6.02%	3.78%	12.64%	19.61%	11.19%	-23.18%	-23.18%	-23.18%	7.95%	9.09%	7.65%
Annual Std.	14.10%	17.78%	14.93%	8.04%	12.16%	8.33%	24.75%	27.92%	27.15%	11.55%	15.37%	12.28%
Sharpe Ratio	0.04	0.09	-0.04	0.59	1.03	0.49	-1.95	-0.97	-1.00	0.25	0.42	0.41

Table 6: Portfolio construction using spillover as a screening tool(contd.)

Panel F: Health Care

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	10.07%	10.30%	7.66%	8.49%	9.97%	4.54%	-8.41%	-8.29%	-15.37%	16.85%	18.93%	13.97%
Annual Std.	9.94%	10.51%	12.05%	7.45%	7.81%	10.33%	12.89%	14.69%	15.89%	9.22%	9.83%	11.36%
Sharpe Ratio	0.57	0.56	0.27	0.41	0.37	-0.25	-1.29	-0.83	-1.21	1.26	1.66	1.00

Panel G: Industrials

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	6.85%	8.67%	3.78%	15.52%	16.58%	7.71%	-23.18%	-22.23%	-23.18%	11.57%	9.36%	11.09%
Annual Std.	13.14%	14.38%	14.38%	9.42%	9.50%	13.98%	20.04%	20.77%	23.74%	11.19%	13.83%	11.85%
Sharpe Ratio	0.19	0.30	-0.04	0.85	1.00	0.04	-2.10	-1.26	-1.14	0.55	0.49	0.72

Panel H: Oil and Gas

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	5.37%	6.31%	3.78%	19.01%	19.38%	15.82%	-16.18%	-17.61%	-2.16%	3.53%	3.53%	3.53%
Annual Std.	15.77%	16.50%	19.37%	12.12%	13.01%	14.97%	22.49%	22.89%	30.46%	14.76%	14.76%	19.93%
Sharpe Ratio	0.06	0.12	-0.03	0.93	0.94	0.58	-1.30	-0.94	-0.20	-0.05	0.06	0.05

Panel I: Technology

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	5.03%	5.09%	3.78%	8.20%	8.73%	4.54%	-19.58%	-23.18%	-16.15%	12.84%	13.72%	10.89%
Annual Std.	15.33%	15.71%	20.22%	14.49%	14.67%	22.66%	19.66%	19.98%	25.92%	12.47%	13.24%	14.69%
Sharpe Ratio	0.04	0.05	-0.03	0.25	0.11	-0.11	-1.56	-1.36	-0.77	0.55	0.84	0.57

Panel J: Telecommunication

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	3.78%	3.78%	3.80%	4.54%	4.75%	4.54%	-10.37%	-9.75%	-14.28%	6.25%	5.91%	8.09%
Annual Std.	10.94%	12.67%	14.70%	10.16%	11.80%	13.80%	15.69%	16.02%	20.29%	8.38%	10.02%	10.41%
Sharpe Ratio	-0.05	-0.05	-0.04	0.01	-0.20	-0.19	-1.35	-0.85	-0.90	0.17	0.33	0.53

Panel K: Utilities

	2002-2015			Pre-financial Crisis			Financial Crisis			Post Financial Crisis		
	No Screening	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**	**No screening**	**Low vol.**	**High vol.**
Annual Return	4.81%	3.78%	5.18%	12.23%	12.56%	11.29%	-10.60%	-16.43%	-10.28%	3.53%	3.53%	3.92%
Annual Std.	9.64%	11.63%	11.32%	6.33%	8.10%	7.99%	14.95%	17.58%	17.85%	8.71%	10.83%	9.28%
Sharpe Ratio	0.05	-0.05	0.07	0.82	0.67	0.53	-1.55	-1.16	-0.79	-0.09	0.09	0.14

Table 6: Portfolio construction using spillover as a screening tool (contd)

(Panel L: Statistical significance of Sharpe Ratios, Select Strategies

P-values for Portfolio VS. S&P 500 Sharpe Ratios	Boot-iid (1)	Boot-TS (2)
Broad Market, No Screening	0.438	0.338
Broad Market, Low Vol.	0.228	0.158
Broad Market, High Vol.	0.942	0.906
All Sectors, No Screening	0.072*	0.046**
All Sectors, Low Vol.	0.070*	0.034**
All Sectors, High Vol.	0.278	0.21

Ledoit and Wolfe (2008) test for the difference between two Sharpe ratios, bootstrapped method [i.i.d. bootstrap (1) and Block bootstrap (2)]. Full-Sample period (2002-2015), daily frequency. The number of bootstrapped simulations = 250, block size for (2) = 5 periods. *,**,*** correspond with 10%, 5%, and 1% significance, respectively. We compare Sharpe ratios of spillover-based strategies against the Sharpe ratio of S&P 500 returns. Risk-free rate used to compute excess return is the 10-year Treasury yield.

Figure 1: 200-day Dynamic Total Spillover and Spillover to Others in selected sectors

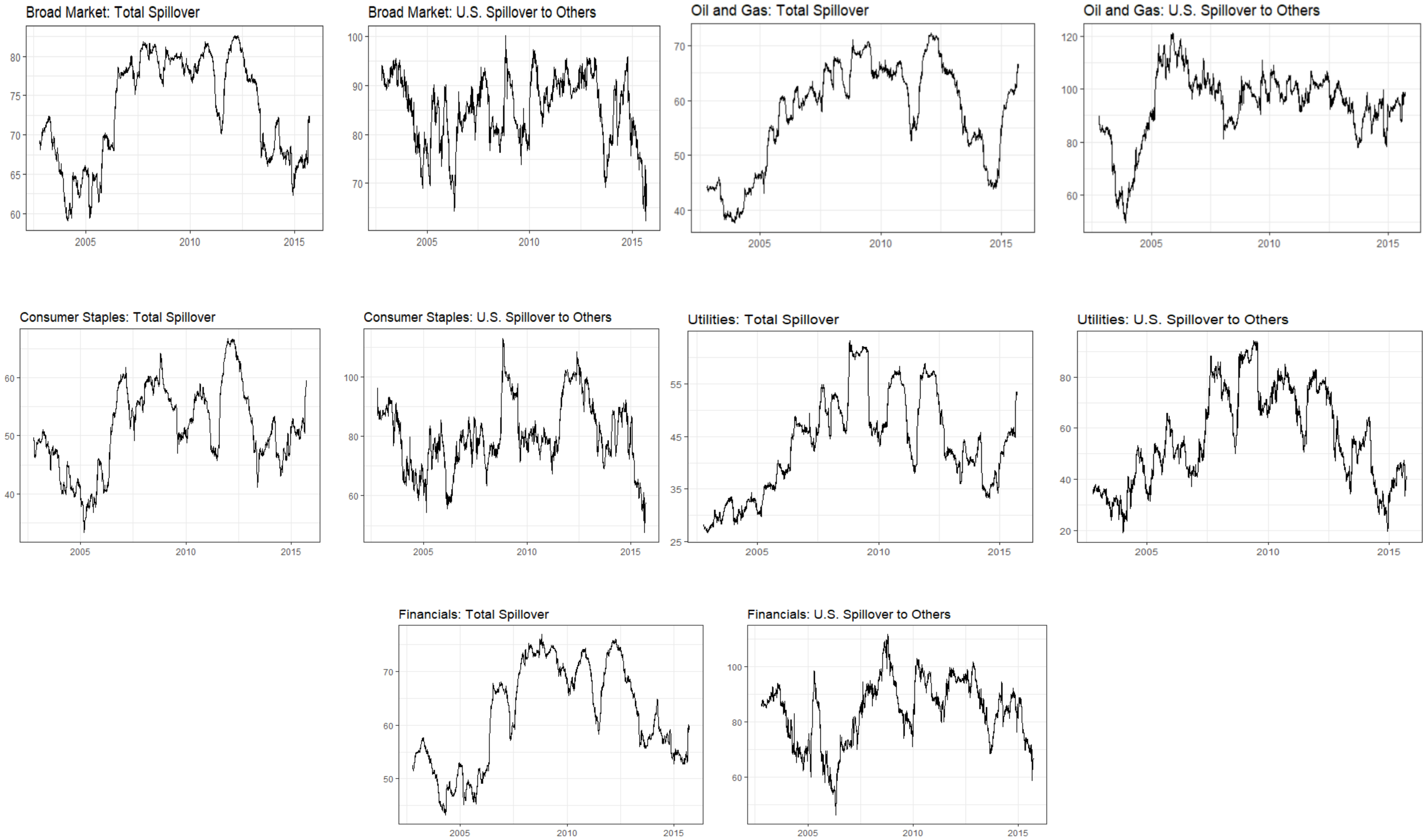


Table 7: Out-of-sample Rolling Portfolio Performance

Dynamic Low Spillover Asset Allocation Strategies	Sector Strategy	Broad Market Strategy	S&P 500
Mean Return	7.18%	4.88%	6.37%
Standard Deviation	8.49%	14.90%	19.30%
Sharpe Ratio	0.41	0.06	0.11

Dynamic strategy is based on 1-day ahead out-of-sample performance. Each period, Indices are sorted based on spillover from the U.S., which is estimated on a 200-day rolling basis. Below-median spillover indices are selected (always including U.S. indices), and minimum variance optimization is conducted to select portfolio weights (covariance matrix is estimated on the same 200-day rolling period). Holding period for the portfolio is assumed to one day. Subsequently, spillover estimates are updated and portfolio weights are rebalanced. Based on Ledoit and Wolfe (2008), the difference in Sharpe ratios between spillover-based asset allocation strategies and S&P 500 excess returns are not statistically significant. Risk free rates for Sharpe Ratio calculations are based on the 10-Year Treasury yield.

Figure 2,Panel A: Relative Performance of sectoral low-spillover vs. S&P 500

Figure 2, Panel B: Dynamic Broad Market Strategy Portfolio Weights

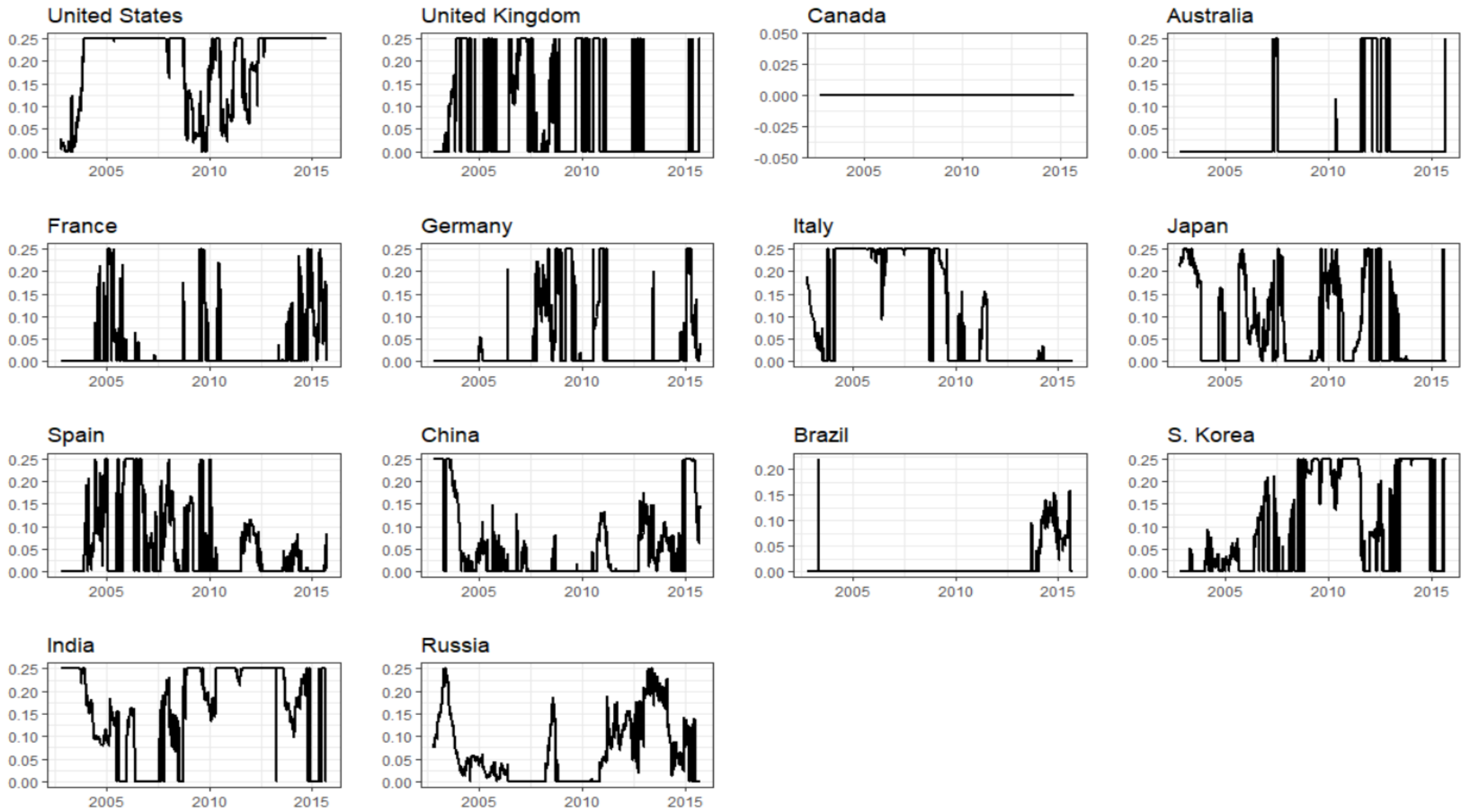
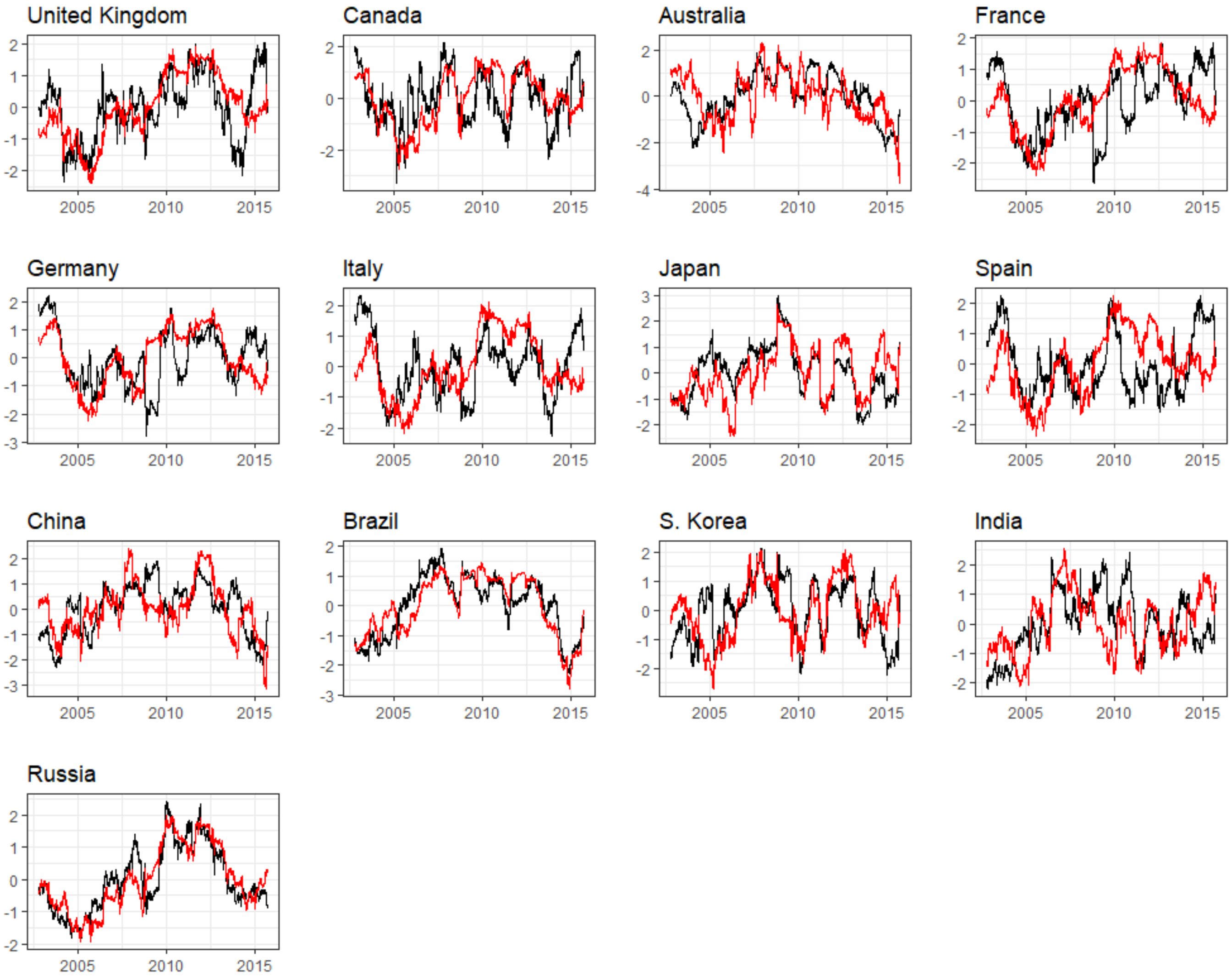


Figure 3: Dynamic Spillover from U.S. to country 'n' (black) vs. Rolling Return Correlation of country 'n' with U.S. (red)

Note: Both series are standardized, Y-axis is Z-score. Rolling window = 200 Days



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