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The Transmission of U.S. Equity Shocks to Emerging Stock Markets and the Role of U.S. Monetary Policy

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Abstract

This master thesis examines the equity return connectedness between the U.S. and 12 emerging market countries between 1994 to 2017, applying a network approach based on variance decompositions from a vector autoregressive model (VAR), proposed by Diebold and Yilmaz (2012). Our findings suggest that return spillovers between the countries exist in varying strength, and that overall spillovers increase in crisis periods. There is empirical evidence for the existence of two regional connectedness clusters, one in Asia and one between the U.S. and Latin America. The majority of emerging market countries are net receivers of equity shocks whereas the U.S. and Mexico play the largest role in transmitting directional shocks to other markets. Financial integration significantly determines return spillovers from the U.S. to emerging markets which provides support for the portfolio channel theory. Finally, the reaction of countries to shocks arising from U.S. monetary policy surprises is widely consistent with our spillover analysis. Our results suggest that Mexico and Brazil are most sensitive to U.S. shocks both in general and to target rate surprises in specific.

1. Introduction

The degree of co-movement between global equity markets has been extensively discussed in financial research[1]. The aim of these studies is to assess potential portfolio diversification benefits for investors and to create enhanced knowledge for trading and hedging strategies. Being initially centered around mature markets, the focus of this research has shifted over the past decades to interdependence of emerging markets (EM). The economic growth of these economies has gained substantial momentum. They were responsible for more than half of global growth between 2000 and 2016 (International Monetary Fund, 2016). This rapid development was accompanied by integration in global trade networks, as well as increased financial integration, with growing and better developed capital markets. The countries have in the past been characterized by consistently high average returns at a relatively low correlation with developed markets (Mensi, Hammoudeh, Nguyen, & Kang, 2016). Thus, emerging market stocks have increasingly become attractive targets for foreign equity investment. Over the past years however, studies as those performed by John Wei, Liu, Yang, and Chaung (1995) or Samarakoon (2011) report that the interdependence between developed markets and emerging markets has increased.

In this thesis, we apply a network approach based on variance decompositions from a vector autoregressive model (VAR) to investigate the return spillovers amongst 12 emerging equity markets and between these emerging markets and the U.S.. This approach, proposed by Diebold and Yilmaz (2012), allows us to highlight both total connectedness and the directional connectedness between emerging market countries with the U.S. and amongst themselves, resulting in a more differentiated picture about of the nature of the network. The analysis is based on weekly stock market returns for Brazil, Chile, Colombia, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Thailand, Turkey and the U.S. between 1994 to 2017. We also explore whether financial and real integration of each country with the U.S. can explain the existence and dynamics of directional spillovers with the U.S.. Existing literature either investigates only the existence of transmission effects across stock markets without hypothesizing about its potential sources or is dedicated solely to identifying the drivers of cross-market spillovers. We

[1] See i.e. Eun and Shim (1989) Longin and Solnik (1995), Bekaert, Hodrick, and Zhang (2008), Samarakoon (2011). A more detailed discussion is provided in the Section 3.

complement this work by examining both the existence and the drivers of international spillovers, thus gaining deeper insights into the transmission mechanisms of U.S. equity shocks to EM countries.

Finally, we deepen our main analysis by considering how specifically spillovers from U.S. monetary policy surprises propagate to emerging stock markets. We measure the stock markets' reaction to a surprise change in the U.S. federal funds target rate and draw conclusions whether the results are consistent with the findings of our general spillover analysis. Since concrete risk factors triggering transmission effects are generally not object of investigation in international spillover studies, we aim to combine the two research areas for a more wholistic view on spillovers. This thesis set-up allows us to give indications not only on whether diversification benefits in emerging markets exists but also whether, if already invested in those countries, investors should monitor U.S. monetary policy as a relevant risk factors and include it into value forecasts for their portfolios.

The rest of this paper is organized as follows: Section 2 provides an overview about the relevant background theory for our analysis. Section 3 presents relevant research findings about international spillovers and U.S. monetary policy transmission. Section 4 lays out the hypotheses, followed by an outline of the empirical model in Section 5. Section 6 specifies the data set. Section 7 discusses the empirical results and limitations of the analysis. In Section 8, set-up and results of the digression to monetary policy spillovers are presented. Section 9 summarizes and provides concluding remarks.

2. Theory

Identifying the transmission channels of equity shocks from the U.S. to foreign capital markets requires a sound understanding of asset value drivers. The following section presents the most prominent theories on that topic.

One of the most widely known and used models of asset valuation is the Discounted Cash Flow (DCF) Model. The concept in its most basic form was first formalized by Irving Fisher (1930) and incorporated in John Burr Williams' 'The theory of Investment Value' from 1938. It is based on the fundamental idea that the value of an asset is determined by the sum of all expected future cashflows, capitalized at a discount factor which captures several factors determining the individual's time preference, such as size and riskiness of the income stream.

$$V = \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t}$$

CF_t represent the cashflows to the company at time t and r represents the discount rate. According to the DCF model, fluctuations observed in asset prices can arise either from a change in expected cashflows or from a change in the discount rate r.

William's work also lay the foundation for Gordon (1959) in his stock valuation model. The Gordon Growth Model states that the price of a stock is determined by the present value of all expected future dividends.

$$V = \frac{D_1}{1+k} + \frac{D_1(1+g)}{(1+k)^2} + \frac{D_1(1+g)^2}{(1+k)^3} + \frac{D_1(1+g)^3}{(1+k)^4} + \cdots + \frac{D_1(1+g)^{n-1}}{(1+k)^n}$$

D_1 is the value of the dividend next period, whereas g represents the dividend growth rate and k the discount rate.

Assuming constant dividend growth and that the stock is hold for an undetermined amount of time, the price calculation simplifies to a growing perpetuity of the dividend next period.

$$V = \frac{D_1}{(k-g)}$$

Thus, the stock price adjusts based on changes in the required market return, as well as in expectations about the size of upcoming dividend per share and about dividend growth.

There are also theories exploring causes for asset price changes within one market which go beyond changes in intrinsic value drivers. These models often ascribe stock price fluctuations to a portfolio channel, i.e. the changes are caused by investors who reallocate their asset holdings in reaction to domestic shocks. In this theory, financial integration – when measured by investors' portfolio holdings – serves as proxy for the portfolio channel. One of these models was introduced by Lastrapes (1998) for the impact of a monetary policy shock on capital markets. Imposing long-run monetary neutrality, he showed a 'liquidity effect': investors react to excess real money supply by rebalancing their portfolios from bonds into stocks, thus causing shifts in demand and supply, which in turn lead to changes in equity prices.

The portfolio channel also plays a role in so-called Contagion theories, which aim to explain asset price changes across markets. There exists a plethora of definitions for contagion. Forbes and Rigobon state that ‘there is widespread disagreement about what this term entails.’ (Forbes & Rigobon, 2002, p. 2223). Previous studies associate the terminology more narrowly with shocks in extreme situations. Kyle and Xiong (2001, p. 1402) define it as the rapid cross-market spread of ‘declining prices, declining liquidity and increased volatility’. Kaminsky and Reinhart (2000) and Pericoli and Sbracia (2003) refer to contagion as the transmission of a shock not explained by fundamental linkages, whereas Markwat, Kole, and van Dijk (2009) and Samarakoon (2011) distinguish between ‘transmission’ as impact of shocks during stable times and ‘contagion’ as the impact of extreme shocks during crisis. For this thesis, we follow the latter definition, and focus on transmission effects in general rather than only contagion. Moreover, we use ‘transmission’ and ‘spillover’ interchangeably.

There are several explanations for observed cross-market equity price variations in the literature. If countries share common macroeconomic risk factors, such as business cycles, commodity prices or trade dependencies, stock price changes may be caused by trades of long-term investors who respond to shocks in one country by readjusting their portfolios’ risk profile based on expectations about the risk factors in in other markets. In this framework, the spillover effect should be symmetric for both market upswings and downswings (Kodres & Pritsker, 2002).

Kyle and Xiong (2001) on the other hand propose that for countries without common fundamental factors, the cause for cross-market price changes can be a domestic wealth shock. They argue that, when suffering a large loss, wealth-constrained investors – e.g. short-term traders – might be forced to liquidate positions in several markets simultaneously, thus causing a cross-country decline in equity markets. Consequently, market co-movement should increase during crises.

3. Literature review

This section provides a literature review of relevant studies. The first part investigates how international equity markets, especially the U.S. and emerging countries, are interconnected, as well as which factors can explain the existence and dynamics of these cross-country spillovers. The second part presents findings about how specifically spillovers from U.S. monetary policy surprises propagate to global stock markets.

3.1 Transmission between international stock markets

It is widely argued that increased capital market integration lead to increased co-movements between stock markets, even though empirical evidence is mixed. Early studies mainly investigated stock market co-movements of developed countries, with the U.S. dominating research interest. The studies relied on cross-correlation analysis to detect transmission effects and contagion was defined as increased or excessive cross-market correlation between two countries.

Longin and Solnik (1995) were amongst the first to report an increase in correlation between seven major stock markets over the period of 1960 to 1990. Their findings confirmed the results of Schöllhammer and Sand (1985), King and Wadhwani (1990) and Lee and Kim (1993). In addition to significant interrelations between major stock markets in both returns and volatility, they also found that co-movements increase after crisis periods.

Other studies documented deviating results. Bekaert et al. (2008) investigated the period from 1980 to 2005 and did not find increased cross-country return correlations which exception for European markets. They argued for their results by pointing to the advantages of their risk-based model in fitting return co-movements over hence-used approaches.

Since the correlation approach entails several statistical problems, such as heteroscedasticity during crisis periods and omitted variable biases, other researchers applied alternative methodologies to analyze cross-market transmissions. Analyzing impulse responses from a VAR system estimated on daily returns between 1980 and 1985, Eun and Shim (1989) found significant spillovers between the nine developed equity markets Australialia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the U.S. and the United Kingdom. The U.S. was found to have by far the largest impact on other countries, opposed to which no single country could significantly explain return variations in the U.S.

Hamao, Masulis, and Ng (1990) also documented results that indicate a key role of the U.S. in determining international market movements. They utilized a general autoregressive conditionally heteroskedastic (GARCH) model to investigate return and volatility spillovers between the New York, Tokyo and London stock exchange and reported significant transmission from the U.S. to Japan and the United Kingdom of both return and volatility.

3.2 Transmission between emerging stock markets and the U.S.

With economic growth in emerging markets picking up, a new strand of research began to investigate the co-movements of the U.S. with emerging equity markets to assess their attractiveness for investors' portfolio diversification. Research widely agreed on increasing linkages both between mature and emerging markets, and linkages amongst emerging markets.

John Wei et al. (1995) examined transmission of returns and volatility from the U.S. and other developed markets to Asian markets. They utilized a GARCH model to show the existence of both bilateral and unilateral spillover effects. They also proposed that emerging market openness to foreign investors does not increase spillovers from developed countries.

Estimating return shocks from a VAR system on daily data of 62 emerging and frontier markets indices and the U.S., Samarakoon (2011) analyzed transmission and contagion between those markets. Their results suggested significant transmission from the U.S. to all markets; the strongest fraction being spilled to European emerging markets. However, they stipulated that contagion from the U.S. is only relevant in Latin America, whereas both significant transmission and contagion effects to the U.S. were being sent from emerging markets whose trading hours partially overlap with the United States. Lastly, while bi-directional, shocks were transmitted asymmetrically in their study.

Other papers focused on connectedness of only emerging markets without considering the U.S.. Christofi and Pericli (1999) analyzed Latin American economies. They identified mean and volatility spillovers between five Latin American countries by modelling their stock market interaction in a VAR/GARCH framework during 1992-1997. For the same region, Chen, Firth, and Meng Rui (2002) obtained similar results, applying an error correction VAR on a set of six countries. They found that a large fraction of domestic stock price fluctuations is caused by shocks from foreign markets, with Mexico transmitting shocks to all other countries except to Colombia.

Research also investigated linkages among emerging Asian Markets. A study by Worthington and Higgs (2004) analyzed weekly lagged returns of stock market indices in Hongkong, Singapore Japan, Thailand, Indonesia, Korea, Malaysia, Taiwan and the Philippines in a multivariate GARCH (MGARCH) model. It identified large positive spillovers among emerging Asian Markets. The authors also concluded that returns are transmitted asymmetrically between different markets which is in line with the results obtained by Samarakoon (2011).

Beirne, Caporale, Schulze-Ghattas, and Spagnolo (2010) applied a tri-variate VAR-GARCH-in-mean model to capture spillovers in returns, volatility and GARCH-in-mean effects. The analysis included a sample of 41 emerging markets in Europe, Latin America, Asia and the Middle East and indicated the existence of cross-market spillovers between different regions. Spillovers varied in nature and strength. It further showed that return spillovers dominate in Latin America and Asia, whereas volatility spillovers are more relevant in emerging Europe.

3.3 Economic and financial determinants of spillovers

While the literature discussed so far does not hypothesize about potential sources of transmission across stock markets, several studies are dedicated solely to identifying the drivers of existence and time-variation in cross-market spillovers.

Forbes and Chinn (2004) explored real and financial integration as potential source of spillover effects. Their study is based on the international capital-asset-pricing model (ICAPM) which stipulates that in integrated capital markets, ‘expected asset returns are determined by the asset’s covariance with the world market portfolio’ (Forbes & Chinn, 2004, p. 706). For the period between 1986 to 2000, they built a factor model for cross-country linkages between 40 developed and emerging markets and the world’s five largest economies (the U.S., the U.K., Germany, France and Japan). Their model relates market’s return to two proxies each of economic and financial integration: trade flows and competition in third countries as well as bank lending and foreign direct investment. They found significant evidence for both trade and finance starting from the late 1990s. In this period, trade flows from large economies to single stock markets strongly determined shock transmission, whereas bilateral bank-lending and competition had a significant, but weaker impact. They found no significant impact from foreign direct investments.

Goetzmann, Li, and Rouwenhorst (2005) analyzed the time-variation in average global equity market correlations over a horizon of 150 years. Based on several econometric tests on the stationarity of the correlation matrix over time, they concluded that market co-movements vary strongly and are highest during periods of economic integration and free capital flow.

A recent study by Chuluun (2017) focused on how financial connectedness influences international stock market co-movement when trade integration is controlled for. Constructing a global portfolio investment network from bilateral cross-border portfolio holdings for 49 countries and subsequently conducting a regression analysis, it showed that between 2001 and 2014 countries who were more central in the network were more sensitive to movements on other stock markets. Using bilateral exports, the study also constructed a trade network to show that cross-market correlations increase further if the country simultaneously has a high financial and trade connectedness. They argued that a country with more finance and trade linkages is more exposed to foreign financial markets and thus shows higher correlation with those. Since during the last decades, cross-country trade flows have been surpassed by capital flows in many countries, they also suggested that financial linkages should increase in relevance for spillovers over trade.

Extensive research has also been conducted on determinants of stock market spillovers during crises. Van Rijckeghem and Weder (2001) tested financial integration measured by bank lending, trade links and a set of country characteristics as explanatory factors for spillovers during the Mexican, Thai and Russian crisis. Their results suggested that stronger countries linkages via common bank lenders significantly relates to heightened probability of contagion, while trade links play a less important role and are not at all significant in the Asian crisis. They also noted that high correlations between measures for trade and financial integration might distort inference and lower the robustness of the measures.

Boyer, Kumagai, and Yuan (2006) investigated the importance of the portfolio channel versus fundamentals for spillovers in emerging markets during the 1997 Asian crisis. They formed two groups of emerging markets based on their accessibility for foreign investors to test whether portfolio rebalancing or wealth constraints significantly explain contagion [2]. Their results suggested that reallocation of foreign investors' portfolio holdings is the dominant transmission channel of shocks during crises when compared to changes in economic fundamentals.

3.4 Monetary policy and U.S. capital markets

The spillover literature broadly refers to 'shocks' inducing equity market co-movements. One of these shocks that studies have found to spill over from U.S. equity markets to emerging markets are monetary policy shocks. While the early literature of U.S. monetary policy transmission to capital markets focused only on the impact within the U.S., the later scope of investigation widened to the international financial markets. Most articles agree on the existence of U.S. monetary policy shocks transmission to foreign equity markets, but they do not agree on reasons why the strength of impact varies among countries. The most discussed determinants of strength are economic and financial integration, exchange rate regime, industry structure and local monetary policy.

Kuttner's (2001) event-study was one of the first studies, which differentiated between anticipated and unanticipated policy actions. The study showed that interest rates reacted more to policy surprises than to changes of the Federal funds rate itself. Kuttner suggested to use FED funds futures rates to differentiate between expected and unexpected policy actions. He showed that the regression coefficients for the surprise part were large and statistical significant, whereas the coefficients for the expected component were small and statistical insignificant (Kuttner, 2001).

Bernanke and Kuttner (2005) examined the impact of monetary policy changes on U.S. equity returns. They found a symmetric relationship between monetary policy surprises and equity returns. A hypothetical unanticipated decrease of 0.25% in the target rate led to an 1% increase in stock prices, while target rate increases caused stock prices to decline. In addition, the authors investigated the question of why equity prices react to FOMC announcements. The results showed that equity returns responded mostly to anticipated future dividends and anticipated future excess returns, which were affected by monetary policy surprises. High-tech and

[2] The portfolio rebalancing hypothesis (Kodres & Pritsker, 2002) and the wealth constraint hypothesis (Kyle & Xiong, 2001) are laid out more detailed in Section 2 (Theory).

telecommunications were the most exposed sectors to FOMC announcements (Bernanke & Kuttner, 2005).

An alternative approach to estimate the strength of stock market reaction is a VAR model. The rise of VAR models was motivated by the fact that U.S. monetary policy could be treated as an endogenous variable. The endogeneity problem was addressed by several authors. There are numerous studies which examined the effect by using a VAR model. VAR models are sometimes difficult to implement and to interpret (Kuttner, 2001). The advantage of an event-study approach is the usage of higher frequency data compared to a VAR model, which is usually based on monthly or quarterly data (Ehrmann & Fratzscher, 2009).

Thorbecke (1997) applied both, an event-study regression and a VAR model to investigate the transmission of U.S. monetary policy to the U.S. equity market. He found that consistent with theory, U.S. equity returns were influenced positively (negatively) by unexpected U.S. monetary policy expansions (contractions). Furthermore, the strength of reaction depended on the industry and the company size (Thorbecke, 1997).

The Vector Autoregressive study by Rigobon and Sack (2003) found an inverse relationship, the U.S. equity market influenced the FED's monetary policy by affecting the economy. They argued that the stock market did not respond to monetary policy changes.

3.5 Monetary policy and international capital markets

Wongswan (2009) investigated the transmission of U.S. monetary policy shocks to 15 foreign equity indices from 1998 through 2004. His study was based on high-frequency data to control for unrelated news. The study results suggested a strong and significant relationship. Following Gurkaynak, Sack, and Swanson (2005) paper, monetary policy surprises were deconstructed into two components, target and path surprises. The results showed that equity indices reacted mostly to target surprises. The second part of Wongswan's paper focused on exploring why foreign equity indices reacted to U.S. monetary policy surprises. Three different reasons were suggested. Firstly, economic integration with the United States may have impacted the cash flows of foreign companies. Secondly, discount rates may be impacted through financial integration. Thirdly, the relationship could have been influenced by other factors, such as the indices' industrial composition, the exchange rate regime or the equity market riskiness. A cross-section regression showed that the equity indices' reactions were more correlated with financial integration proxies. This was an indication that foreign companies were more affected through the discount rate (Wongswan, 2009).

A study by Ehrmann and Fratzscher (2009) focused on the transmission of U.S. monetary shocks to 50 equity markets. They also found that the strength of reaction differed across countries. Developed stock markets and equity markets of countries with a more volatile exchange rate responded more to U.S. monetary shocks. Moreover, they found that financial integration in terms of foreign financial assets held by domestic investors and in terms of domestic financial assets held by foreigners influenced the strength of reaction. In addition, they argued that the degree of global integration was more important for the transmission than the degree of integration with the United States (Ehrmann & Fratzscher, 2009).

Hausman and Wongswan (2011) conducted a similar study to Wongswan (2009), but they extended the scope of assets to short- and long-term interest rates, exchanges rates and foreign equity indices for 49 countries. They found that equity indices reacted mainly to target surprises, FX rates and long-term rates responded mostly to path surprises and short-term rates reacted to both. In addition, they documented that a country's exchange rate regime affected the reaction of equity markets and interest rates to FOMC announcements surprises. A country with a less flexible exchange rate responded more to surprises. Furthermore, the number of assets held by U.S. investors was an important factor for the shock transmission. U.S. investors may want to adjust their portfolio allocation after FOMC announcements (Hausman & Wongswan, 2011).

A recent study by Chortareas and Noikokyris (2017) investigated how local monetary policy influenced the strength of reaction. The findings suggested that countries which had a monetary policy stance similar to that of the United States, were less affected by U.S. monetary policy changes. These countries internalized the external shocks via local monetary policy (Chortareas & Noikokyris, 2017).

4. Methodology

To illustrate the degree of connectedness among the countries, we adopt the approach developed by Diebold and Yilmaz (2009), (2012) and (2014) and construct a network of weekly equity index returns for our 12 considered countries and for the U.S. For that, a 13-variable VAR model is constructed to estimate measures for connectedness based on variance decompositions. A N-variate VAR(p) model takes on the following form:

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t$$

where $x_t = (x_{1t}, x_{2t} \dots, x_{Nt})$ is a vector of equity index returns and $\epsilon_t \sim (0, \Sigma)$ is a vector of IID disturbances. For a covariance stationary VAR, the model can be formulated in moving average (MA) representation as

$$x_t = \sum_{i=0}^{\infty} A_i \, \epsilon_{t-i}$$

where A_i are $N \; x \; N$ parameter matrices which follow the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + A_{i-p}$, A_0 is the $N \; x \; N$ identity matrix and $A_i = 0$ for $i < 0$.

Connectedness, measured as the share θ_{ij} of forecast error variations in country i's equity index which are caused by shocks to country j's equity index, is derived from variance decompositions. In the standard VAR model popularized by Sims (1980), variance decompositions are based on Cholesky factorizations, where orthogonalized shocks make the results highly sensible to ordering of variables and can complicate our analysis. To achieve invariance to ordering, we use a generalized variance decomposition (GVD) framework as proposed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), to measure connectedness.

4.1 Pairwise directional connectedness

In the GVD framework, country $j's$ contribution to country $i's$ H-step-ahead generalized forecast error variance decompositions $\theta_{ij}^{g}(H)$, for H=1,2,… , is

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\kappa_i{}' A_h \Sigma \kappa_j\right)^2}{\sum_{h=0}^{H-1} (\kappa_i{}' A_h \Sigma \mathrm{A}_h{}' \kappa_i)}$$

Σ is the variance matrix of vector ϵ, of which σ_{jj} is the of jth diagonal element, κ_i is a selection vector with one as the i^{th} element and zeros otherwise. These cross-variance shares depict pairwise directional connectedness of equity indices, for

$i, j = 1,2, \dots N$, such that $i \neq j$. The *pairwise directional connectedness* from country j to country i and thus country $j's$ contribution to country $i's$ stock return variation therefore is

$$C^H_{i \leftarrow j} = \theta^g_{ij}(H)$$

Also, the strength of pairwise directional connectedness differs when shocks are asymmetric, thus

$$C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i}.$$

Consequently, the *net pairwise connectedness* can be defined as

$$C^H_{ij} = C^H_{j \leftarrow i} - C^H_{i \leftarrow j}.$$

Because shocks are not orthogonalized, the sum of forecast error variance contributions is not automatically equal to one. Therefore, the return connectedness table explained below is based on a variance decomposition matrix normalized along the row sum:

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}$$

It holds that $\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H) = 1$ and $\sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H) = N$.

4.2 Total Directional Connectedness, 'From' and 'To'

As described by Diebold and Yılmaz (2014), the total directional connectedness to country $i's$ equity index received *'From'* others is the fraction of $i's$ H-step forecast error variance arising from shocks to all other countries j:

$$C^H_{i \leftarrow \bullet} = \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^g_{ij}(H)$$

and the total directional connectedness from country $i's$ equity index *'To'* all other countries j is

$$C^H_{\bullet \leftarrow i} = \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^g_{ji}(H)$$

A connectedness table summarizes the connectedness measures. It contains the $N \; x \; N$ variance decomposition matrix $\Theta^g = [\tilde{\theta}^g_{ij}(H)]$ whose $N^2 - N$ off-diagonal entries measure pairwise directional connectedness. Θ^g is augmented by a column on the right containing N off-diagonal row sums for $C_{i\leftarrow\bullet}$, and a bottom row containing N off-diagonal column sums for $C_{\bullet\leftarrow i}$, connectedness transmitted 'To' others. The focus of our analysis lies on the pairwise directional connectedness between the U.S. and different emerging equity markets, showing how strongly shocks to U.S. markets transmit to other markets.[3]

Since equity return connectedness can be time-varying, we conduct both a full-sample and a rolling-window estimation with a 104 weeks estimation horizon. A full-sample estimation yields a static picture of the connectedness in our network, a rolling-window estimation characterizes the dynamic network connectedness.

4.3 Determinants of connectedness

We consider economic and financial integration as explanatory factors for the return spillovers from the U.S. to emerging market stocks. We proceed by performing a panel regression of yearly 'To' connectedness from the U.S. to each of the 12 EM markets on proxies of real and financial integration of each country with the U.S.. The proxies chosen - trade with the U.S. and U.S. foreign portfolio investment - can be thought of as proxies for the cashflow channel and the portfolio channel as potential transmission channels.

'To' spillovers are estimated over a 52-week window. A short time window compared to the previous 104-week estimation might impact the quality of the coefficient estimates. However, an estimation over 52 weeks better isolates the effect of the previous year's trade and foreign holdings on this year's spillovers. Due to data availability the sample is reduced to 169 observations over the period from 2001-2015. The regression reads as follows:

$$\begin{aligned}\ln(C_{i\leftarrow US}) = {} & \alpha_i + \beta_1 * \ln(Trade_{t-1}) + \beta_2 * \ln(Financial_{t-1}) + \beta_3 * Size_{t-1} \\ & + \beta_4 * FI_{t-1} + \beta_5 * (FM_{t-1}) + \beta_6 * (KA\ Open_{t-1}) + \beta_7 * Crisis \\ & + \beta_8 * Post\ Crisis + \varepsilon_t\end{aligned}$$

Real integration is proxied by the ratio of yearly bilateral exports and imports with the U.S. as a share of GDP ($Trade_{t-1}$). Financial integration is measured yearly as U.S. investors' equity holdings of the respective MSCI index's market

[3] For ease of reading, we refer in the following to 'pairwise directional' as 'directional' and 'total directional' as 'total'.

capitalization ($Financial_{t-1}$). Following the International Monetary Fund (2016), we also include a number of control variables to mitigate endogeneity problems: $Size_{t-1}$ is defined as the ratio of stock market capitalization to world GDP. According to the IMF, larger capital markets may possess superior ability to absorb shocks unrelated to fundamentals. Similarly, the financial development of countries may improve countries' resilience against foreign shocks. Financial development is measured by the IMF's Financial Development Index introduced by Svirzdyenka (2016). Specifically, we separate the development of financial institutions (FI_{t-1}) and of financial markets (FM_{t-1}). $KA\ Open_{t-1}$ represents the integration of the domestic capital market with the global financial system. Markets with many internationally active financial institutions are assumed to be more responsive to spillovers from foreign financial markets. $KA\ Open_{t-1}$ is measured by the Chin-Ito Index (Chinn and Ito, 2008), which measures a country's degree of capital account openness and is normalized to a number between 0 and 1. Lastly, $Crisis$ and $Post\ Crisis$ are indicator variables which capture the effect of the financial crisis of 2007. $crisis$ is a dummy variable which takes on the value one for the years between 2007 and 2009, and 0 otherwise. $Post\ Crisis$ is 1 for the years from 2010, and zero otherwise.

5. Hypotheses

Based on the theoretical and methodological foundations as well as the previous empirical findings discussed above, we form the following hypotheses about spillovers between the U.S. and the 12 emerging markets in our sample:

H1. Shocks to the U.S. equity market transmit to emerging stock markets.

$$H_0 : C_{i\leftarrow US}^{12} = 0$$

$$H_A : C_{i\leftarrow US}^{12} \neq 0$$

H2. The transmitted shocks are not symmetric in size.

$$H_0 : C_{ij}^{12} = 0$$

$$H_A : C_{ij}^{12} \neq 0$$

H3. There are return spillovers between emerging equity markets.

$$H_0 : \tilde{\theta}_{ij}^{g}(12) = 0$$

$$H_A : \tilde{\theta}_{ij}^{g}(12) \neq 0$$

H4. Return spillovers from the U.S. to emerging markets can be partially explained with bilateral trade and finance integration of respective countries with the U.S.

$$H_0: \beta_1, \beta_2 = 0$$
$$H_A: \beta_1, \beta_2 \neq 0$$

6. Data

Our analysis comprises a period of 24 years, from 1994 to 2017 and includes the following 12 emerging market economies: Brazil, Chile, Colombia, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Thailand and Turkey. The sample of countries was chosen based on the classification of the MSCI Emerging Markets Index. The index was introduced in 1988 and follows a consistent methodology based on various selection criteria, such as market accessibility for foreign investors, liquidity and size of the stock market and economic growth (MSCI, 2012). The MSCI EM Index currently includes 24 countries , of which we further select only those which have been members of the MSCI Emerging Market Index over the whole horizon without being excluded in between (Bambaci, Chia, & Ho, 2012) (MSCI, 2017). This ensures that our estimation is based on an equal amount of data for all countries.

We obtain daily closing prices in local currency for the 12 MSCI EM indices as well as for the U.S. from Datastream. When a market is closed the missing value is replaced with the last available price. Following Diebold and Yilmaz (2015), we compute weekly log-returns (Friday-Friday) for the period from 14.01.1994 to 29.12.2017.

When exploring potential determinants of equity shock transmission, we choose the fraction of U.S. investors' equity holdings of emerging stock market capitalization as proxy for financial integration and bilateral trade to the U.S. as fraction of GDP as proxy for real economic integration. The former is calculated from the Coordinated Portfolio Investment Survey (CPIS) compiled by the International Monetary Fund (IMF) and the market capitalization of each of the MSCI indices. The latter is based on data for yearly exports and imports to the U.S. obtained from the World Integrated Trade Solution (WITS) software and on GDP data from the World Development Indicators provided by the World Bank. As a robustness check, global financial and real integration is considered using data on portfolio holdings of the Top 10 GDP countries and global trade data, both obtained from the same sources as for the bilateral proxies. The analysis also includes a set of control variables suggested by the International Monetary Fund (2016), such as financial development, capital account openness, and size of the domestic market. They are obtained from the sources listed in the IMF paper.

7. Results

7.1 Preliminary data analysis

Table 1 shows summary statistics for weekly stock returns of the sample between 14.01.1994 to 29.12.2017. The underlying data and calculation is described in the Data section. The mean annualized return over the period was highest for Turkey and Brazil with 28.26%, respectively 21.05% and lowest for Thailand with 0.13%. The MSCI USA Index returned on average 7.58%.

Returns are non-normal, with heavy tails and negative skewness except for Brazil, Thailand and Malaysia. Table 2 presents the Jarque-Bera normality test, complimented by an analysis of Kernel densities which delivers confirmatory results (see Appendix 1). The results of individual Augmented Dicky Fuller tests (ADF) suggest that all return series are covariance stationarity (see Table 2). The null hypothesis of a unit root can be rejected for all 13 data series at the 5% significance level.

Table 1: Returns - descriptive statistics

	USA	*Mexico*	*Brazil*	*Colombia*	*Peru*	*Chile*	*Thailand*
Mean	0.14%	0.23%	0.37%	0.23%	0.23%	0.11%	0.00%
Std. dev.	2.34%	3.23%	4.34%	3.28%	3.96%	2.66%	4.21%
Annualized mean	7.80%	12.45%	21.05%	12.68%	12.90%	5.92%	0.13%
Median	0.24%	0.34%	0.45%	0.17%	0.22%	0.07%	0.04%
Minimum	-20.1%	-19.3%	-22.7%	-22.0%	-28.2%	-23.0%	-28.6%
Maximum	11.5%	18.0%	23.5%	15.9%	22.0%	16.7%	23.9%
Skewness	-0.79	-0.15	0.10	-0.24	-0.16	-0.56	0.08
Exc. Kurtosis	6.95	3.92	4.54	4.62	4.55	6.96	5.14

	Indonesia	*Malaysia*	*Philippines*	*India*	*Korea*	*Turkey*
Mean	0.17%	0.03%	0.04%	0.17%	0.13%	0.48%
Std. dev.	4.40%	2.93%	3.31%	3.35%	3.95%	5.62%
Annualized mean	9.34%	1.63%	2.19%	9.36%	6.72%	28.26%
Median	0.24%	0.15%	0.14%	0.37%	0.26%	0.52%
Minimum	-24.59%	-20.17%	-20.55%	-19.00%	-21.40%	-34.61%
Maximum	28.26%	26.30%	16.76%	13.66%	18.82%	33.27%
Skewness	-0.05	0.19	-0.05	-0.32	-0.26	-0.11
Exc. Kurtosis	6.49	11.42	4.46	2.61	3.94	4.96

Notes: Log returns are measured weekly from Friday to Friday. 1251 observations per country.

Table 2: Normality and unit root test for return series

	USA	*Mexico*	*Brazil*	*Colombia*	*Peru*	*Chile*	*Thailand*
J-Bera	2651***	805.89***	1076.9***	1124.5***	1083.4***	25878***	1376***
ADF(10)	-11***	-11.1***	-10.1***	-11.4***	-10.4***	-11.4***	-10.5***

	Indonesia	*Malaysia*	*Philippines*	*India*	*Korea*	*Turkey*
J-Bera	2192.7***	6800.4***	1089.6***	376.3***	823.86***	1285.4***
ADF(10)	-12.5***	-10.2***	-10.4***	-10.2***	-10.3***	-11.4***

Notes: *, ** and *** indicate the rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% levels respective.

7.2 Full sample spillover estimation

We first consider static return spillovers over the whole sample period, estimated from a VAR (2) model with 12-week forward estimation horizon. The VAR model estimated takes the following form:

$$x_t = \phi_0 + \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \epsilon_t \qquad (1)$$

x_t is a vector of the 13 countries' stock returns, ϕ_0 is a (13 x 1) vector of country specific constants and Φ_1, Φ_2 are the (13 x 13) coefficient matrices. ϵ_t a vector of error terms. The lag length was chosen by the information criterion AIC. White's heteroskedasticity tests showed heteroskedastic errors for each data series. While these might influence the forecast error variance decompositions (FEVD) resulting from the model and interpreted as spillovers, no solution has so far been suggested in the scrutinized literature to correct this bias. The full estimation results are presented in Appendix 5.

The sample period includes two major crises: the Asian crisis of 1997 and its aftershocks in South America in 1999, as well as the financial crisis of 2007-2009. These might have affected the interaction between the countries' stock returns in respective periods and in consequence might distort the full sample spillover estimation. To test this assumption, we include an interaction term between crisis and lagged country return to the VAR model and re-estimate equation (1) as follows:

$$x_t = \phi_0 + (\Phi_1 + \Phi_2 * Cr)x_{t-1} + (\Phi_3 + \Phi_4 * Cr)x_{t-2} + \epsilon_t \quad (2)$$

Cr is a dummy vector which takes on the value 1 in the crisis periods (07/1997-12/1999 and 2007 – 2009) and zero otherwise. For each individual equation of the VAR system, we then perform a Wald test on the coefficients of the interaction terms to check whether the relationship of the 13 countries in our sample significantly changed during crisis periods.

Table 3: The impact of crisis on return interdependencies

The table shows the results of a Wald-test on the crisis interaction terms in the individual equations of the VAR system. *** indicates significance at 1%, ** significance at 5%, * significance at 10%.

	USA	*Mexico*	*Brazil*	*Colombia*	*Peru*	*Chile*	*Thailand*
F-statistic	1.151	1.979***	1.645**	2.221***	1.416*	2.083***	1.707**
P-value	0.271	0.002	0.02	0.000	0.078	0.001	0.014

	Indonesia	*Malaysia*	*Philippines*	*India*	*Korea*	*Turkey*
F-statistic	2.039***	2.879***	1.498**	1.717**	2.165***	1.552**
P-value	0.001	0.000	0.049	0.013	0.001	0.036

The results shown in Table 3 suggest that the stock returns in our sample do influence each other differently in crisis compared to tranquil times. The null hypothesis that all interaction terms are jointly zero can be rejected at least at 10% for all countries except for the U.S.. Therefore, the subsequent spillover estimation might be biased, which should be considered when interpreting the results in the connectedness table (Table 4).

Table 4 presents the full sample connectedness table with directional, 'To' (the fraction of shocks transmitted from country $i's$ equity index to all other countries), 'From' (the fraction of shocks received by country i from all other countries) and 'Net' (the difference between 'To' and 'From') connectedness[4]. The directional links within the network are illustrated graphically in Figure 1. All directional connectedness measures between emerging markets are significantly different from zero at a 1% level. This indicates that return spillovers between EM countries exist, which is consistent with our hypothesis and current literature (Beirne et al., 2010; Christofi & Pericli, 1999; John Wei et al., 1995; Samarakoon, 2011; Worthington & Higgs, 2004). Furthermore, we can confirm our hypothesis that shocks from the U.S. transmit to emerging markets. All U.S. directional connectedness measures are significantly different from zero at a 1% level. Brazil and Mexico show the strongest reaction. 9.3% and 13% of their forecast error return variance is attributable to U.S. shocks. Overall, the U.S. equity market is the second largest transmitter of returns shocks within the network, as shown by the high 'To' connectedness (84.88%) and 'From' connectedness (67.15%), which result in a net connectedness of 17.74%. Only Mexico has a higher impact ('Net' connectedness 22.28%) on other capital markets due to the high connectedness amongst the Latin American markets. Both stock markets, U.S. and Mexico, are highly interdependent. For the whole sample, spillovers are responsible for 59.29% of the forecast error variance, illustrating how interconnected emerging market stock markets and the US stock market are.

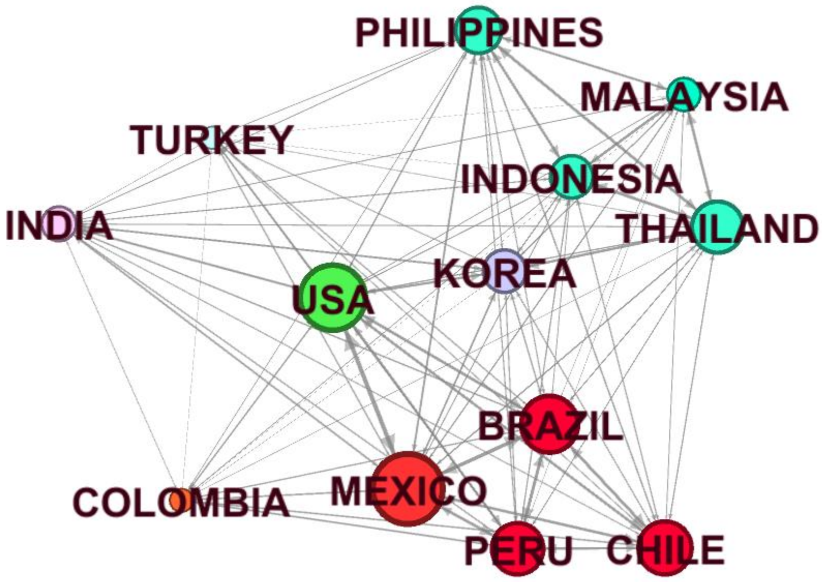
[4] Appendix 2 shows the connectedness table with standard errors. A model-based method is used to bootstrap VAR residuals (5000 drawings). We construct bootstrap confidence intervals for all the values in the connectedness table to determine the significance at a certain level. We used the "tsDyn" package in R for the model-based bootstrapping method (VAR.boot). For more details on the model and implementation in R see Chernick and LaBudde (2011).

Table 4: Connectedness table (local currency)

	Indonesia	Thailand	India	Philippines	Turkey	Korea	Malaysia	Brazil	Mexico	Colombia	Peru	Chile	USA	From
Indonesia**	40.7	9.7	4.0	8.5	1.4	4.5	7.4	3.6	4.2	2.4	4.7	4.5	4.3	59.3
Thailand**	9.0	38.0	3.2	8.4	2.2	7.7	7.2	4.2	5.3	1.8	3.8	4.4	4.9	62.0
India**	4.2	4.1	43.4	3.8	1.9	6.4	3.5	5.5	6.8	2.8	5.1	4.2	8.1	56.6
Philippines**	8.1	9.7	3.0	38.9	2.4	3.6	6.5	4.0	7.0	2.2	4.1	5.1	5.4	61.1
Turkey**	1.7	3.1	2.4	3.5	57.2	3.9	1.3	5.2	5.6	1.6	4.8	4.3	5.3	42.8
Korea**	4.4	8.3	5.9	3.6	3.2	41.3	3.6	5.0	6.5	1.4	4.2	4.6	8.1	58.7
Malaysia**	8.8	9.2	3.6	7.7	1.3	5.0	46.3	2.3	5.1	1.1	2.3	3.6	3.8	53.7
Brazil**	2.8	3.8	3.7	3.7	3.1	4.0	1.8	34.7	11.9	2.7	9.3	9.0	9.3	65.3
Mexico**	2.8	4.2	4.1	5.1	2.9	4.8	3.5	10.3	30.9	2.9	7.6	7.7	13.0	69.1
Colombia**	3.4	2.9	2.9	3.3	1.5	2.0	1.4	5.3	6.4	52.7	6.5	5.8	5.8	47.3
Peru**	3.9	3.8	3.8	3.8	3.5	3.8	1.7	9.9	9.6	4.1	36.3	7.8	8.0	63.7
Chile**	3.7	4.2	3.1	4.6	3.0	3.6	2.8	9.7	9.3	3.6	7.5	36.0	8.8	64.0
USA**	2.8	3.9	5.1	3.8	2.8	6.0	2.2	8.5	13.6	3.3	7.1	8.0	32.9	67.1
To**	55.5	66.8	45.0	59.8	29.2	55.4	43.0	73.7	91.3	30.0	67.1	69.1	84.9	
Net	-3.8	4.8	-11.6**	-1.3	-13.6**	-3.4	-10.7**	8.3*	22.3**	-17.3**	3.4	5.1	17.7**	**59.3****

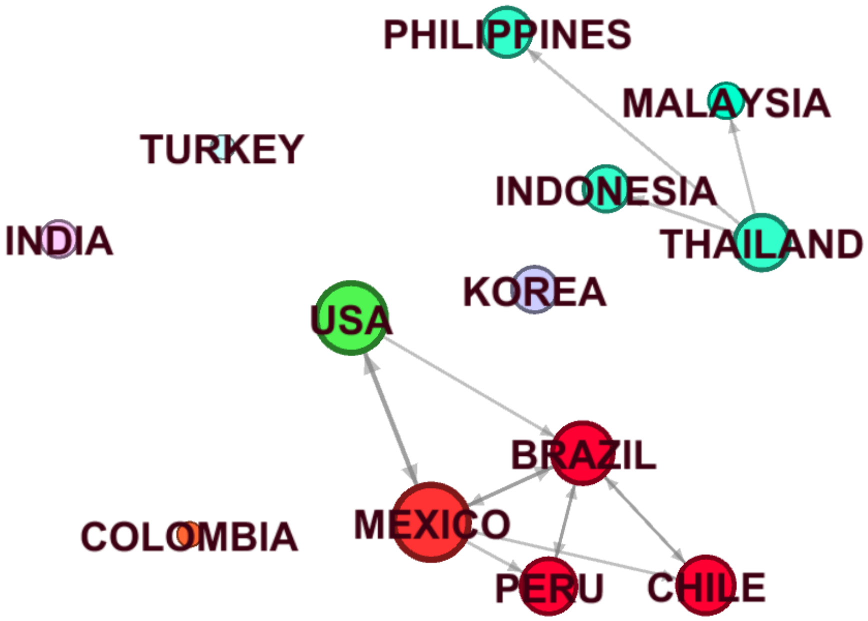
Notes: The sample is taken from January 14, 1994 to January 29, 2017. 'From' is the fraction of shocks to country i's equity index received ‘From’ others. 'To' is the the fraction of shocks transmitted from country i's equity index ‘To’ all other countries. 'Net' is the difference between 'To' and 'From' connectedness of each country. Full-sample spillovers with nonparametically bootstrapped standard errors (5000 drawings) are presented in Appendix 2. * and ** indicate statistical significance at the 1% and 5% levels. * or ** next to the row heading indicates that all entries of the row are significantly different from zero at the 1% or 5% level.

Figure 1: Connectedness network



In Figure 2, directional connectedness is filtered for spillovers above the median, i.e. those explaining at least 9% of the forecast error variance of other countries. This reveals two clusters within the stock return network related to geographical proximity. We observe that Mexico and the United States are highly interconnected with other Latin American countries, except for Colombia. This is consistent with the research findings of Chen et al. (2002). Shocks to the Southeastern Asian countries Malaysia, Indonesia, Thailand and the Philippines are transmitted mainly between the four countries. The 'Net' directional connectedness is statistically different from zero at 5% level for all countries, except for Indonesia, Thailand, Korea, Philippines, Peru and Chile. These findings indicate that asymmetric shocks exist for some EM countries. These results are consistent with previous studies about asymmetric shocks such as those performed by Samarakoon (2011) or Worthington and Higgs (2004).

Figure 2: Strongest links in the connectedness network



Since the analysis is performed on local denominated returns, the interdependency of currency and equity markets may influence the measured connectedness. Research findings show that a dynamic relationship between both markets exists. Currency markets may play a significant role in the transmission of equity shocks (Francis, Hasan, & Hunter, 2006), which in turn may lead to an underestimation of the effect transmitted via returns when measured in local currency. Therefore, we re-estimate the network from weekly equity index returns in USD to see whether the spillovers change significantly or not. Table 5 presents the connectedness table based on USD as a common currency. The results suggest that the return transmissions are qualitatively alike. As expected, the total connectedness is higher in USD, with an increase from 59.3% to 64.9%. However, there is only limited deviation of directional connectedness measures in size and no impact of exchange rates on the significance of return spillovers for our sample, except for Chile. A possible explanation for the insensitivity to currency could be the strong co-movement of USD and other EM currencies (Mai, Chen, Zou, & Li, 2018). Given these results, our analysis seems robust to the choice of local currency versus USD.

Table 5: Connectedness table (USD)

	Indonesia	Thailand	India	Philippines	Turkey	Korea	Malaysia	Brazil	Mexico	Colombia	Peru	Chile	USA	From
Indonesia**	36.1	10.9	3.5	10.8	1.0	6.3	9.3	4.1	3.7	2.6	3.7	4.6	3.5	64.0
Thailand**	9.6	34.2	3.7	9.1	2.1	8.0	7.1	5.0	5.0	2.2	4.1	5.6	4.2	65.7
India**	3.6	4.4	37.9	4.1	3.0	6.9	3.7	6.8	7.1	3.7	5.3	6.1	7.5	62.2
Philippines**	9.3	10.1	3.4	34.1	2.1	5.1	7.1	5.3	6.0	2.6	4.1	5.8	4.9	65.8
Turkey**	1.4	2.9	3.5	3.2	47.7	4.3	1.7	7.5	7.6	2.9	5.2	6.3	5.8	52.3
Korea**	6.4	8.2	6.0	5.2	3.1	34.3	4.1	6.0	6.5	2.3	4.6	6.0	7.3	65.7
Malaysia**	10.1	9.2	3.8	9.1	1.5	5.6	42.8	3.0	4.2	1.3	2.4	3.7	3.3	57.2
Brazil**	2.9	4.0	4.3	4.1	4.2	4.6	1.9	27.6	12.6	4.8	9.3	10.8	8.9	72.4
Mexico**	2.5	4.0	4.6	4.6	4.2	5.0	2.8	12.0	27.7	4.2	7.6	9.4	11.5	72.4
Colombia**	3.1	3.1	3.6	3.4	2.5	2.8	1.5	8.1	7.4	42.3	7.5	8.4	6.5	57.9
Peru**	3.1	4.0	4.2	3.8	3.7	4.4	1.8	11.0	9.6	5.4	32.4	9.6	7.0	67.6
Chile**	3.3	4.8	4.3	4.7	3.8	4.6	2.5	11.2	10.0	5.3	8.3	28.7	8.3	71.1
USA**	2.4	3.4	5.1	3.8	3.3	6.0	2.2	9.6	12.9	4.6	6.6	8.9	31.1	68.8
To**	57.7	69.0	50.0	65.9	34.5	63.6	45.7	89.6	92.6	41.9	68.7	85.2	78.7	
Net	-6.3	3.3	-12.2**	0.1	-17.8**	-2.1	-11.5**	17.2**	20.2**	-16**	1.1	14.1**	9.9**	**64.9****

Notes: The sample is taken from January 14, 1994 to January 29, 2017. 'From' is the fraction of shocks to country i's equity index received ‘From’ others. 'To' is the the fraction of shocks transmitted from country i's equity index ‘To’ all other countries. 'Net' is the difference between 'To' and 'From' connectedness of each country. * and ** indicate statistical significance at the 1% and 5% levels. * or ** next to the row heading indicates that all entries of the row are significantly different from zero at the 1% or 5% level.

7.3 Dynamic spillover estimation

To investigate the development of spillovers over time, we perform a rolling window estimation of 12-step ahead FEVDs from a VAR(2) model. For robustness, we test alternative model specifications, namely a VAR(1) and VAR(3) with 6 and respectively 18 steps forecast windows, both of which yield similar results (see Appendix 3). This shows that the model is relatively insensitive to the parameters lag length and forecast window.

The spillover index, which shows the total return connectedness, is presented in Figure 3. It is estimated both from a 52-weeks and 104-weeks rolling window. As the graph shows, the length of the rolling window is a sensitive parameter for the model predictions. Whereas the estimation over 52 weeks is more volatile, the 104-weeks rolling window index gives a clearer picture of the development of spillovers over time. We can observe that the index increases significantly during the Asian crisis of 1997 and during the financial crisis of 2007-09. This suggests that the impact of crisis periods on return interdependencies which was reported in Table 3 before may translate into increased spillovers. It is further consistent with the findings of Diebold and Yilmaz (2015) that the total return connectedness increased during the global financial crisis.

Figure 3: Spillover index

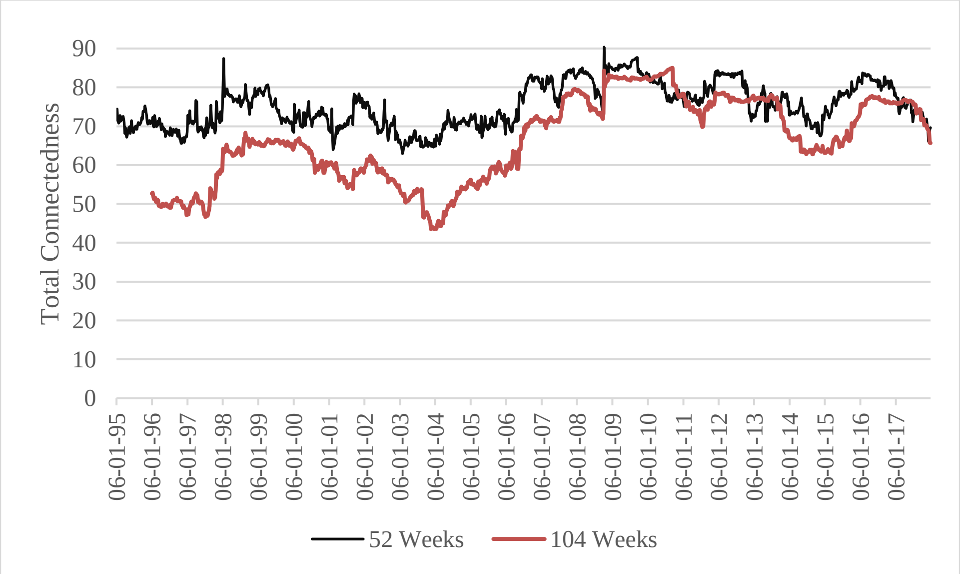


Table 6 provides support for the observations above, illustrated for the global financial crisis. The total return connectedness is higher during the period of 2007-2009 for both the 104-weeks and the 52-weeks rolling window, by 13.43, respectively 8.66 index points. To confirm our observation that spillovers are stronger during the global financial crisis, we compare the means during and outside the global crisis with an independent sample t-test. $\mu_{non-crisis}$ is the mean spillover for the period from 1995-2006 (1996-2006 for the 104-week rolling window) and 2010-2017. μ_{crisis} is the mean spillover for the period between 2007 and 2009. For both rolling window estimations, we can reject the null hypothesis that the mean difference $\mu_{non-crisis} - \mu_{crisis}$ is greater than zero at the 1% level.

Table 6: Spillover comparison - normal times vs. crisis periods

The significance levels of the means are based on a one-sided *t*-test for the hypothesis $\mu_{non-crisis} - \mu_{crisis} \geq 0$. *** indicates significances at 1%, ** significance at 5%, * significance at 10%. Standard errors in parentheses.

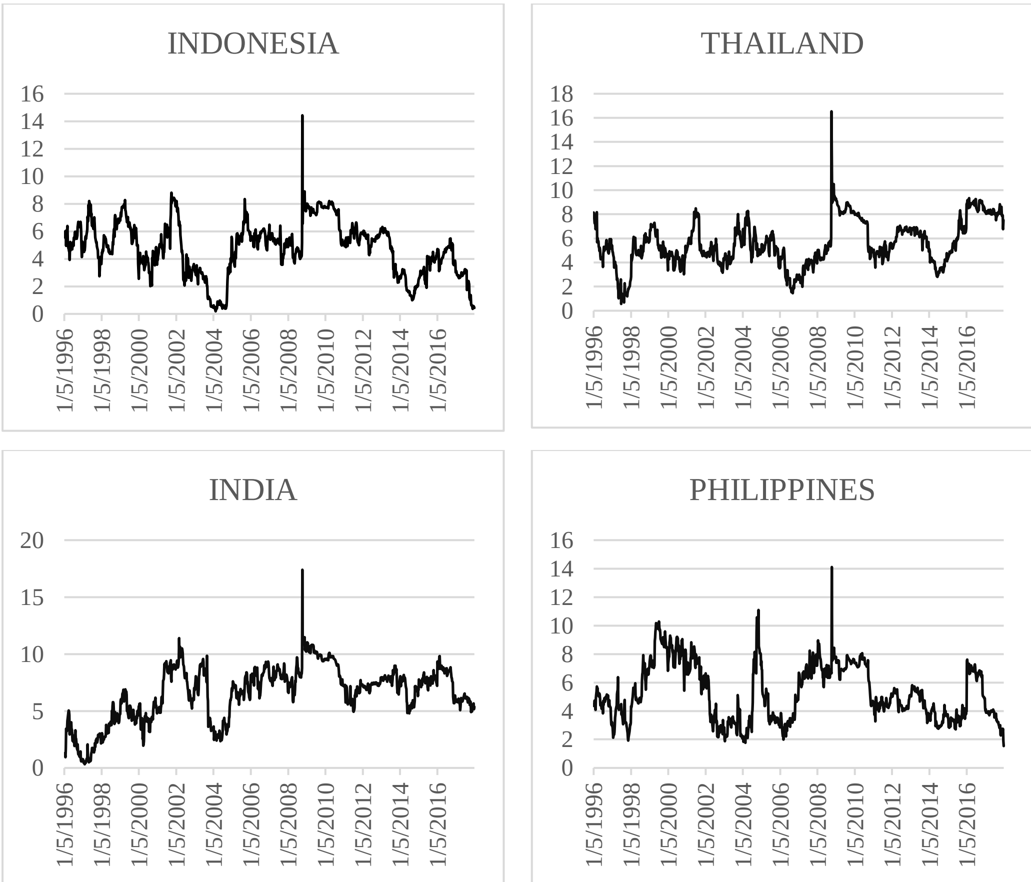
	104-Weeks Rolling Window			52-Weeks Rolling Window		
Period	**Mean**	**N**	**Δ Mean**	**Mean**	**N**	**Δ Mean**
Non-Crisis	64.54 (10.28)	992	-13.43***	74.12 (4.98)	1044	-8.66***
Crisis	77.96 (4.36)	156		82.78 (3.1)	156	

7.4 Spillovers from the U.S. to EM countries

Our analysis is particularly concerned with the transmission of shocks from the U.S. to emerging equity markets. Therefore, directional connectedness from the U.S. to the other countries is extracted from the 104-weeks rolling-window estimation. The graphs in Figure 4 illustrate how the impact of shocks transmitted from the U.S. to EM countries changed over time.

The directional connectedness from the United States to Indonesia and to Thailand appears to be relatively volatile over time. The values range from close to 0% to 14.4%, respectively to 16.5%. Both countries have their peak values in 2008, during the financial crisis. The contribution of U.S. shocks to the Indian stock market variation was quite low in the 90s, but the country has become increasingly sensitive to return spillovers from the U.S. over time. The directional connectedness from the U.S. to the Philippines fluctuated between 2% and 14% during the period of 1996 to 2017. The peak occurred during the collapse of Lehman Brothers in 2008. The Philippine stock market was also strongly impacted by the bursting of the Dot-com bubble in the U.S. with a local maximum in spillovers of 10.3%. Another local maximum value was reached in 2004 with 11%. The directional connectedness from the U.S. to Turkey and to Chile increased during the period of the Dot-com bubble and the financial crisis. During the period of 2003 to 2005, the Turkish stock market was barely impacted by the United States. The MSCI USA Index seems to have impacted the MSCI Korea Index quite equally over the period of 1998 to 2013. The directional connectedness from the U.S. to Korea reached its peak of 16% during the collapse of Lehman Brothers. The spillovers from the U.S. to Malaysia increased significantly during the financial crisis and after 2014. In the case of Brazil, the directional connectedness from the U.S. soared during the bursting of Dot-com bubble and during the global financial crisis. The measure decreased significantly after the collapse of Lehman Brothers. During the period of 1998 to 2016, the directional connectedness from the U.S. to Mexico was mostly over 10% and peaked in 2006 when the FED decided to tighten monetary policy (Demirer, Diebold, Liu, & Yilmaz, 2018). Contrary to most other countries, the collapse of Lehman Brothers did not make the highest contribution to spillovers to the Mexican stock market. The connectedness measure from the United States to Peru and Colombia soared significantly during the financial crisis and decreased afterwards.

Figure 4: Directional connectedness from the U.S. to EM countries

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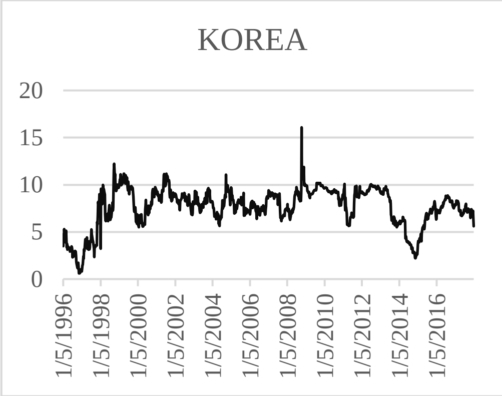
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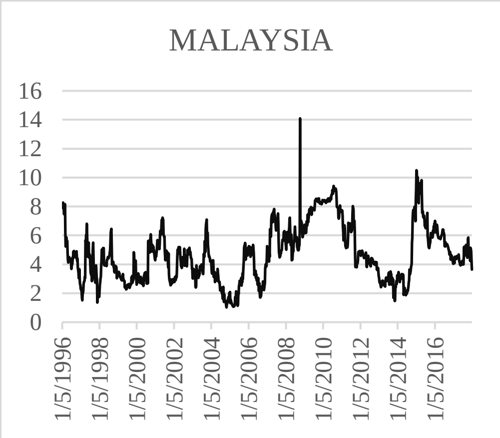
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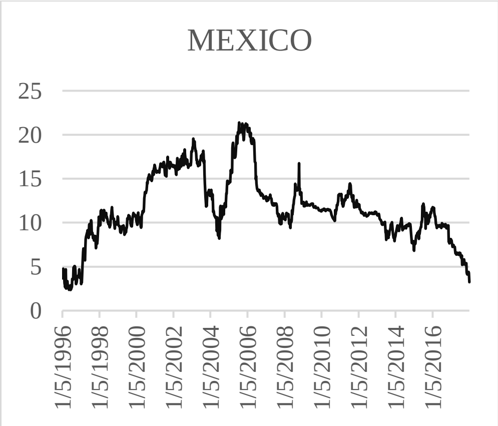
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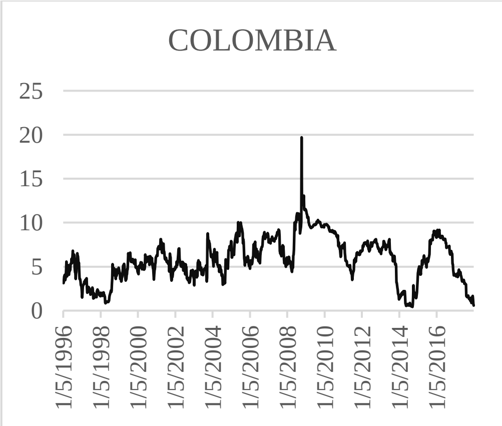
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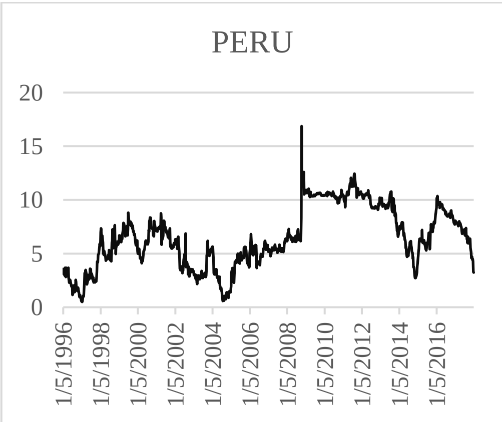
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7.5 The determinants of return spillovers

Next, we are interested in whether economic and financial integration with the U.S. act as transmission channels for spillovers from the U.S. to emerging equity markets. We test how the proxies for trade - yearly exports and imports to the U.S. as fraction of local GDP - and finance integration – the ratio of U.S. foreign portfolio investment to each emerging stock market capitalization - relate to the 'To' connectedness from the U.S. to other EM countries. Table 7 presents selected summary statistics. Complete summary statistics are shown in Appendix 4. As can be seen from the table, the trade ratio with the U.S. varies both across countries and across time. Over the sample period, countries traded on average 10.66% of GDP with the U.S., ranging from 2.22% in Turkey to 36.57% in Mexico. The intertemporal change is highest for the Philippines, where trade integration peaked at 22.52% in 2002 and then consecutively decreased to 5.18%. India's trade ratio on the other hand remained relatively stable in a range between 2.43% and 3.87% of GDP. Financial integration shows the same variation in cross-section and time. U.S. investors held on average 27.88% of a single EM country's market capitalization. Mexico again is on the upper end of the range at 45.87% U.S. portfolio investment, followed by the Philippines and Brazil at 41.49% and 35.04%, whereas the Peruvian market attracted only 12.89% foreign investment. There is noticeable change in the fraction of portfolio investment in each country between 2001 and 2015. In Colombia, there is a gap from peak to trough of approximately 23%. Malaysia and Peru show similarly large variation, from 5.53% and 7.72% to 19.61% and 23.01% respectively. As a result, to the extent that trade and finance integration has explanatory power for spillovers from the U.S., it is likely that countries with a higher average degree of integration - such as Mexico and Brazil- are more sensitive to the U.S. equity market movements. The connectedness table (Table 4) indeed shows that these two countries are impacted most by shocks transmitted from the U.S.. One can also expect that at times when a country is highly integrated in i.e. trade, spillover effects are higher than at times of low integration.

Table 7: Trade and financial integration - Selected descriptive statistics

Statistics A. Economic integration (Trade with U.S./GDP)

	Brazil	*Chile*	*Colombia*	*India*	*Indonesia*	*Korea*	*Malaysia*	*Mexico*	*Peru*	*Philippines*	*Turkey*	*Thailand*	*Total*
Mean	3.35%	9.21%	9.83%	2.99%	3.74%	8.40%	20.69%	36.57%	7.96%	11.60%	2.22%	11.41%	10.66%
Median	3.16%	9.10%	9.84%	2.91%	3.57%	8.28%	18.04%	35.53%	7.98%	9.16%	2.08%	10.84%	8.45%
Maximum	5.12%	11.13%	10.85%	3.87%	6.42%	10.09%	32.32%	43.09%	9.83%	22.52%	3.19%	16.92%	43.09%
Minimum	2.12%	7.75%	8.65%	2.43%	2.72%	7.42%	10.56%	33.02%	6.28%	5.18%	1.83%	8.92%	1.83%

Statistics B. Financial integration (U.S. Portfolio Investment)

	Brazil	*Chile*	*Colombia*	*India*	*Indonesia*	*Korea*	*Malaysia*	*Mexico*	*Peru*	*Philippines*	*Turkey*	*Thailand*	*Total*
Mean	35.04%	16.31%	15.36%	31.38%	29.59%	26.45%	15.35%	45.87%	12.89%	41.49%	30.28%	34.60%	27.88%
Median	32.84%	17.64%	14.57%	30.53%	29.00%	24.79%	17.13%	46.28%	12.36%	41.68%	31.69%	37.21%	28.69%
Maximum	41.76%	22.02%	31.55%	44.75%	39.65%	35.73%	19.61%	57.27%	23.01%	51.78%	38.98%	51.82%	57.27%
Minimum	30.81%	10.14%	8.01%	16.46%	25.11%	19.03%	5.53%	34.80%	7.72%	27.09%	17.16%	16.86%	5.53%

Notes: 15 observations per country. Economic integration is yearly trade with the U.S. / GDP. Financial integration is U.S. Portfolio Investment/emerging stock market capitalization. 'Total' are the cross-sectional statistics for trade and finance integration with 180 observations each.

Table 8 presents the results of the estimation from the panel regression. Column 1 shows the relationship between economic and financial integration and the return spillover from the U.S. to other countries. The results from column 1 confirm our expectation that trade and financial integration have a positive impact on the spillovers. The coefficients are significant at a 5% level. The results are consistent with the findings of Chuluun (2017) and support the theories proposing
that cross-market shocks are transmitted by the cashflow channel and the portfolio channel. The Hausman tests for regression 1 and 2 indicate that a random effect model is suitable for the data. In column 2, we control for other determinants of return spillovers suggested by the International Monetary Fund (2016). Among the control variables, size, post crisis and capital account openness have no significant effect on the U.S. return spillovers to EM countries. During the financial crisis of 2007, emerging market countries tend to have a higher interdependence with the U.S, consistent with the empirical literature that the financial interdependence during a crisis increases (Diebold & Yilmaz, 2015). More developed financial markets have significant abilities to absorb U.S. shocks. The positive and significant coefficient of financial institutions appears to be inconsistent with our expectation that more developed institutions should improve the resilience of a country against foreign shocks. The positive relationship could be explained by the fact that more developed financial institutions are globally more interconnected and therefore global shocks are easier transmitted. Overall, the results of column 2 are consistent with column 1. Trade and financial integration have a positive impact on return spillovers in both specifications, with coefficients being significant at the 1% and 5% level.

Table 8: Panel regression - the determinants of return spillovers

In Panel A, the dependent variable is the pairwise connectedness from the U.S. to the other countries, which is extracted from the 52-weeks rolling-window estimation. *Trade* is a proxy for real economic integration between the United States and the individual countries. It is the natural logarithm of yearly exports and imports to the U.S. as fraction of local GDP in USD. *Financial* is the natural logarithm of the fraction of U.S. investors' equity holdings of emerging stock market capitalization used as proxy for financial integration with the United States. *Size* is defined as the ratio of stock market capitalization to world GDP. *FI* and *FM* (Svirydzenka, 2016) are measures for the depth, access and efficiency of financial institutions and financial markets. *KA Open is* the Chinn-Ito Index (Chinn and Ito, 2008), which measures a country's degree of capital account openness and is normalized to a number between 0 and 1. *Crisis* and *Post Crisis* are dummy variables for the period during and after the financial crisis of 2007 and 2008. All independent variables, except for the dummy variables, are lagged. *** indicates significance at 1%, ** significance at 5%, * significance at 10%. Both equations were estimated with cross-section random effects, standard errors in equation (1) are corrected for autocorrelation. The standard errors for the coefficients are in parentheses.

Panel A. Spillover Regression		
	(1)	(2)
Constant	0.956	0.840
	(0.30)***	(0.4)**
Trade	0.140	0.088
	(0.51)**	(0.06)
Financial	0.200	0.283
	(0.09)**	(0.10)***
Size		14.374
		(23.76)
FI		0.726
		(0.35)**
FM		-0.799
		(0.35)**
KA Open		0.032
		(0.18)
Crisis		0.275
		(0.11)**
Post Crisis		-0.144
		(0.10)
Panel Observations	180	168
Number of countries	12	12
R-Squared	0.042	0.165
Adjusted R-Squared	0.031	0.123

7.6 Robustness of trade and financial integration

The proxy variables for trade and financial integration chosen in panel A (Table 8) may underestimate the true impact of trade and financial integration. In panel A, the financial proxy is calculated by the fraction (natural logarithm) of U.S.

investors' equity holdings of emerging stock market capitalization. However, U.S. spillovers might affect EM countries indirectly via trade or finance integration with third countries as well. To the extent that U.S. equity shocks transmit to those third countries, they might respond with portfolio reallocations and trade adjustment of trade volumes with emerging markets. Therefore, we extend the proxies to represent global financial and economic integration. The results are presented in Table 9. The financial integration variable is now calculated as the natural logarithm of the fraction of the top 10 countries, by 2016 GDP, equity holdings of emerging stock market capitalization in USD. The proxy for trade integration is calculated as the natural logarithm of yearly global exports and imports as fraction of local GDP in USD. We re-run the regression to see if our results from panel A are robust or not. The regression in column 1 indicates that financial integration has a positive impact on U.S. return spillovers. The coefficient is still significant on a 5% level as it is in Panel A. However, trade integration, when measured globally, has a negative, not significant relationship with the pairwise conntectedness from the U.S. to the other countries in panel B, which is both inconsistent with the results from panel A and our expectation. These results remain unchanged when the control variables suggested by the International Monetary Fund (2016) are included in the regression in column 2. All control variables, except for the crisis dummy and the FM variables, are insignificant.

We can conclude that financial integration has a positive and significant effect on U.S. return spillovers independent of the choice of a local or global proxy. However, for our sample bilateral trade integration with the U.S. seems to play a larger role in determining spillovers than global trade integration. A potential reason might be that financial integration may be a stronger determinant of U.S. return spillovers to Emerging Markets countries than real integration. This would suggest that the portfolio channel is more relevant for shock transmission to our sample countries than the cashflow channel.

Table 9: Robustness panel regression – global proxies

In Panel B, the dependent variable is the pairwise connectedness from the U.S. to the other countries, which is extracted from the 52-weeks rolling-window estimation. *Trade* is a proxy for real economic (trade) integration between the world and the individual countries. It is the natural logarithm of yearly global exports and imports as fraction of local GDP in USD. *Financial* is the natural logarithm of the fraction of the top 10 countries, by 2016 GDP, equity holdings of emerging stock market capitalization used as proxy for financial integration with the world. *Size* is defined as the ratio of stock market capitalization to world GDP. *FI* and *FM* (Svirydzenka, 2016) are measures for the depth, access and efficiency of financial institutions and financial markets. *KA Open is* the Chinn-Ito Index (Chinn and Ito, 2008), which measures a country's degree of capital account openness and is normalized to a number between 0 and 1. *Crisis* and *Post Crisis* are dummy variables for the period during and after the financial crisis of 2007 and 2008. All independent variables, except for the dummy variables, are lagged. *** indicates significance at 1%, ** significance at 5%, * significance at 10%. Both equations were estimated with cross-section random effects and White's standard errors. The standard errors for the coefficients are in parentheses.

Panel B. Robustness Spillover Regression		
	(1)	(2)
Constant	1.312	1.351
	(0.32)***	(0.49)**
Trade	-0.025	-0.017
	(0.10)	(0.13)
Financial	0.183	0.211
	(0.09)**	(0.13)*
Size		16.863
		(35.93)
FI		0.550
		(0.39)
FM		-0.942
		(0.48)*
KA Open		0.034
		(0.14)
Crisis		0.282
		(0.11)***
Post Crisis		-0.115
		(0.1233)
Panel Observations	180	168
Number of countries	12	12
R-Squared	0.012	0.111
Adjusted R-Squared	0.001	0.066

7.7 Limitations

There are several factors to consider when interpreting the results of the preceding analysis. First, even though we found significant spillover effects within our sample, they are smaller in size than what would have been expected, especially those transmitted from the U.S. to other markets. A potential cause to that might be that because of non-simultaneous trading the reaction of stock markets which have different trading hours than the U.S. might not be accurately captured. In this case, the actual transmission of U.S. equity shocks to our sample would be underestimated. Samarakoon (2011) develops two different models for the investigated countries to solve this problem when estimating spillovers from daily returns. We mitigate the effect of simultaneous trading to a certain extent by using weekly returns to measure spillovers. However, we cannot fully exclude the possibility that it impacts our results.

The larger caveat in our analysis is the suitability of the VAR model to the data underlying the spillovers estimation. First, one of the standard assumptions of VAR models is asymptotic normality of the input data (Hamilton (1994); Lütkepohl and Poskitt (1991)). As generally known - and also confirmed for our sample – returns are not normally distributed(see 7.1 Preliminary Data Analysis). The estimates of the model therefore smoothens out those extreme positive and negative returns which might constitute large transmission effects. As a result, the spillover index and the role of the U.S. as shock transmittor might be underestimated. Second, it is questionable whether a VAR model is the appropriate fit for return data in the first place. For the VDs obtained from the model to accurately capture the fraction of forecast variation caused by shocks from other countries, the initial model is assumed to fully explain all of the variation in returns. In reality however, the R^2 of the individual equations in the VAR estimation system are low. Table 10 shows the explanatory power of the other countries' lagged returns ranges between only 0.36% for the U.S. and 4.59% for the Philippines. This is further evidence that the actual spillovers between the countries might be stronger than estimated from the system. It also leads to instability of the VAR coefficients which explains the heightened sensibility of our model to the rolling window length.

Table 10: Pseudo r-squared of VAR equations

	Adj. R^2		**Adj. R^2**		**Adj. R^2**
Brazil	2.51%	Korea	4.24%	Philippines	4.59%
Chile	3.35%	Malaysia	3.42%	Thailand	3.71%
Colombia	3.98%	Mexico	2.07%	Turkey	2.97%
India	4.53%	Peru	3.73%	USA	0.36%
Indonesia	4.52%				

Note: Pseudo r-squared are the r-squared of each individual return series when regressed on the first and second lag of all 13 country returns series in the sample.

The robustness of our spillover results could be improved by including a measure which is not dependent on a normality assumption. Eiling and Gerard (2015) use a measure based on dispersion and short-term correlations to explore emerging market co-movements. Given the limited scope of this thesis, such an additional analysis could not be included and remains a task for future research.

Lastly, the importance of financial integration for spillovers should also be evaluated with caution. When measuring financial integration, we use MSCI indices to capture the local market capitalization of our sample countries. MSCI follow the same methodology for all countries, which ensures consistency among our sample. The downside is that due to the selection criteria applied, such as investability and free-float, the MSCI indices cover only about 85% of the local equity universe. Therefore, we underestimate the local market capitalization, leading to a larger-than-actual financial integration.

8. Extension: U.S. Monetary policy spillovers

Existing studies on international spillovers are mainly concerned about documenting the existence and strength of market co-movements to inform investors about diversification benefits of investing abroad. They do, however, mostly refrain from hypothesizing about concrete risk factors triggering those transmission effects. This question has been investigated by a different area of economic research, covering the discussion about the role of U.S. monetary policy in determining global asset prices[5].

By extending the scope of our analysis to spillovers of U.S. monetary policy surprises to emerging countries we aim to bridge the two areas by investigating whether monetary policy spillovers exist and whether the existence and strength of general connectedness reported in our main analysis is reflected in the transmission of monetary policy specifically. This is relevant for investors to not only gain enhanced knowledge about diversification benefits, but also about whether

[5] See i.e. Thorbecke (1997), Bernanke and Kuttner (2005), Ehrmann and Fratzscher (2009), Chortareas and Noikokyris (2017). A more detailed discussion is provided in Section 3.

monetary policy constitutes a risk factor in their portfolio. Both can lead to more accurate value forecasts and therefore to better informed investment decisions.

Based on the literature review provided in Section 3 we expect the following:

H5. U.S. monetary policy surprises significantly impact domestic and foreign equity returns.

$$H_0: \beta_1, \beta_2 = 0$$
$$H_A: \beta_1, \beta_2 \neq 0$$

H6. Countries with higher pairwise directional connectedness with the U.S. show a higher sensibility to U.S. monetary policy shocks.

8.1 Methodology

We apply an event-study approach to measure the impact of U.S. monetary policy surprises of FOMC announcements on emerging equity markets. According to Gurkaynak, Sack and Swanson (2005), monetary policy surprises consist of two dimensions, the target surprise (TS) and path surprise (PS). We adopt the regression set-up of Hausman and Wongswan (2011) to measure the effects on a one-day window around FOMC announcements,

$$R_{i,t} = \alpha + \beta_1 * TS_t + \beta_2 * PS_t + \varepsilon_{i,t}$$

The dependent variable $R_{i,t}$ is the equity index return of country i on day t, TS is the target surprise, PS is the path surprise and Ɛ is a residual term for country i on day t.

The target surprise is the difference between the actual target rate and expectations, which are derived from the FED funds futures prices (Kuttner, 2001). The FED funds futures prices are adjusted for the time average effect because they are settled on an average basis. We use next month unadjusted FED funds futures if the FOMC announcements take place in the last 7 days of the month. Target surprises are calculated on a 30-min window around FOMC announcements (Hausman & Wongswan, 2011),

$$TS_t = \frac{D}{D-d} * (ff_{t+20} - ff_{t-10})$$

The path surprise (PS) is defined as the surprise change related to the expected future path. It is extracted by running the following regression:

$$\Delta ed_{t-10,t+20} = \alpha_0 + \alpha_1 TS_t + PS_t$$

where $\Delta ed_{t-10,t+20}$ represents the change in 1-year-ahead Eurodollar interest rate futures, calculated on a 30 minutes time window. The path surprise is the error term of the regression (Hausman & Wongswan, 2011).

8.2 Data

For this part of the analysis, the initial sample period was restricted to 1994 - 2007 and includes monetary policy surprises from eight scheduled FOMC meetings per year[6]. Before 1994, there was no explicit press release of the FOMC on decisions about the interest rate target. Instead, the type and size of the open market operation on the following day conveyed information about U.S. target rate changes. Therefore, one would have to identify the first open market operation after the FOMC meeting to determine the exact timing of announcements.

In line with Hausman and Wongswan (2011) and Chortareas and Noikokyris (2017), we constrain our analysis to the period before the global financial crisis. Not only were equity returns heavily influenced by the market turmoil during the crisis. In 2008, the FOMC also hit the zero lower bound on the federal funds rate in an effort to stimulate the economy after the financial crisis and began implementing unconventional policy instruments. Swanson (2017) argues that for that reason post-crisis U.S. monetary policy shocks should be measured in particular by unexpected changes in 'large-scale asset purchases' and the FED's 'forward guidance' since monetary surprises are essentially zero.

We calculate daily returns for all MSCI indices specified in the main analysis in local currency. Since scheduled FOMC announcements usually take place at 2.15pm EST, when Asian stock markets are closed, returns are measured between closing quotes to capture the effect of the policy shock, as suggested by Ehrmann and Fratzscher (2009). Accordingly, for countries where stock markets have been open at the time of the policy announcement, the effect of the policy shock is more accurately isolated when measuring returns from market opening to closing.

[6] We kindly thank Refet S. Gürkaynak for providing the monetary policy surprise dataset used by Swanson (2017).

However, due to data availability, no such measurement adjustment could be made[7].

We make several adjustments to the return series to clean outlier events, as suggested by Hausman and Wongswan (2011). The announcement on September 17th, 2001 was excluded from the sample since it was an emergency rate cut decided in a joint effort of the FED, financial markets and other central banks in response to the terrorist attacks on September 11th. Additionally, we exclude three observations which coincide with major domestic macro-economic news. For example, the 12th November 1997 was excluded for Brazil, because on that day the Brazilian stock market fell by 10.8% as consequence of the Asian crisis.[8]

8.3 Results

Table 11 reports the responses of U.S. and foreign equity returns to FOMC announcements. The results show that emerging countries react differently to monetary policy surprises. The sample equity markets are more sensible to the target surprise than the path surprise. For the five countries U.S., Brazil, Mexico, India and Korea, the target component is highly siginificant, whereas only three countries react significantly to the path surprise. This is consistent with the findings of Wongswan (2009) and Hausman and Wongswan (2011) who report that equities react mostly to the target component of monetary surprises. Hausman and Wongswan (2011) also found that higher reaction to path surprise can be observed mainly in Asian Pacific countries. However, in our sample, the countries reacting to the path surprise are Chile, Brazil and Turkey. The coefficients are significant at 10% level for Chile, respectively 1% for the other two markets.

Consistent with Hausman and Wongswan (2011), we find that closed economy countries, like Peru or Malaysia, either do not react or react less to FOMC announcements. Further, U.S. monetary policy surprises have a similar impact on the MSCI Mexico index than on the MSCI USA index. This shows that the Mexican equity market is strongly linked to the U.S.. On average, the MSCI Mexico index decreased by 1.84% in response to a 0.25% surprise increase of the U.S. target rate.

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[7] MSCI does not provide opening quotes for their emerging market indices.
[8] The two other observations excluded are: 1) Mexico, 1st February 1995: the announcement of a loan package from the U.S. caused the Mexican peso to strengthen by 6.7% against the dollar.
2) Thailand, 2th July 1997: The Bank of Thailand decided to switch to a floating currency regime, leading to a rise 8.3% rise of the Thai stock market.

The U.S. equity index decreased by 1.9% in response to an 0.25% surprise monetary tightening. Brazil and Korea are also highly sensitive to the target component. The reason for Korea's high sensitivity may be the high concentration of technology companies, which are more sensitive to FOMC announcements (Ehrmann and Fratzscher (2009), Hausman and Wongswan (2011)). The stock markets of Chile and Turkey are not significantly affected by changes in the target component but react greatly to the path surprise, which indicates that the FED forward guidance is more relevant to the market participants in these countries. Lastly, U.S. monetary policy explains poorly the variation equity returns in Colombia, Indonesia, Malaysia and Philippines. The adjusted R^2 for these equity markets are negative and indicate the insignificance of the explanatory variables.

Table 11: Event study on U.S. monetary policy surprises to EM equity markets

The table shows the individual regression results of U.S. monetary policy surprises. The dependent variable is the MSCI equity index return of country *i* on FOMC announcement days. The target surprise is the difference between the actual target rate and expectations incorporated in future rates. The path surprise represents the forward guidance on the future path of rates of the FED announcement. *** indicates significance at 1%, ** significance at 5%, * significance at 10%. The coefficients were estimated with HAC standard errors. The standard errors for the coefficients are in parentheses.

	Target Surprise		**Path Surprise**		**Adj. R^2**
United States	-0.076***	(0.017)	-0.068	(0.044)	0.32
Panel A: Latin America					
Brazil	-0.062**	(0.027)	-0.101*	(0.059)	0.11
Chile	-0.008	(0.011)	-0.118***	(0.031)	0.19
Colombia	0.001	(0.014)	-0.002	(0.030)	-0.02
Mexico	-0.074***	(0.025)	-0.113	(0.074)	0.19
Peru	-0.010	(0.017)	-0.071	(0.064)	0.02
Panel B: Asia					
India	-0.040**	(0.019)	0.027	(0.030)	0.06
Indonesia	0.025	(0.020)	-0.021	(0.044)	-0.001
Korea	-0.054**	(0.024)	-0.049	(0.053)	0.04
Malaysia	0.006	(0.014)	0.035	(0.038)	-0.005
Philippines	0.010	(0.016)	-0.009	(0.035)	-0.01
Thailand	-0.030	(0.020)	-0.070	(0.045)	0.02
Turkey	0.014	(0.031)	-0.112*	(0.063)	0.02

To allow comparisons of the relative strength of target and path surprise for each country, we present the standardized coefficients of each explanatory variable in

Table 12. The coefficients are interpreted as changes in standard deviation of the dependent variable with a change in one standard deviation of an explanatory variable. For example, a one standard deviation increase in the target surprise results in a 0.288 standard deviation decrease for Brazilian equity returns. Standardized coefficients are calculated the following way:

$$\beta_{standardized} = \beta_{unstandardized} * \frac{\sigma_x}{\sigma_y}.$$

When not standardized, the path surprise coefficient for Brazil is higher than the target surprise coefficient. However, in relative terms, target surprise has a higher impact on MSCI Brazil returns.

In general, the presented standardized coefficients are only informative for one country and cannot be compared among regression equations. However, in our case, the explanatory variables (path and target surprise) are the same for each regression. Hence, the standard deviation σ_x is identical for all countries. This enables us to compare coefficients among those regressions where the unstandardized coefficient $\beta_{unstandardized}$ is approximately equal. For example, Mexico and the United States have almost the same unstandardized coefficient for target surprise (-0.076 and -0.074). In terms of relative strength, the target surprise impacts U.S. equity returns more than Mexican ones. Furthermore, the unstandardized path surprise coefficients for Chile and Turkey are quite similar. Despite that, we notice that the Chilean stock market reacts relatively stronger to changes in the path surprise than Turkey. This is consistent with the connectedness table in Section 7.2, where the connectedness between the U.S. and Chile is stronger than the one for Turkey.

Table 12: Standardized event study coefficients

The table below shows both original and standardized coefficients of the regression on U.S. monetary policy surprises performed in Table 11. Standardized coefficients are calculated as $\beta_{standardized} = \beta_{unstandardized} * \frac{\sigma_x}{\sigma_y}$. The underlined coefficients are at least significant at a 10% level.

	Target Surprise		**Path Surprise**	
	Unstandardized	*Standardized*	*Unstandardized*	*Standardized*
United States	<u>-0.076</u>	<u>-0.536</u>	-0.068	-0.217
Panel A: Latin America				
Brazil	<u>-0.062</u>	<u>-0.288</u>	<u>-0.101</u>	<u>-0.214</u>
Chile	-0.008	-0.068	<u>-0.118</u>	<u>-0.443</u>
Colombia	0.001	0.001	-0.002	-0.005
Mexico	<u>-0.074</u>	<u>-0.371</u>	-0.113	-0.259
Peru	-0.010	-0.058	-0.071	-0.180

Panel B: Asia				
India	-0.040	-0.271	0.027	0.085
Indonesia	0.025	0.124	-0.021	-0.047
Korea	-0.054	-0.211	-0.049	-0.085
Malaysia	0.006	0.043	0.035	0.106
Philippines	0.010	0.062	-0.009	-0.023
Thailand	-0.030	-0.141	-0.070	-0.147
Turkey	0.014	0.032	-0.112	-0.169

The results of the event study broadly support the general findings of the connectedness table in the main analysis. The U.S. equity market reacts strongly to the target surprise with an unstandardized response of -0.076. Thus, monetary policy does qualify as one 'type' of domestic equity shock hitting the U.S. stock market and propagating from there to emerging markets. Furthermore, both analyses arrive at similar conclusions for some countries. The connectedness table in Section 7.2 documents strong connectedness between Mexico and the U.S.. The event study on equity responses to FOMC announcements confirms this. The Mexican stock market is the highest receiver of U.S. shocks, besides the U.S. itself, in both analysis parts. A similar conclusion can be drawn for Brazil. According to the connectedness table, Brazil is the highest receiver of U.S. shocks after Mexico, which is corroborated by a strong reaction to both components of U.S. monetary policy surprises. The Chilean market is the third-largest receiver of U.S. shocks in general and is impacted significantly by the path surprise component. In the case of Peru, the sensitivity to U.S. shocks found in the spillover analysis is not reflected by a significant reaction of Peru equities to U.S. monetary policy. This suggests that there might be other causes for spillovers than U.S. monetary policy.

The results of the connectedness table are not directly confirmed by the event study for Malaysia, Thailand and the Philippines. The countries have a directional connectedness with the U.S. between 3.8% and 5.4% but show no significant sensitivity towards U.S. monetary policy surprises. Again, it might be that U.S. news unrelated to U.S. monetary policy are more relevant to cause domestic market variations.

8.4 Limitations

First, due to data availability, returns were measured from market closing on FOMC announcement day to closing on the following day for all countries in our sample.

The responses of countries with overlapping trading hours with the U.S. might therefore not fully be captured and distorted by other factors influencing equity prices on the day after the announcement.

Second, other news, both domestic and global, might influence the estimation of market reactions to U.S. monetary policy announcements. This problem can be mitigated by using high-frequency data, which were unavailable for our analysis. Compared to the results of Wongswan (2009), Ehrmann and Fratzscher (2009) and Chortareas and Noikokyris (2017), all of whome based their studies on high-frequency data, our results therefore show less pronounced evidence of equity shock transmission.

9. Conclusion

This thesis examines return spillovers between the 12 emerging markets Brazil, Chile, Colombia, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Thailand, Turkey and the U.S. between 1994 to 2017 adopting the approach of Diebold and Yilmaz (2012) to use variance decompositions obtained from a VAR model. We found spillovers within our sample in varying strength, with two regional connectedness clusters, one amongst Latin American countries one and amongst Asian markets. Further, our results confirm the finding of previous research that times of crisis lead to higher total spillovers or ‘contagion’ between the countries. Most countries are net receivers of equity shocks, with exception of the U.S., Mexico and Brazil. The U.S. and Mexico play the largest role in transmitting directional shocks to other markets in our sample. Countries are more sensible towards variations of the U.S. equity market the more financially integrated they are and the higher their trade ratio with the U.S., whereas there is evidence that global trade integration is not relevant. This indicates that investors’ asset holdings are a dominant channel of transmitting shocks across countries, consistent with the research that has been conducted on the portfolio channel as transmission channel of equity spillovers. U.S. monetary policy surprises constitute relevant shocks only for part of the sample countries. We found significant transmission to Chile, Brazil, India, Korea, Mexico, Turkey and the U.S.. As expected, the countries reacting strongest to FOMC announcements are the ones having the highest directional connectedness with the U.S..

Our results suggest that emerging markets are sensitive to U.S. shocks and thus provide only limited diversification benefits for investors. Further, the monetary policy stance of the U.S. can constitute a relevant risk factor for policy makers and investors being invested in Chile, Brazil, India, Korea, Mexico, Turkey and the U.S..

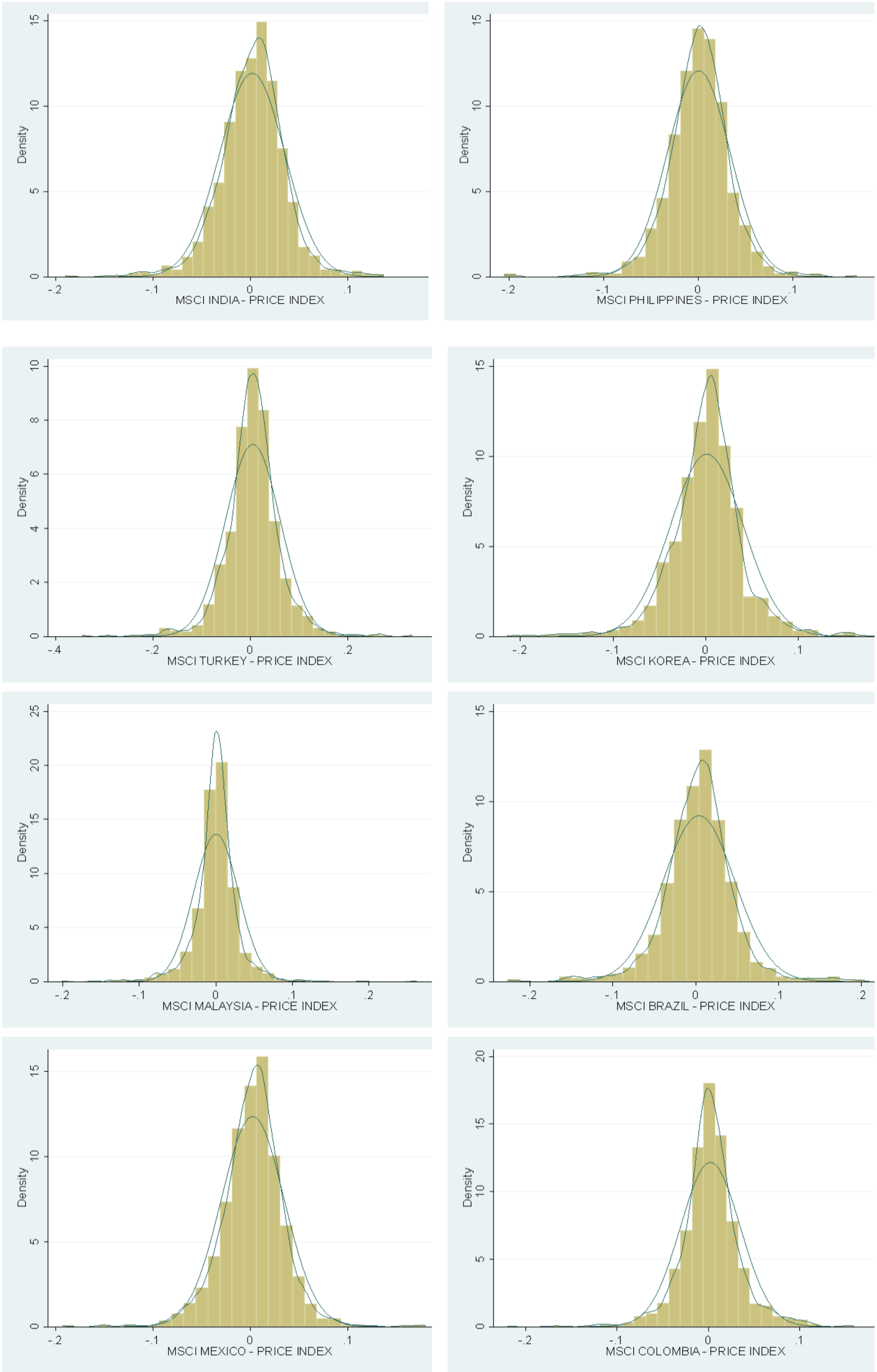
For future research, it might be interesting to disentangle the effect of different crisis periods on return spillovers between countries more granularly in the framework of a Markov Regime Switching VAR. In addition, it is yet to answer how the current trend towards increased protectionism of some large economies influence the future co-movements between markets.

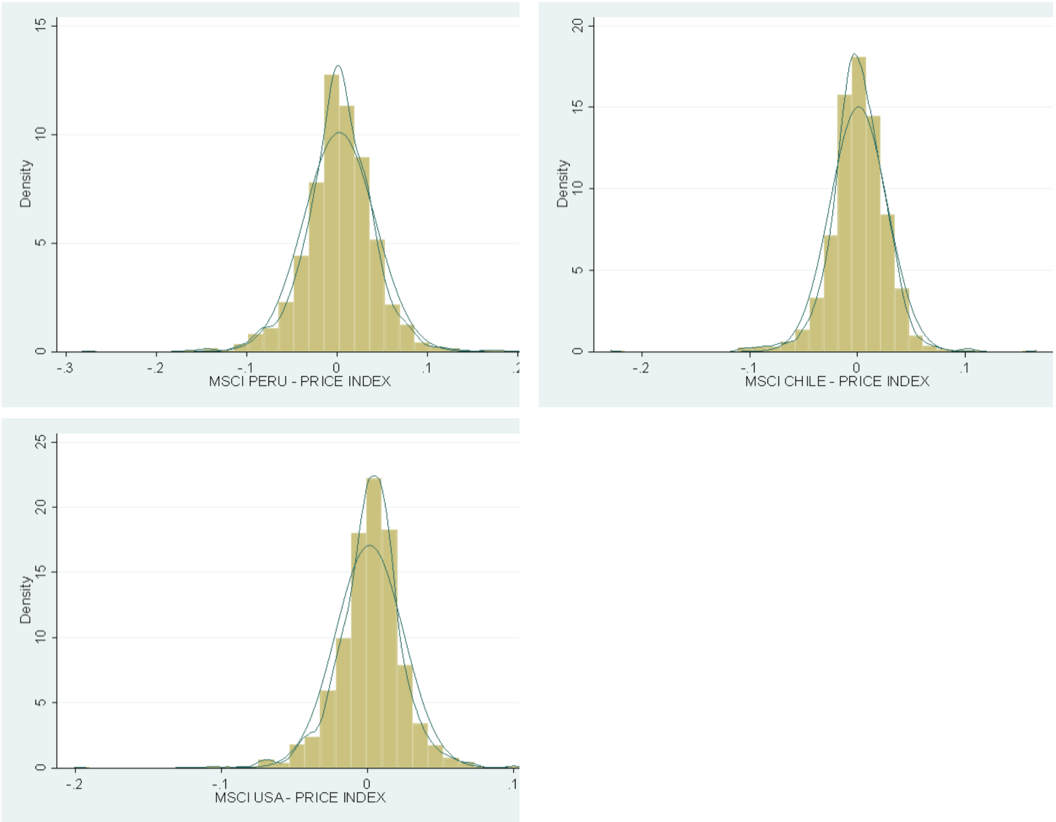
10. Appendix

Abbreviations

ADF	Augmented Dicky Fuller
CPIS	Coordinated Portfolio Investment Survey
DCF	Discounted Cashflow
EM	Emerging Markets
FED	Federal Reserve (U.S. central bank)
FEVD	Forecast Error Variance Decomposition
FOMC	Federal Open Market Committee
GARCH	General Autoregressive Conditionally Heteroskedastic
GVD	Generalized Variance Decomposition
IMF	International Monetary Fund
PS	Path surprise
TS	Target surprise
VAR	Vector Autoregressive

Appendix 1: Kernel densities of MSCI returns



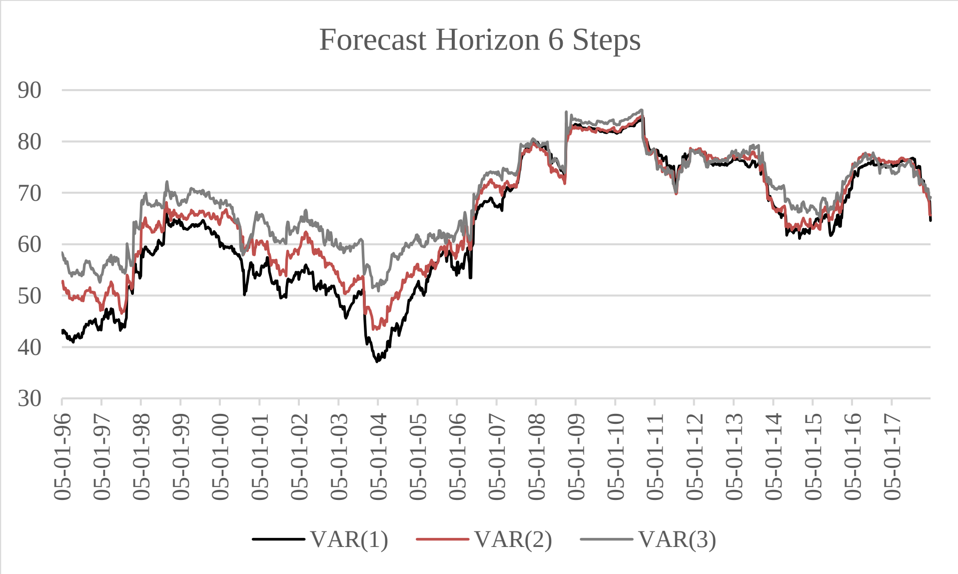

Density
MSCI PERU - PRICE INDEX
Density
MSCI CHILE - PRICE INDEX
Density
MSCI USA - PRICE INDEX

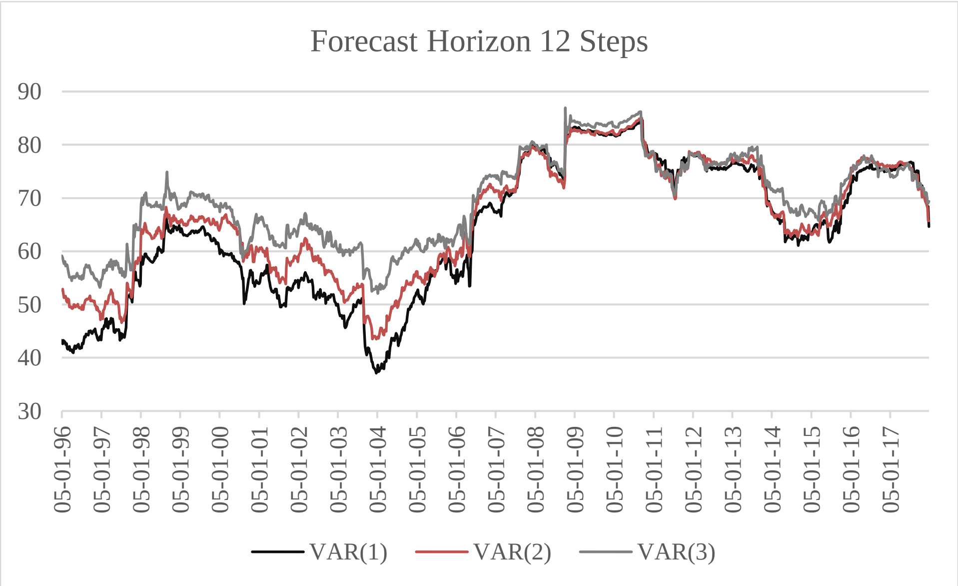
Appendix 2: Connectedness table with bootstrapped standard errors

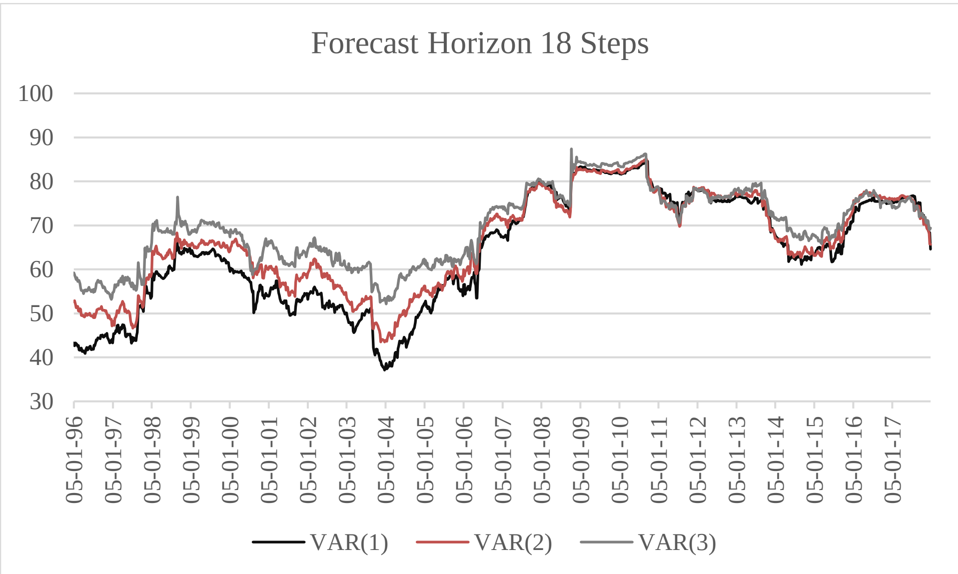
	Indonesia	Thailand	India	Philippines	Turkey	Korea	Malaysia	Brazil	Mexico	Colombia	Peru	Chile	USA	From
Indonesia**	40.7	9.7	4.0	8.5	1.4	4.5	7.4	3.6	4.2	2.4	4.7	4.5	4.3	59.3
	(0.047)	(0.014)	(0.010)	(0.015)	(0.007)	(0.013)	(0.016)	(0.011)	(0.012)	(0.009)	(0.011)	(0.012)	(0.010)	(0.033)
Thailand**	9.0	38.0	3.2	8.4	2.2	7.7	7.2	4.2	5.3	1.8	3.8	4.4	4.9	62.0
	(0.016)	(0.038)	(0.010)	(0.012)	(0.007)	(0.014)	(0.015)	(0.009)	(0.01)	(0.008)	(0.010)	(0.012)	(0.011)	(0.041)
India**	4.2	4.1	43.4	3.8	1.9	6.4	3.5	5.5	6.8	2.8	5.1	4.2	8.1	56.6
	(0.011)	(0.011)	(0.050)	(0.009)	(0.008)	(0.013)	(0.009)	(0.011)	(0.012)	(0.01)	(0.012)	(0.011)	(0.013)	(0.070)
Philippines**	8.1	9.7	3.0	38.9	2.4	3.6	6.5	4.0	7.0	2.2	4.1	5.1	5.4	61.1
	(0.016)	(0.013)	(0.008)	(0.042)	(0.008)	(0.011)	(0.014)	(0.01)	(0.01)	(0.009)	(0.011)	(0.011)	(0.011)	(0.051)
Turkey**	1.7	3.1	2.4	3.5	57.2	3.9	1.3	5.2	5.6	1.6	4.8	4.3	5.3	42.8
	(0.009)	(0.010)	(0.010)	(0.011)	(0.06)	(0.012)	(0.010)	(0.016)	(0.013)	(0.009)	(0.012)	(0.011)	(0.013)	(0.046)
Korea**	4.4	8.3	5.9	3.6	3.2	41.3	3.6	5.0	6.5	1.4	4.2	4.6	8.1	58.7
	(0.013)	(0.014)	(0.012)	(0.010)	(0.010)	(0.04)	(0.012)	(0.011)	(0.012)	(0.007)	(0.009)	(0.010)	(0.010)	(0.04)
Malaysia**	8.8	9.2	3.6	7.7	1.3	5.0	46.3	2.3	5.1	1.1	2.3	3.6	3.8	53.7
	(0.017)	(0.014)	(0.010)	(0.015)	(0.008)	(0.015)	(0.052)	(0.010)	(0.011)	(0.007)	(0.008)	(0.012)	(0.011)	(0.052)
Brazil**	2.8	3.8	3.7	3.7	3.1	4.0	1.8	34.7	11.9	2.7	9.3	9.0	9.3	65.3
	(0.010)	(0.009)	(0.009)	(0.009)	(0.011)	(0.010)	(0.009)	(0.033)	(0.012)	(0.010)	(0.012)	(0.013)	(0.010)	(0.027)
Mexico**	2.8	4.2	4.1	5.1	2.9	4.8	3.5	10.3	30.9	2.9	7.6	7.7	13.0	69.1
	(0.01)	(0.009)	(0.009)	(0.009)	(0.008)	(0.01)	(0.009)	(0.011)	(0.027)	(0.009)	(0.01)	(0.009)	(0.010)	(0.041)
Colombia**	3.4	2.9	2.9	3.3	1.5	2.0	1.4	5.3	6.4	52.7	6.5	5.8	5.8	47.3
	(0.012)	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)	(0.009)	(0.013)	(0.012)	(0.071)	(0.014)	(0.015)	(0.014)	(0.043)
Peru**	3.85	3.77	3.81	3.81	3.54	3.76	1.70	9.92	9.62	4.11	36.26	7.81	8.02	63.74
	(0.009)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.006)	(0.012)	(0.011)	(0.01)	(0.042)	(0.013)	(0.012)	(0.038)
Chile**	3.7	4.2	3.1	4.6	3.0	3.6	2.8	9.7	9.3	3.6	7.5	36.0	8.8	64.0
	(0.010)	(0.011)	(0.009)	(0.010)	(0.008)	(0.009)	(0.011)	(0.014)	(0.010)	(0.011)	(0.013)	(0.041)	(0.012)	(0.06)
USA**	2.8	3.9	5.1	3.8	2.8	6.0	2.2	8.5	13.6	3.3	7.1	8.0	32.9	67.1
	(0.008)	(0.01)	(0.01)	(0.009)	(0.008)	(0.01)	(0.008)	(0.010)	(0.012)	(0.01)	(0.011)	(0.012)	(0.035)	(0.035)
To**	55.5	66.8	45.0	59.8	29.2	55.4	43.0	73.7	91.3	30.0	67.1	69.1	84.9	
	(0.070)	(0.085)	(0.076)	(0.074)	(0.079)	(0.079)	(0.078)	(0.063)	(0.080)	(0.074)	(0.071)	(0.058)	(0.080)	
Net	-3.80	4.80	-11.6**	-1.30	-13.6**	-3.40	-10.7**	8.3*	22.3**	-17.3**	3.40	5.10	17.7**	**59.3****
	(0.045)	(0.050)	(0.030)	(0.040)	(0.046)	(0.054)	(0.047)	(0.049)	(0.045)	(0.043)	(0.044)	(0.032)	(0.052)	(0.0362)

Notes: The sample is taken from January 14, 1994 to January 29, 2017. Nonparametrically bootstrapped standard errors (5000 drawings) are presented in parentheses. ** and * indicate statistical significance at the 1% and 5% levels. ** or * next to the row heading indicates that all entries of the row are significantly different from zero at the 1% or 5% level.

Appendix 3: Spillover index, robustness to lag and forecast horizon selection







Appendix 4: Trade and financial integration - Summary statistics

Statistics A. Economic integration (Trade with U.S./GDP)

	Brazil	*Chile*	*Colombia*	*India*	*Indonesia*	*Korea*	*Malaysia*	*Mexico*	*Peru*	*Philippines*	*Turkey*	*Thailand*	*Total*
Mean	3.35%	9.21%	9.83%	2.99%	3.74%	8.40%	20.69%	36.57%	7.96%	11.60%	2.22%	11.41%	10.66%
Median	3.16%	9.10%	9.84%	2.91%	3.57%	8.28%	18.04%	35.53%	7.98%	9.16%	2.08%	10.84%	8.45%
Maximum	5.12%	11.13%	10.85%	3.87%	6.42%	10.09%	32.32%	43.09%	9.83%	22.52%	3.19%	16.92%	43.09%
Minimum	2.12%	7.75%	8.65%	2.43%	2.72%	7.42%	10.56%	33.02%	6.28%	5.18%	1.83%	8.92%	1.83%
Std. Dev.	1.09%	0.91%	0.66%	0.38%	1.02%	0.73%	9.02%	2.80%	1.12%	6.22%	0.36%	2.55%	9.82%
Skewness	0.47	0.48	-0.22	0.70	1.20	0.75	0.16	0.85	0.15	0.51	1.39	0.69	1.75
Kurtosis	1.67	2.70	2.16	2.97	4.07	3.17	1.27	2.96	1.90	1.69	4.61	2.32	5.14
J-Bera Probability	0.44	0.72	0.75	0.54	0.12	0.49	0.38	0.40	0.66	0.43	0.04**	0.48	0.00***

Statistics B. Financial integration (U.S. Portfolio Investment)

	Brazil	*Chile*	*Colombia*	*India*	*Indonesia*	*Korea*	*Malaysia*	*Mexico*	*Peru*	*Philippines*	*Turkey*	*Thailand*	*Total*
Mean	35.04%	16.31%	15.36%	31.38%	29.59%	26.45%	15.35%	45.87%	12.89%	41.49%	30.28%	34.60%	27.88%
Median	32.84%	17.64%	14.57%	30.53%	29.00%	24.79%	17.13%	46.28%	12.36%	41.68%	31.69%	37.21%	28.69%
Maximum	41.76%	22.02%	31.55%	44.75%	39.65%	35.73%	19.61%	57.27%	23.01%	51.78%	38.98%	51.82%	57.27%
Minimum	30.81%	10.14%	8.01%	16.46%	25.11%	19.03%	5.53%	34.80%	7.72%	27.09%	17.16%	16.86%	5.53%
Std. Dev.	3.91%	4.19%	6.87%	7.08%	3.59%	4.81%	4.13%	8.53%	4.28%	6.34%	5.91%	9.26%	11.96%
Skewness	0.63	-0.06	1.33	-0.04	1.54	0.55	-0.96	-0.01	0.91	-0.44	-0.69	-0.22	0.22
Kurtosis	1.80	1.35	3.84	2.90	5.38	2.27	3.06	1.39	3.32	3.21	2.91	2.60	2.38
J-Bera Probability	0.39	0.42	0.09*	0.99	0.01***	0.58	0.32	0.44	0.34	0.78	0.55	0.89	0.11

Notes: 15 observations per country. Economic integration is yearly trade with the U.S. / GDP. Financial integration is U.S. Portfolio Investment/emerging stock market capitalization. 'Total' are the cross-sectional statistics for trade and finance integration with 180 observations each.

Appendix 5: Vector autoregression estimates

	Brazil	Chile	Colombia	India	Indonesia	Korea	Malaysia	Mexico	Philippines	Peru	Thailand	Turkey	USA
Intercept	0.0031	0.0006	0.0014	0.0010	0.0011	0.0010	0.0002	0.0023	0.0003	0.0019	-0.0004	0.0035	0.0014
	(-0.0012)	(-0.0008)	(-0.0009)	(-0.0009)	(-0.0012)	(-0.0011)	(-0.0008)	(-0.0009)	(-0.0009)	(-0.0011)	(-0.0012)	(-0.0016)	(-0.0007)
	[2.5794]	[0.8561]	[1.5211]	[1.01]	[0.8484]	[0.9002]	[0.2276]	[2.4847]	[0.2952]	[1.6931]	[-0.3256]	[2.1881]	[2.1389]
Brazil (lag 1)	0.0190	0.0140	0.0845	0.0555	0.0277	-0.0229	-0.0212	0.0232	0.0075	-0.0262	0.0277	0.1984	0.0115
	(-0.0382)	(-0.0236)	(-0.029)	(-0.0296)	(-0.0389)	(-0.035)	(-0.026)	(-0.0288)	(-0.0292)	(-0.0351)	(-0.0374)	(-0.0499)	(-0.0211)
	[0.4978]	[0.5946]	[2.9109]	[1.8792]	[0.7129]	[-0.6536]	[-0.8164]	[0.8033]	[0.2563]	[-0.7466]	[0.7428]	[3.9789]	[0.5453]
Brazil (lag 2)	0.0604	0.0446	-0.0137	0.0346	-0.0102	0.0377	-0.0074	-0.0145	-0.0118	0.0300	0.0066	-0.0199	-0.0254
	(-0.0379)	(-0.0234)	(-0.0288)	(-0.0293)	(-0.0386)	(-0.0347)	(-0.0258)	(-0.0286)	(-0.0289)	(-0.0348)	(-0.0371)	(-0.0495)	(-0.0209)
	[1.5919]	[1.9076]	[-0.4769]	[1.1799]	[-0.264]	[1.0869]	[-0.2866]	[-0.5084]	[-0.4091]	[0.8618]	[0.1775]	[-0.4021]	[-1.2154]
Chile (lag 1)	-0.0482	0.0029	0.0153	-0.0060	0.0085	-0.0144	0.0215	-0.0948	0.0650	0.0090	-0.0908	-0.1282	-0.0308
	(-0.0587)	(-0.0362)	(-0.0446)	(-0.0454)	(-0.0597)	(-0.0537)	(-0.0399)	(-0.0443)	(-0.0448)	(-0.0539)	(-0.0573)	(-0.0766)	(-0.0324)
	[-0.8207]	[0.0806]	[0.3428]	[-0.1325]	[0.142]	[-0.2686]	[0.5396]	[-2.1408]	[1.4531]	[0.1676]	[-1.5829]	[-1.6748]	[-0.9517]
Chile (lag 2)	-0.0599	-0.0342	0.0132	-0.0157	0.1067	0.1163	-0.0400	0.0142	-0.0166	0.0857	0.0245	0.0389	0.0138
	(-0.0587)	(-0.0362)	(-0.0446)	(-0.0454)	(-0.0597)	(-0.0537)	(-0.0399)	(-0.0443)	(-0.0448)	(-0.0539)	(-0.0573)	(-0.0766)	(-0.0324)
	[-1.0209]	[-0.9454]	[0.2969]	[-0.3456]	[1.7876]	[2.1651]	[-1.0047]	[0.3217]	[-0.3713]	[1.5915]	[0.4278]	[0.5078]	[0.4255]
Colombia (lag 1)	-0.0347	-0.0304	0.0556	0.0169	0.0746	-0.0140	0.0450	0.0101	-0.0180	0.0176	0.0700	0.1129	-0.0271
	(-0.041)	(-0.0253)	(-0.0311)	(-0.0317)	(-0.0417)	(-0.0375)	(-0.0278)	(-0.0309)	(-0.0313)	(-0.0376)	(-0.04)	(-0.0535)	(-0.0226)
	[-0.8461]	[-1.2035]	[1.7884]	[0.5344]	[1.7891]	[-0.3739]	[1.6176]	[0.3259]	[-0.577]	[0.467]	[1.7489]	[2.1121]	[-1.1992]
Colombia (lag 2)	-0.0389	-0.0493	0.0584	0.0434	-0.0118	0.0136	-0.0253	-0.0503	-0.0222	0.0169	-0.0054	-0.0176	-0.0104
	(-0.041)	(-0.0253)	(-0.0312)	(-0.0317)	(-0.0417)	(-0.0376)	(-0.0279)	(-0.031)	(-0.0313)	(-0.0377)	(-0.0401)	(-0.0535)	(-0.0227)
	[-0.9485]	[-1.9489]	[1.8736]	[1.3666]	[-0.2823]	[0.3614]	[-0.9087]	[-1.6244]	[-0.7109]	[0.4498]	[-0.1342]	[-0.3295]	[-0.4608]
India (lag 1)	-0.0281	-0.0412	-0.0728	-0.0363	-0.0253	-0.0074	0.0174	-0.0162	0.0019	0.0053	0.0197	0.1322	-0.0125
	(-0.0423)	(-0.0261)	(-0.0321)	(-0.0327)	(-0.043)	(-0.0387)	(-0.0287)	(-0.0319)	(-0.0323)	(-0.0388)	(-0.0413)	(-0.0552)	(-0.0234)
	[-0.6638]	[-1.5777]	[-2.2686]	[-1.1106]	[-0.5873]	[-0.1918]	[0.6052]	[-0.5087]	[0.0604]	[0.1368]	[0.476]	[2.3954]	[-0.5334]

Appendix 5 continued: Vector autoregression estimates

	Brazil	Chile	Colombia	India	Indonesia	Korea	Malaysia	Mexico	Philippines	Peru	Thailand	Turkey	USA
India (lag 2)	0.0438	-0.0125	-0.0428	0.0530	-0.0191	-0.0573	-0.0272	0.0195	-0.0252	-0.0167	-0.0542	-0.0869	-0.0046
	(-0.0417)	(-0.0257)	(-0.0316)	(-0.0322)	(-0.0424)	(-0.0381)	(-0.0283)	(-0.0314)	(-0.0318)	(-0.0382)	(-0.0407)	(-0.0544)	(-0.023)
	[1.0507]	[-0.4845]	[-1.3533]	[1.6449]	[-0.4516]	[-1.5035]	[-0.9622]	[0.6207]	[-0.7943]	[-0.437]	[-1.3315]	[-1.5984]	[-0.1998]
Indonesia (lag 1)	-0.0333	-0.0153	0.0177	-0.0642	-0.1579	-0.0403	0.0397	0.0075	0.0123	0.0000	-0.0688	-0.0290	0.0099
	(-0.035)	(-0.0216)	(-0.0266)	(-0.0271)	(-0.0356)	(-0.032)	(-0.0238)	(-0.0264)	(-0.0267)	(-0.0321)	(-0.0342)	(-0.0457)	(-0.0193)
	[-0.9518]	[-0.7083]	[0.6662]	[-2.3736]	[-4.4342]	[-1.2589]	[1.6685]	[0.2826]	[0.4597]	[0.0014]	[-2.0119]	[-0.6362]	[0.5136]
Indonesia (lag 2)	-0.0095	0.0218	0.0381	-0.0692	0.0132	0.0046	0.0191	-0.0291	-0.0321	-0.0679	-0.0089	0.0528	0.0230
	(-0.0348)	(-0.0215)	(-0.0265)	(-0.0269)	(-0.0354)	(-0.0319)	(-0.0237)	(-0.0263)	(-0.0266)	(-0.032)	(-0.034)	(-0.0454)	(-0.0192)
	[-0.2714]	[1.0136]	[1.4395]	[-2.5692]	[0.372]	[0.1441]	[0.8073]	[-1.1084]	[-1.2096]	[-2.1241]	[-0.2606]	[1.1616]	[1.1967]
Korea (lag 1)	-0.0260	0.0197	0.0255	-0.0533	0.0935	-0.1713	0.0197	-0.0182	-0.0041	-0.0089	-0.0338	-0.1052	-0.0216
	(-0.0376)	(-0.0232)	(-0.0286)	(-0.0291)	(-0.0383)	(-0.0344)	(-0.0256)	(-0.0284)	(-0.0287)	(-0.0345)	(-0.0368)	(-0.0491)	(-0.0208)
	[-0.6907]	[0.8469]	[0.8943]	[-1.8312]	[2.4428]	[-4.9757]	[0.7729]	[-0.6414]	[-0.1443]	[-0.2589]	[-0.9184]	[-2.144]	[-1.0425]
Korea (lag 2)	-0.0027	0.0183	-0.0155	-0.0209	0.0069	-0.0157	0.0665	0.0214	-0.0179	0.0114	0.0876	0.0106	0.0115
	(-0.0378)	(-0.0233)	(-0.0287)	(-0.0292)	(-0.0384)	(-0.0346)	(-0.0257)	(-0.0285)	(-0.0288)	(-0.0347)	(-0.0369)	(-0.0493)	(-0.0209)
	[-0.0722]	[0.7863]	[-0.5409]	[-0.7158]	[0.1794]	[-0.4545]	[2.5905]	[0.7523]	[-0.6215]	[0.3285]	[2.3738]	[0.2159]	[0.5511]
Malaysia (lag 1)	-0.0058	-0.0223	-0.0144	0.0631	-0.1189	-0.0349	-0.0631	-0.0910	0.0238	0.0103	-0.0811	0.0396	0.0101
	(-0.0493)	(-0.0304)	(-0.0374)	(-0.0381)	(-0.0501)	(-0.0451)	(-0.0335)	(-0.0372)	(-0.0376)	(-0.0452)	(-0.0481)	(-0.0643)	(-0.0272)
	[-0.117]	[-0.7343]	[-0.3858]	[1.6572]	[-2.3729]	[-0.7751]	[-1.8856]	[-2.4492]	[0.6338]	[0.2272]	[-1.6839]	[0.6155]	[0.3697]
Malaysia (lag 2)	0.0667	0.0591	0.0727	0.0087	0.0202	-0.0153	0.0107	0.0804	0.0827	0.0480	0.1413	0.0125	-0.0513
	(-0.049)	(-0.0302)	(-0.0372)	(-0.0379)	(-0.0499)	(-0.0449)	(-0.0333)	(-0.037)	(-0.0374)	(-0.045)	(-0.0479)	(-0.0639)	(-0.0271)
	[1.3605]	[1.9558]	[1.9533]	[0.2304]	[0.4052]	[-0.3402]	[0.3229]	[2.1755]	[2.214]	[1.0666]	[2.9512]	[0.196]	[-1.8962]
Mexico (lag 1)	0.0341	0.1254	0.1017	0.0622	-0.0019	0.0303	-0.0384	0.0406	0.0396	0.2497	0.1183	-0.0495	-0.0060
	(-0.0554)	(-0.0342)	(-0.0421)	(-0.0428)	(-0.0564)	(-0.0507)	(-0.0376)	(-0.0418)	(-0.0423)	(-0.0509)	(-0.0541)	(-0.0723)	(-0.0306)
	[0.6156]	[3.668]	[2.417]	[1.4521]	[-0.0333]	[0.598]	[-1.0205]	[0.9713]	[0.9374]	[4.9103]	[2.1841]	[-0.6841]	[-0.1956]

Appendix 5 continued: Vector autoregression estimates

	Brazil	Chile	Colombia	India	Indonesia	Korea	Malaysia	Mexico	Philippines	Peru	Thailand	Turkey	USA
Mexico (lag 2)	0.0676	0.0642	0.0704	-0.0288	-0.0146	-0.0402	0.0201	-0.0600	0.0276	0.0792	-0.0912	0.1590	0.0259
	(-0.0555)	(-0.0342)	(-0.0421)	(-0.0429)	(-0.0564)	(-0.0508)	(-0.0377)	(-0.0419)	(-0.0423)	(-0.0509)	(-0.0542)	(-0.0724)	(-0.0306)
	[1.2189]	[1.8751]	[1.6715]	[-0.6721]	[-0.2587]	[-0.7915]	[0.533]	[-1.4337]	[0.653]	[1.5558]	[-1.6826]	[2.1976]	[0.8468]
Philippines (lag 1)	-0.1408	-0.0456	-0.0531	0.0616	-0.0355	-0.0119	-0.0185	-0.0311	-0.1258	-0.0910	0.0385	-0.0817	-0.0176
	(-0.0462)	(-0.0285)	(-0.035)	(-0.0357)	(-0.0469)	(-0.0422)	(-0.0313)	(-0.0348)	(-0.0352)	(-0.0424)	(-0.0451)	(-0.0602)	(-0.0255)
	[-3.052]	[-1.6019]	[-1.5159]	[1.7255]	[-0.7566]	[-0.2811]	[-0.5905]	[-0.8929]	[-3.574]	[-2.1496]	[0.8538]	[-1.3573]	[-0.6908]
Philippines (lag 2)	0.0125	0.0295	-0.0086	0.0501	0.0127	-0.0297	0.0480	0.0089	0.0219	0.0189	-0.0019	0.0127	0.0128
	(-0.0459)	(-0.0283)	(-0.0349)	(-0.0355)	(-0.0467)	(-0.042)	(-0.0312)	(-0.0347)	(-0.035)	(-0.0422)	(-0.0449)	(-0.0599)	(-0.0254)
	[0.2724]	[1.0394]	[-0.2472]	[1.4112]	[0.2719]	[-0.7056]	[1.5391]	[0.2555]	[0.6246]	[0.4474]	[-0.0423]	[0.2124]	[0.5062]
Peru (lag 1)	0.0493	-0.0076	-0.0125	0.0035	0.0516	0.0092	0.0049	-0.0356	-0.0011	-0.0131	0.0189	-0.1179	-0.0171
	(-0.0398)	(-0.0245)	(-0.0302)	(-0.0307)	(-0.0405)	(-0.0364)	(-0.027)	(-0.03)	(-0.0303)	(-0.0365)	(-0.0389)	(-0.0519)	(-0.022)
	[1.24]	[-0.3098]	[-0.4124]	[0.1153]	[1.2749]	[0.2517]	[0.1828]	[-1.185]	[-0.0356]	[-0.3584]	[0.487]	[-2.2719]	[-0.7811]
Peru (lag 2)	-0.0111	-0.0578	0.0117	-0.0029	-0.0063	-0.0347	-0.0155	0.0170	-0.0113	-0.0425	-0.0481	0.0055	-0.0359
	(-0.0393)	(-0.0242)	(-0.0298)	(-0.0304)	(-0.04)	(-0.036)	(-0.0267)	(-0.0296)	(-0.03)	(-0.0361)	(-0.0384)	(-0.0513)	(-0.0217)
	[-0.2835]	[-2.3855]	[0.3921]	[-0.0956]	[-0.1571]	[-0.965]	[-0.5791]	[0.5742]	[-0.377]	[-1.1781]	[-1.2518]	[0.108]	[-1.6558]
Thailand (lag 1)	0.0933	0.0258	0.0172	0.0159	0.1066	0.1045	0.0746	0.0820	0.0940	0.0520	-0.0081	0.0042	0.0125
	(-0.0374)	(-0.0231)	(-0.0284)	(-0.0289)	(-0.0381)	(-0.0343)	(-0.0254)	(-0.0282)	(-0.0286)	(-0.0344)	(-0.0366)	(-0.0488)	(-0.0207)
	[2.4919]	[1.115]	[0.6054]	[0.5506]	[2.7999]	[3.0493]	[2.9348]	[2.9037]	[3.2916]	[1.5123]	[-0.2222]	[0.0859]	[0.606]
Thailand (lag 2)	0.0218	-0.0218	0.0150	0.0236	0.0251	0.0741	0.0214	0.0162	0.0903	0.0171	0.0612	-0.0477	-0.0016
	(-0.0373)	(-0.023)	(-0.0283)	(-0.0289)	(-0.038)	(-0.0342)	(-0.0254)	(-0.0282)	(-0.0285)	(-0.0343)	(-0.0365)	(-0.0487)	(-0.0206)
	[0.584]	[-0.9489]	[0.5283]	[0.8197]	[0.6624]	[2.1681]	[0.8462]	[0.5759]	[3.1741]	[0.4983]	[1.6771]	[-0.9799]	[-0.0772]
Turkey (lag 1)	-0.0699	0.0053	0.0011	-0.0037	-0.0040	-0.0314	-0.0178	-0.0152	-0.0342	-0.0799	-0.0103	0.0004	0.0130
	(-0.0235)	(-0.0145)	(-0.0179)	(-0.0182)	(-0.0239)	(-0.0215)	(-0.016)	(-0.0178)	(-0.0179)	(-0.0216)	(-0.023)	(-0.0307)	(-0.013)
	[-2.9697]	[0.3684]	[0.0622]	[-0.2034]	[-0.1691]	[-1.4561]	[-1.1136]	[-0.8571]	[-1.9091]	[-3.6996]	[-0.4502]	[0.0123]	[1.003]

Appendix 5 continued: Vector autoregression estimates

	Brazil	Chile	Colombia	India	Indonesia	Korea	Malaysia	Mexico	Philippines	Peru	Thailand	Turkey	USA
Turkey (lag 2)	0.0257	0.0493	0.0172	0.0217	0.0448	0.0372	0.0221	0.0343	0.0036	0.0450	0.0302	0.0547	0.0199
	(-0.0234)	(-0.0145)	(-0.0178)	(-0.0181)	(-0.0238)	(-0.0214)	(-0.0159)	(-0.0177)	(-0.0179)	(-0.0215)	(-0.0229)	(-0.0306)	(-0.0129)
	[1.0949]	[3.408]	[0.9687]	[1.1971]	[1.8811]	[1.7329]	[1.3867]	[1.9378]	[0.2037]	[2.0924]	[1.3183]	[1.7901]	[1.5398]
USA (lag 1)	0.0950	-0.0769	-0.1085	0.1079	0.0785	0.2264	0.0901	-0.0219	0.0798	-0.1100	0.1000	0.1763	-0.0337
	(-0.0723)	(-0.0446)	(-0.0549)	(-0.0559)	(-0.0736)	(-0.0662)	(-0.0491)	(-0.0546)	(-0.0551)	(-0.0664)	(-0.0707)	(-0.0943)	(-0.0399)
	[1.3138]	[-1.7237]	[-1.9767]	[1.9298]	[1.0671]	[3.4218]	[1.8344]	[-0.4006]	[1.4464]	[-1.6579]	[1.415]	[1.8687]	[-0.8447]
USA (lag 2)	0.0928	0.0006	0.0503	0.1645	0.1624	0.1873	0.0131	0.1227	0.1556	0.0096	0.1146	0.0444	0.0628
	(-0.0723)	(-0.0446)	(-0.0549)	(-0.0559)	(-0.0736)	(-0.0662)	(-0.0491)	(-0.0546)	(-0.0552)	(-0.0664)	(-0.0707)	(-0.0943)	(-0.0399)

Notes: The sample is taken from January 14, 1994 to January 29, 2017 and contains 1249 observations per series. Standard errors are presented in parentheses, t-statistics are in square brackets. The critical t-values are 2.58, 1.96 and 1.65 for statistical significance at the 1%, 5% and 10% levels.

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