DOI: 10.1002/ijfe.2194

SPECIAL ISSUE ARTICLE

WILEY

Stock market dynamics and the relative importance of domestic, foreign, and common shocks

Martin Ademmer[1] | Wolfram Horn[2] | Josefine Quast[3]

[1]Kiel Institute for the World Economy, Kiel, Germany

[2]Department of Economics, European University Institute, San Domenico di Fiesole (FI), Italy

[3]Faculty of Business Management and Economics, University of Würzburg, Würzburg, Germany

Correspondence
Josefine Quast, Faculty of Business Management and Economics, University of Würzburg, Sanderring 2, Würzburg, 97070, Germany
Email: josefine.quast@uni-wuerzburg.de

Abstract

We quantify the contemporaneous relationships among stock markets in the euro area, the United States, and a group of emerging economies over the period from 2008 to 2017. Exploiting the heteroskedasticity in the stock market data, we identify shocks that originated in the respective domestic markets and shocks that are common to all markets. Our results underline the leading role of the United States in international equity markets, but also point to the importance of indirect spillovers for all economies. Variance decompositions show that while domestic shocks explain the bigger part of the variation in each stock market, a substantial part of the variation in the euro area and the emerging economies can be attributed to foreign shocks. A comparison with a sample covering the pre-crisis period from 1999 to 2007 suggests a strengthening of the linkages among global stock markets in recent years. In particular, the spillovers from advanced to emerging economies have become more pronounced.

KEYWORDS

financial linkages, heteroskedasticity, identification, spillovers, stock markets

JEL CLASSIFICATION

C32; F30; G15

1 | INTRODUCTION

For market participants and policymakers alike it is crucial to understand and be able to quantify the strength of financial linkages between domestic and foreign markets. This is all the more important as financial markets have become increasingly integrated over the past decades (Kose, Prasad, Rogoff, & Wei, 2006; Lane & Milesi-Ferretti, 2008). In particular, emerging economies have made significant progress not only in terms of contributions to world GDP but also in terms of financial development (Lane & Milesi-Ferretti, 2017). This suggests that financial markets in both, advanced and emerging economies, are likely to be more susceptible to external shocks today than in the past.

In this article, we aim at improving the understanding of international financial linkages in recent times by empirically investigating the contemporaneous relationships between the stock markets in the euro area (EA), the United States (US), and a group of emerging markets (EM) over the period from 2008 to 2017. We specify a structural model that allows us to identify market-specific shocks, that is, shocks that originated in either the EA,

[Correction added on 16 November 2020, after first online publication: Projekt Deal funding statement has been added.]

the US, or the EM, as well as 'global' shocks that are common to all markets. We estimate the contemporaneous effects of a change in one stock market variable on the other stock market variables keeping all other variables fixed or, in other words, the *direct* effects of a shock. Moreover, we quantify the *overall* contemporaneous effects of the shocks on the stock market variables. The overall effects include the direct as well as indirect effects, resulting from the contemporaneous reaction of the other variables. We then investigate the relative importance of domestic, foreign, and common shocks by calculating their respective contribution to the variability of the stock returns in each market. Finally, we explore to what extent the financial linkages and the relative importance of the different shocks may have changed over time.

An empirical analysis of the contemporaneous relationships between stock markets is complicated by the fact that stock prices are highly endogenous and that typical identifying restrictions for simultaneous equation models, such as zero restrictions, are hard to justify in this context. To solve the problem of identification, we, therefore, follow the approach of Rigobon (2003) and exploit the heteroskedasticity that exists in the data. We distinguish between different heteroskedastic regimes assuming that the structural shocks in our model are orthogonal and that the effects of the shocks on the variables are stable over time. Under these assumptions, each heteroskedastic regime adds more equations than unknowns and, given a sufficient number of regimes, this ultimately allows us to identify the parameters of interest.[1]

Identification through heteroskedasticity has proven to be particularly useful for studying different aspects of financial transmission and contagion. Rigobon (2003), for instance, exploits increases in volatility during crisis periods to estimate the contemporaneous relationship between the returns on sovereign bonds in Latin America, finding strong linkages among Argentina, Brazil, and Mexico. Rigobon (2002) uses this technique to measure financial contagion in Latin American and Southeast Asian countries around a series of emerging market crises. Ehrmann, Fratzscher, and Rigobon (2011) study the transmission between money, bond, and equity markets within and between the US and the EA based on the heteroskedasticity in the data together with some additional identifying restrictions. They find that asset prices react strongest to other domestic asset price shocks, but that there are also substantial international spillovers. Furthermore, Bayoumi and Bui (2012) use identification through heteroskedasticity to analyse linkages among bond as well as equity markets in the US, Japan, the United Kingdom, and Germany, providing evidence for the dominance of the US market.[2]

Several other studies have used reduced-form GARCH models to analyse financial transmissions. For instance, Hamao, Masulis, and Ng (1990), King, Sentana, and Wadhwani (1994), and Lin, Engle, and Ito (1994) report significant return and volatility spillovers from the US to the Japanese and the United Kingdom's equity market. The leading role of the US among equity markets of industrialized countries is also confirmed by Rapach, Strauss, and Zhou (2013) who use pairwise Granger-causality tests to show that lagged US returns have substantial predictive power for equity prices in many non-US industrialized countries.

Spillovers from developed to emerging equity markets have been analysed, for instance, by Beirne, Caporale, Schulze-Ghattas, and Spagnolo (2010, 2013). Based on a GARCH framework, covering a variety of developed and emerging markets from the mid-1990s to 2008, they find evidence of mean and volatility spillovers from developed to emerging markets both in turbulent and normal times. The role of emerging economies for financial markets in developed economies has often been analysed in view of global financial integration (Bekaert, 1995; Bekaert & Harvey, 1995) or contagion during emerging market crises (Corsetti, Pericoli, & Sbracia, 2005; Kaminsky & Reinhart, 2003). Moreover, Cuadro-Sáez, Fratzscher, and Thimann (2009) provide evidence for the systemic importance of emerging market economies for global financial markets. Using a novel database of exogenous economic and political shocks, they argue that emerging economies influence global equity markets about just as much in normal times as during crises or periods of financial turbulence.

Our paper contributes to this literature in several ways. First, we analyse the relationships between the stock markets in the US and the EA since the financial crisis, explicitly taking into account developments in a larger group of emerging markets. Accounting for the role of emerging markets in the analysis of international financial spillovers might be of increasing importance, especially in recent times (IMF, 2016). Second, our structural model allows us to identify market-specific shocks that originated in either one of the three markets and to disentangle them from common shocks like changes in risk preferences or investors' sentiments. We then provide a comprehensive analysis of direct and indirect spillovers across markets as well as the relative economic importance of domestic, foreign, and common shocks. Third, we explore to what extent the stock market linkages may have changed over time. To do so, we compare our results based on the sample period from 2008 to 2017 with the results based on a pre-crisis sample, covering the years from 1999 to 2007.[3]

In line with previous studies, our results suggest that there is a strong direct effect from the US to the EA and the EM but no significant direct effects from these two markets to the US. In addition, we find a direct reaction of the EA to the EM stock index. Our results also emphasize the importance of indirect spillovers. Each market-specific shock has a significant overall contemporaneous effect on the respective other two markets. By means of variance decompositions we show that the larger part of the variation in each market is explained by domestic shocks. However, more than 40% of the variation in the EA and the EM group, respectively, can be attributed to shocks from foreign markets. Common shocks also seem to play a non-negligible role for the variation in US and EA returns, but primarily so during tranquil periods. In volatile times, most of the variation in all return series arises from shocks that originated in one of the three markets. Finally, the comparison with a pre-crisis sample indicates that foreign shocks from the EA and the US have become a more important driver of fluctuations in the EM stock index in recent years. The relative importance of EM shocks for advanced economies has increased only slightly over time as a strengthened transmission coincides with a smaller volatility of EM shocks.

The remainder of this article is organized as follows. Section 2 describes the data used in our study, the model specification, the determination of volatility regimes, and the estimation procedure. Section 3 presents our results with regard to the direct and the overall effects of the shocks, the variance decompositions, as well as several robustness checks. While Section 4 presents the comparison with a pre-crisis sample, Section 5 concludes.

2 | EMPIRICAL FRAMEWORK

In this section, we first describe our data set and the model specification. We then explain the determination of the volatility regimes and our estimation procedure.

2.1 | Data

Our empirical analysis is based on daily stock market data for the US, the EA, and a set of emerging markets over the period from January 2008 to January 2017. In line with Ehrmann et al. (2011), we use the S&P 500 Index for the US stock market and the S&P Euro Index for the EA stock market. We use the MSCI Emerging Markets Index to represent stock market developments in important emerging markets.[4] The data source for all-time series is Datastream. We consider an aggregate index for the group of emerging markets and the EA rather than individual country variables to keep our model tractable and, at the same time, mitigate the risk of omitting potentially important economies. Moreover, considering the EM and EA as a whole facilitates the interpretation of the results and allows us to uncover general linkages among markets that are more similar in terms of their economic strength.[5]

When financial spillovers are measured based on daily data, trading times across the different markets only overlap partially. To deal with this issue, we again follow Ehrmann et al. (2011) and change the data frequency to 2-day periods. In a 2-day period, the share of non-overlapping trading times is smaller than in daily data. We calculate the stock returns by taking the log first difference of the 2-day average prices. Figure 1 plots the resulting return series for the three markets. The time series exhibit different phases of low and high volatility. We exploit these changes in volatility to identify the structural relations in our model.

2.2 | The model

We assume that stock returns in the EA (y_t^{EA}), the US (y_t^{US}), and the EM (y_t^{EM}) can be described by the following model:

$$Ay_t = c + \sum_{i=1}^{p} B_i y_{t-i} + \Gamma z_t + \varepsilon_t, \tag{1}$$

where $y_t = \left(y_t^{EA}, y_t^{US}, y_t^{EM}\right)'$ is a vector comprising the three endogenous variables, c is a vector of constants, and B_i is a matrix capturing the effects of the endogenous variables at lag i. The vector $\varepsilon_t = \left(\varepsilon_t^1, \varepsilon_t^2, \varepsilon_t^3\right)'$ comprises a set of structural shocks which are assumed to be uncorrelated across equations and over time. Each of these structural shocks can be considered as originating in a specific market.[6] Stock return dynamics, however, are likely to be affected not only by market-specific shocks but also by common 'global' factors (Rey, 2015). These common factors might include, for instance, unanticipated changes in liquidity, risk preferences, investors' sentiments, or any global macroeconomic shock not captured by ε_t (Rigobon, 2003; Rigobon & Sack, 2003). To control for the influence of these (unobservable) factors, we additionally allow for a common heteroskedastic shock z_t in our model.

The contemporaneous relations among the endogenous variables, that is, the direct effects of the market-specific shocks ε_t, are given by matrix A while the direct effects of the common shock z_t are given by Γ. The overall contemporaneous effects of these shocks on the stock price variables are given by A^{-1} and $A^{-1}\Gamma$. It is well-known that A and Γ cannot be recovered directly from

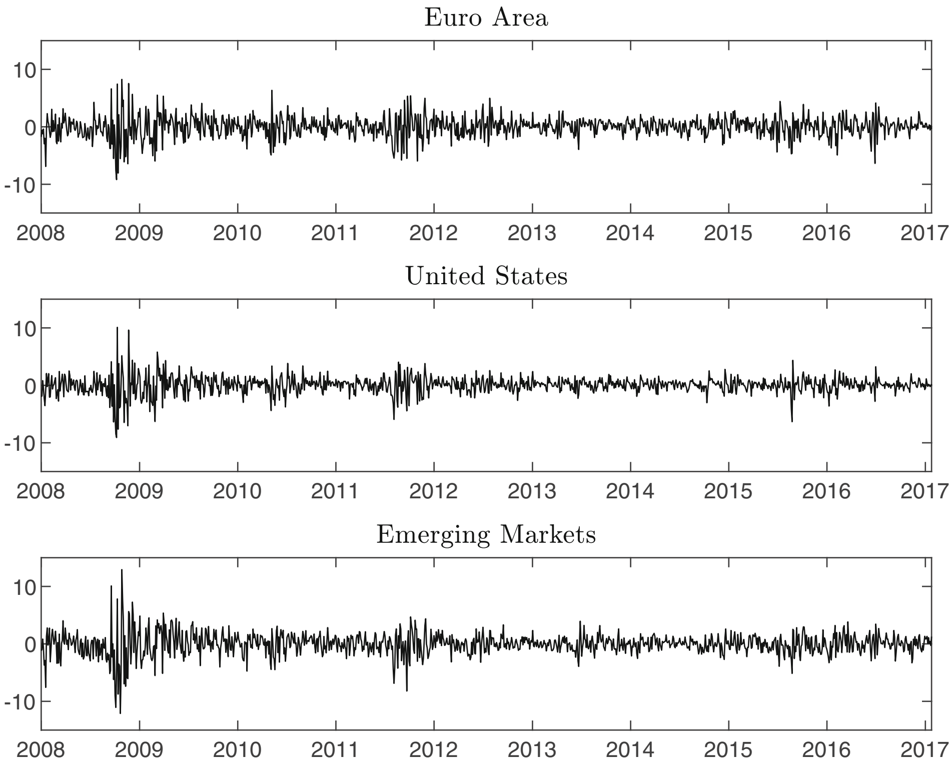

FIGURE 1 Stock returns of selected markets 2008–2017. Returns are calculated as the log first difference of 2-day average prices

the data without further theoretical or statistical assumptions. Thus, our starting point is the estimation of a reduced-form version of the structural model (1). The reduced-form model is given by:

$$\begin{aligned} y_t &= A^{-1}c + \sum_{i=1}^{p} A^{-1}B_i y_{t-i} + A^{-1}(\Gamma z_t + \varepsilon_t) \\ &= c_0 + \sum_{i=1}^{p} B_{0,i} y_{t-i} + \eta_t. \end{aligned} \tag{2}$$

The model (2) can be consistently estimated via ordinary least squares (OLS). The reduced-form residuals η_t, with Cov $[\eta_t] =: \Omega_t$, are a linear combination of the three underlying market-specific shocks and the common shock, $\eta_t = A^{-1}(\Gamma z_t + \varepsilon_t)$. We use information obtained from the heteroskedasticity in the data to identify the parameters of interest in A and Γ from the reduced-form estimates. This allows us to uniquely recover the structural relations in the model without relying on presumably controversial identifying assumptions, such as zero restrictions on the contemporaneous dynamics (Cholesky ordering).

As common in the literature, we normalize the main diagonal elements of A to equal 1. This normalization simply allows us to write, for instance, Equation (1) with y_t^{EA} as the left-hand variable. In addition, we normalize the first element of Γ to equal 1. Therefore, we investigate the effect of the common shock on the US and the emerging markets relative to its effect on the EA. Denoting the number of endogenous variables by K, the number of common shocks by C, and the number of volatility regimes by S, we then have $K(K-1)$ unknowns from A, $C(K-1)$ unknowns from Γ, K unknown variances from the market-specific shocks in each regime S, and C unknown variances from the common shocks in each regime S (Rigobon, 2002). Thus, the total number of unknowns is $K(K-1)+C(K-1)+KS+CS$. On the other hand, each volatility regime S delivers $K(K+1)/2$ knowns from the residual covariance matrix. With $K = 3$ endogenous variables and $C = 1$ common shock we, thus, need $S = 4$ distinct volatility regimes for exact identification of our model.

2.3 | Determination of volatility regimes

We determine the volatility regimes based on the variances of the reduced-form residuals which represent linear combinations of the underlying structural shocks. In a first step, we estimate the reduced-form VAR in Equation (2) by OLS and calculate the reduced-form residuals $\hat{\eta}_t$. Based on standard information criteria, we include two lags ($p = 2$) in the VAR model. We then calculate the variance of each residual series for windows consisting of 20 observations.[7] Subsequently, we compare the variance of each residual series in each window with the variance of the corresponding residual series over the full sample.

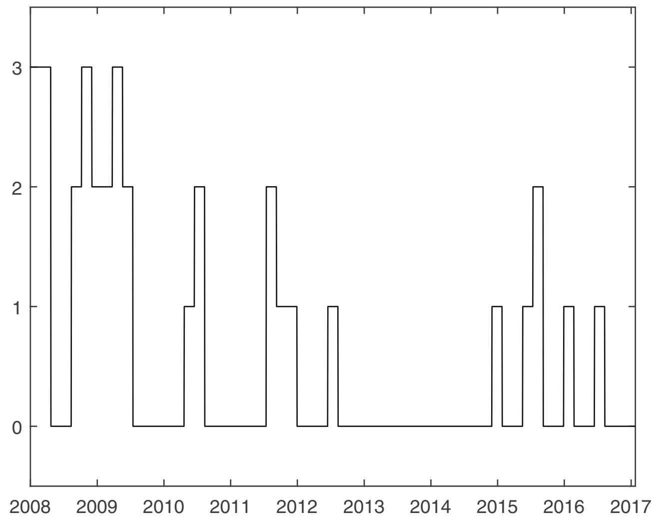

FIGURE 2 Volatility regimes. The plot shows the pattern of the volatility regimes over the sample 2008–2017. Regime 1, 2, and 3 correspond to periods in which the residuals of the euro area (EA), the United States (US), and the emerging market (EM) equation exhibit the highest volatility relative to their full-sample volatility, respectively. Regime 0 denotes the tranquil regime

We then assign each window to one of four regimes based on the following criteria: If the variances of all residual series in a window are lower than their full-sample variances, this window is assigned to the 'tranquil' regime (regime 0). All other windows, therefore, exhibit at least one residual series with an 'above-full-sample' volatility. These windows are then assigned to regime 1, 2, or 3 according to which residual series exhibits the highest shift in the variance relative to its full-sample variance. For instance, the first window would be assigned to regime 3, if the ratio of the variance of the third residual series (the residuals of the EM equation) in this window to its full-sample variance were higher than the corresponding ratio of the first and second residual series.[8]

The classification of these four regimes is sufficient to identify our model and closely corresponds to the idea of exploiting the relative changes in volatility for identification. It is worthwhile to mention that our estimates of propagation coefficients are consistent even if the regimes are slightly misspecified or if the true number of regimes is higher than the presumed number of regimes (Rigobon, 2003). Figure 2 plots the regimes over the entire sample period. We find that the tranquil regime prevails especially in the years 2013 and 2014. The residuals of the EA equation are relatively more volatile in 2011 and 2012 as well as in 2015 and 2016. In contrast, the residuals of the US equation and the residuals of the EM equation are relatively more volatile in the years 2008 and 2009.

Finally, we compute the variance–covariance matrix for each of the four volatility regimes. The four variance–covariance matrices are then used as input for the estimation procedure. Table 1 summarizes the variances of the residuals in each regime and the corresponding share of observations. In general, the residual variances change considerably across the defined regimes. Over the full sample, the residuals of the EM equation exhibit the highest variance while the residuals of the US equation exhibit the lowest variance.

2.4 | Estimation procedure

Based on the variance–covariance matrices of the four volatility regimes, we estimate the parameters of interest by minimizing the following distance[9]:

$$\begin{aligned} &\min \quad \sum_{s=1}^{S} \sqrt{vec(x_s)' vec(x_s)} \quad \text{with} \quad x_s = A\Omega_s A' - \Gamma\Sigma_{z,s}\Gamma' - \Sigma_{\varepsilon,s} \\ &\text{s.t.} \quad \Sigma_{\varepsilon,s}, \Sigma_{z,s} \quad \text{are diagonal,} \end{aligned} \tag{3}$$

where Ω_s, $\Sigma_{\varepsilon,s}$, and $\Sigma_{z,s}$ denote the variance–covariance matrices of the reduced-form residuals, the market-specific structural shocks, and the common shock in regime s, respectively. Since our model includes one common shock, $\Sigma_{z,s}$ is a regime-specific scalar. S refers to the total number of regimes, in our case 4. As mentioned before, the main diagonal elements of A and the first element of Γ are normalized to equal 1.

We use 5,000 distinct starting values in the optimization procedure to ensure the detection of a global minimum. The standard errors are computed by bootstrapping. Following Rigobon (2003), the reduced-form residuals in each of the volatility regimes are bootstrapped to obtain a distribution of covariance matrices. These covariance matrices are then used as input in the optimization procedure. We perform 1,000 bootstrap replications in our application.

3 | RESULTS

In this section, we present our empirical results. We first discuss the economic interpretation of the statistically identified structural shocks. We then discuss the results regarding the direct and overall effects of the shocks as well as the variance decompositions. Finally, we perform several robustness checks.

TABLE 1 Variances of residuals in each regime

	Regimes				
	(0)	(1)	(2)	(3)	Full sample
$\mathrm{Var}(\eta_t^1)$	1.474	5.396	6.743	8.501	3.119
$\mathrm{Var}(\eta_t^2)$	0.835	2.328	7.250	7.127	2.236
$\mathrm{Var}(\eta_t^3)$	1.426	3.426	7.798	13.942	3.291
Obs. (in %)	67	14	12	7	100

TABLE 2 Variances of shocks in different regimes

	Regimes			
	(0)	(1)	(2)	(3)
$\mathrm{Var}(\varepsilon_t^1)$	0.345	1.628	0.868	1.228
$\mathrm{Var}(\varepsilon_t^2)$	0.323	0.757	3.134	2.874
$\mathrm{Var}(\varepsilon_t^3)$	0.459	0.697	1.611	4.362
$\mathrm{Var}(z_t)$	0.331	0.384	0.627	0.129

3.1 | Labelling of shocks

Our statistical identification approach allows us to refrain from typical theory-based parameter restrictions that might be controversial in the present context (Rigobon, 2003). The lack of theory-based restrictions, however, makes the economic interpretation of the statistically identified structural shocks more difficult. In order to attach an economic label to each of the individual shocks, it can thus be helpful to compare their respective volatility pattern over time with periods for which historical economic knowledge suggests a relatively high volatility of a particular shock (Fratzscher, Schneider, & Van Robays, 2014; Herwartz & Lütkepohl, 2014). We follow this approach to associate each of the structural shocks $\varepsilon_t = \left(\varepsilon_t^1, \varepsilon_t^2, \varepsilon_t^3\right)'$ with a specific market. A shock labelled as an EA shock, for instance, is then interpreted as a shock that originated in the EA.[10]

Table 2 shows the estimated variances of the structural shocks across regimes. One clearly recognizes large shifts in the relative variances of the shocks.[11] For instance, even though the volatility of all three shocks is considerably higher in regime 2 than in the tranquil regime, the variance of the second shock ε_t^2 increases almost by a factor of 10. Regime 2 corresponds, inter alia, to the period between mid-August 2008 and the beginning of October 2008 (cf. Figure 2). During this period, the US investment bank Lehman Brothers officially filed for bankruptcy. It seems likely that the shock with the highest volatility in this period is a shock that originated in the US. Thus, we label the second shock as the US shock ($\varepsilon_t^{\mathrm{US}}$).

In regime 1, the first structural shock ε_t^1 exhibits by far the highest volatility. Figure 2 indicates that there is a clustering of periods of regime 1 at the end of our sample. Those periods correspond, for instance, to the turn of the year 2014/2015, mid-2015, or mid-2016, that is, periods that were characterized by several unexpected events in the euro area or the European Union, including the abandoning of the Swiss franc peg to the euro (January 2015), the turmoil associated with the Greek debt crisis (June/July 2015), and the uncertainty after the Brexit referendum (end of June 2016). Therefore, we label the first shock as EA shock ($\varepsilon_t^{\mathrm{EA}}$).

The third shock ε_t^3 exhibits the highest volatility in regime 3, which prevails at the beginning of our sample. While it is more difficult to associate specific economic events with the group of emerging markets, it seems reasonable to interpret the remaining third shock as the EM shock ($\varepsilon_t^{\mathrm{EM}}$) since we have already identified the US and the EA shock and control for possible common factors. This labelling is also supported by the size of the direct effects of each shock on the respective other markets (cf. Section 3.2).

3.2 | Direct effects

We first consider the estimates of the elements in matrix A which represent the contemporaneous effects of a change in one variable on the other variables or, in other words, the direct effects of the market-specific structural shocks on each variable, keeping all other variables fixed. Second, we consider the direct effects of the common shock captured by matrix Γ.

The point estimates for the elements in matrix A and Γ are as follows (with corresponding standard errors in parentheses):

$$\hat{A} = \begin{bmatrix} 1 & \underset{(0.160)}{-0.337} & \underset{(0.134)}{-0.440} \\ \underset{(0.202)}{-0.265} & 1 & \underset{(0.241)}{-0.159} \\ \underset{(0.179)}{-0.320} & \underset{(0.234)}{-0.539} & 1 \end{bmatrix} \quad \text{and} \quad \hat{\Gamma} = \begin{bmatrix} 1 \\ \underset{(0.453)}{0.458} \\ \underset{(0.228)}{-0.969} \end{bmatrix}.$$

To simplify the interpretation of the results, we rewrite the model equation by equation. The stock returns in each of the three markets respond to their counterparts in the other markets and the common shock in the following way:

$$y_t^{\mathrm{EA}} = \underset{(0.160)}{0.337} y_t^{\mathrm{US}} + \underset{(0.134)}{0.440} y_t^{\mathrm{EM}} + \underset{(--)}{1.000} z_t + \ldots \tag{4}$$

$$y_t^{\mathrm{US}} = \underset{(0.202)}{0.265} y_t^{\mathrm{EA}} + \underset{(0.241)}{0.159} y_t^{\mathrm{EM}} + \underset{(0.453)}{0.458} z_t + \ldots \tag{5}$$

$$y_t^{\mathrm{EM}} = \underset{(0.179)}{0.320} y_t^{\mathrm{EA}} + \underset{(0.234)}{0.539} y_t^{\mathrm{US}} - \underset{(0.228)}{0.969} z_t + \ldots \tag{6}$$

Our estimation results indicate a strong direct effect from the US and the EM to the EA stock market. Interestingly, the effect from the EM group to the EA seems to be slightly stronger than the effect from the US to the EA. Both coefficients are statistically different from zero at common significance levels. In contrast, we find no evidence that the US market significantly responds to the EA or the EM. This result is in line with Ehrmann et al. (2011) who also find significant spillovers from the US to the EA but not vice versa. It is also in line with Bayoumi and Bui (2012) who report large and significant outward spillovers from the US to other advanced economies but minimal and insignificant inward spillovers. The EM group is also strongly affected by the US with a coefficient of 0.539. On the other hand, its direct response to the EA is weaker and less significant. Thus, our results confirm the leading role of the US market.

The three markets react quite differently to the common shock variable z_t, which represents, for instance, risk preference or global liquidity shocks. Recall that we have set the first element of Γ equal to 1. We therefore examine the sensitivity of the US and the EM to the common shock relative to the EA's sensitivity. We find that the US is less sensitive to common shocks than the EA. The coefficient for the US is only about half the size of the EA coefficient and statistically not different from zero. The coefficient for the EM is about −1 and strongly statistically significant. This result suggests that the response of the EM group to the common shock is almost a mirror image to the response of the EA market. These estimates, however, do not allow for any conclusions regarding the relative importance of the common shock for each market. The shocks' relative importance is further examined in Section 3.4.

3.3 | Overall effects

We now consider the overall effects of the shocks on the stock market variables which include direct as well as indirect effects. The overall effects of the market-specific structural shocks correspond to the estimates for the elements in matrix A^{-1} and those of the common shock z_t to the estimates for the elements in $\Gamma^* = A^{-1}\Gamma$. The resulting estimates are as follows:

$$\hat{A}^{-1} = \begin{bmatrix} \underset{(0.145)}{1.514} & \underset{(0.135)}{0.951} & \underset{(0.235)}{0.817} \\ \underset{(0.180)}{0.523} & \underset{(0.130)}{1.422} & \underset{(0.263)}{0.456} \\ \underset{(0.209)}{0.767} & \underset{(0.197)}{1.072} & \underset{(0.225)}{1.508} \end{bmatrix} \quad \text{and} \quad \hat{\Gamma}^* = \begin{bmatrix} \underset{(0.342)}{1.157} \\ \underset{(0.394)}{0.733} \\ \underset{(0.443)}{-0.204} \end{bmatrix}.$$

The corresponding standard errors are again given in parentheses below the point estimates. The first column of matrix $\hat{A}^{-1}$ displays the overall effects of the EA shock $\varepsilon_t^{\mathrm{EA}}$ on the EA, the US, and the EM stock returns. The second column displays the corresponding overall effects of the US shock $\varepsilon_t^{\mathrm{US}}$ and the third column of the EM shock $\varepsilon_t^{\mathrm{EM}}$ on the three variables.

Note that the coefficient estimates on the main diagonal of $\hat{A}^{-1}$ are all considerably greater than 1. This implies that the direct effect of a domestic shock on the domestic market is amplified by the immediate indirect spillovers from other markets. Moreover, we find that each of the three market-specific shocks has an economically and statistically significant overall effect on all of the other markets. Hence, although there is no significant evidence for direct spillovers from the EA and the EM to the US, both significantly affect US stock returns when indirect effects are taken into account. These findings highlight the importance of indirect channels for cross-border financial transmissions.

Indirect spillovers can amplify the direct effects, but also counteract them. The latter becomes apparent when one looks at the overall effect of the common shock on the emerging markets. While the direct effect was about −1, the positive spillovers from the other markets reduce the overall impact to about −0.2, which is not statistically distinguishable from zero.

3.4 | Variance decompositions

Next, we are interested in the relative importance of common versus market-specific and domestic versus foreign shocks. To answer these questions, we perform a variance decomposition exercise similar to Rigobon (2002).

We first consider for each market the proportion of the total variance that can be explained by the market-specific shocks (Table 3). We additionally distinguish between the tranquil regime and the (weighted) average of all volatile regimes. For a specific regime s, this proportion is calculated by dividing the variance explained by the market-specific shocks alone $\left(\hat{A}^{-1}\hat{\Sigma}_{\varepsilon,s}\hat{A}'^{-1}\right)$ by the variance when both common and market-specific shocks

TABLE 3 Variance decomposition: Proportion explained by all market-specific shocks in tranquil and volatile times

	Tranquil (0)	Volatile (1),(2),(3)	Total
Euro area	0.758	0.910	0.807
United States	0.826	0.944	0.864
Emerging markets	0.992	0.997	0.993

TABLE 4 Variance decomposition: Proportion explained by domestic shocks compared to foreign market shocks

	Shock ε^{EA}	Shock ε^{US}	Shock ε^{EM}
Euro area	0.512	0.280	0.208
United States	0.081	0.833	0.086
Emerging markets	0.110	0.298	0.592

are included $\left(\hat{A}^{-1}\hat{\Gamma}\hat{\Sigma}_{z,s}\hat{\Gamma}'\hat{A}'^{-1}+\hat{A}^{-1}\hat{\Sigma}_{\varepsilon,s}\hat{A}'^{-1}\right)$. We find that the market-specific shocks explain almost all variation in EM returns. In contrast, up to 20% of the variation in US and EA returns can be attributed to common shocks. This result should not be interpreted as evidence that, for instance, risk preference shocks play no role for emerging markets. It rather indicates that such shocks might be mostly idiosyncratic for the EM (Rigobon, 2002). We also find that most of the variation in all three returns can be explained by market-specific shocks in volatile times. Hence, common shocks have been of little relevance in the recent periods of financial turmoil.

Second, we consider the proportion of the total market-specific variance that can be explained by each individual market-specific shock (Table 4). This allows us to analyse the relative importance of the domestic shock versus foreign market shocks. To calculate the contribution of the shock that originated in market k, we first compute $\left(\hat{A}^{-1}\hat{\Sigma}^{*}_{\varepsilon}\hat{A}'^{-1}\right)$. $\hat{\Sigma}^{*}_{\varepsilon}$ is obtained by setting all elements of $\hat{\Sigma}_{\varepsilon}$, except $\hat{\sigma}_{\varepsilon,kk}$, equal to 0. We then divide this matrix by the total market-specific variance $\left(\hat{A}^{-1}\hat{\Sigma}_{\varepsilon}\hat{A}'^{-1}\right)$. We find that shocks originating in the domestic market explain the larger part of the variation in the domestic returns. This holds especially true for the US where more than 80% of the total market-specific variance is explained by US shocks, while EA and EM shocks only contribute around 10%, respectively. In contrast, almost half of the variation in EA stock returns and about 40% of the variation in EM stock returns can be attributed to foreign market shocks. Therefore, our findings indicate that foreign shocks play an important role for fluctuations in the EM stock index. When it comes to advanced economies, however, foreign shocks play an important role for the EA, but are relatively less substantial for the US market.

3.5 | Robustness checks

We run several robustness checks to test the sensitivity of our results. The first four robustness checks focus on specific subsets of emerging markets, potential oil price effects, and a later start of the sample. The other robustness checks focus on methodological issues, namely a change in the classification of regimes and a specification of the model without a common shock. While the estimated effects change somewhat in magnitude, our main results, that is, the dominant role of the US and the importance of indirect spillovers among markets, are robust across all different set-ups. In the following, each robustness check is discussed in more detail.

First, we shed some light on the role of China in our analysis. To do so, we replace the MSCI EM Index with an index that excludes China from the set of emerging markets (MSCI EM excluding China).[12] The results of this specification are very similar to our baseline results. This indicates that our findings regarding the spillovers from and to emerging markets do not noticeably depend on the Chinese market. These results are also confirmed when looking at the complement to this specification, that is, a specification that includes Chinese stock market data (SSE Composite Index) instead of the MSCI EM excluding China. In this case, we only find very minor direct effects of shocks from China on the EA and the US, where only the effect on the EA is statistically distinguishable from zero. The overall effects on both, the EA and US market, are statistically significant but again relatively small. Moreover, we find only minor spillovers from the two advanced economies to China.

Second, we have a closer look on the spillover effects among the US, the EA, and the EM when only the subset of Asian emerging markets is considered. To that end, we replace the MSCI EM Index with the MSCI EM Asia Index. Note that while this specification focuses on a more homogeneous group of emerging economies, it omits all non-Asian emerging economies which possibly play an important role in the international transmission of shocks. The results of this specification (like the results

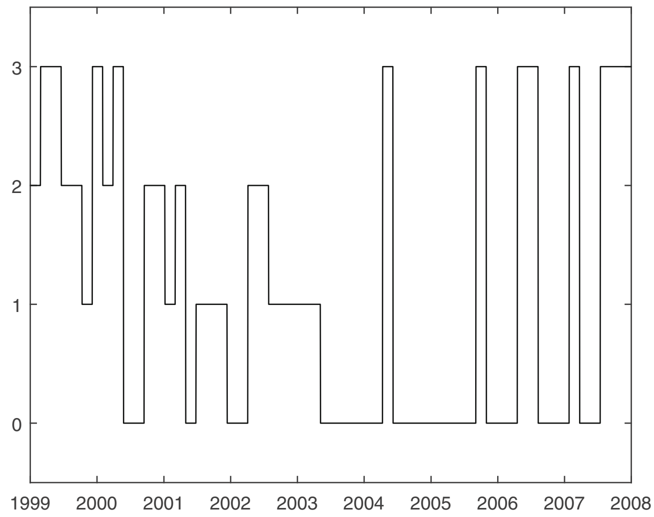

FIGURE 3 Volatility regimes (pre-2008 sample). The plot shows the pattern of the volatility regimes for the pre-2008 sample. Regime 1, 2, and 3 correspond to periods in which the residuals of the euro area (EA), the United States (US), and the emerging market (EM) equation exhibit the highest volatility relative to their full-sample volatility, respectively. Regime 0 denotes the tranquil regime

of the specification with China only) should therefore be taken with a certain degree of caution. Compared to our baseline results, we find an even larger effect of US shocks on the EA market and we again find a relatively small and statistically insignificant direct effect of the EA on the US. Moreover, shocks originating in Asian emerging markets seem to have less impact on the EA than an average emerging market shock. This suggests that the financial link between Asian emerging markets and the EA is somewhat weaker than the average link between emerging markets and the EA.

Third, we follow Ehrmann et al. (2011) and include the change in the price of crude oil as an exogenous variable in our model to additionally control for developments in the global oil market. This could be important due to the strong decline in the price of oil in the years 2014 and 2015 which might have affected asset prices across the globe and particularly in energy-intensive economies. Adding this control variable, however, does not significantly alter our results. We only find a slightly stronger reaction of the EM to the EA but a slightly weaker reaction of the EM group to the US.

Fourth, we start our sample at the beginning of 2009 and thus exclude the very turbulent times at the height of the crisis in the second half of 2008. Compared to our baseline results, we find a somewhat weaker direct effect from the US market to the EM group and, on the other hand, a somewhat stronger direct effect from the EM group to the US market. These findings are in line with the dominance of US shocks in the year 2008. In general, the estimates are relatively close to the baseline results, showing that our baseline results are not primarily driven by contagion effects around extraordinary crisis events.

Turning to the identification and estimation strategy, we first test the sensitivity of our results to a change in the classification of volatility regimes. In our baseline set-up, a window is assigned to the tranquil regime if the variances of all residual series in this window are lower than their respective variances over the full sample. In this robustness exercise, we assign a window to the tranquil regime only if the variances of all residual series in this window are lower than 0.8 times their respective full-sample variances. This significantly reduces (increases) the total number of tranquil (volatile) periods. The main effect from this reclassification of regimes is that the EM index now responds more strongly to the EA than to the US. Moreover, we find a stronger direct response of the EA index to the US.

Second, we assume that there are no common 'global' shocks and exclude them from our model. Consequently, the market-specific shocks ε_t represent the only exogenous input to the system. We find that not accounting for common shocks leads to a stronger reaction of the EM to the EA and a somewhat stronger reaction of the EA to both other markets. The responses are stronger because any effects of common 'global' shocks are now attributed to the market-specific shocks. This indicates that a model without a common shock would potentially suffer from misspecification.

4 | COMPARISON WITH PRE-CRISIS PERIOD

So far, our analysis has focused on the international stock market linkages in recent years. In this section, we explore to what extent these linkages may have changed over time. To do so, we compare our results from the previous section with the results based on a pre-crisis sample ranging from the beginning of 1999 (the introduction of the euro) to the end of 2007. The markets' reaction to domestic, foreign, and common shocks could differ between these two samples, for instance, due to developments associated with the global financial crisis and the subsequent policy measures put in place.[13] Relatedly, the two sample periods are often classified as an upswing and a downswing phase, respectively, of the long-run financial cycle as defined in the corresponding literature (see, amongst others, Borio, 2014; Drehmann, Borio, & Tsatsaronis, 2012; Stremmel, 2015). Differences in the reaction to and the relative importance of domestic, foreign, and common shocks could also arise from the increasingly important role of emerging markets in the global economy.

We again determine the volatility regimes following the procedure described in Section 2.3. The pattern of the

TABLE 5 Variance decomposition: Proportion explained by all market-specific shocks in tranquil and volatile times (pre-2008 sample)

	Tranquil (0)	Volatile (1),(2),(3)	Total
Euro area	0.999	0.999	0.999
United States	0.599	0.741	0.675
Emerging markets	0.940	0.941	0.941

TABLE 6 Variance decomposition: Proportion explained by domestic shocks compared to foreign market shocks (pre-2008 sample)

	Shock ε^{EA}	Shock ε^{US}	Shock ε^{EM}
Euro area	0.569	0.288	0.143
United States	0.141	0.800	0.059
Emerging markets	0.035	0.056	0.909

volatility regimes for the pre-2008 sample is shown in Figure 3. We find that the residuals of the EM equation exhibit the relatively highest volatility in the second half of the sample, especially in 2006 and 2007 while EA and US residuals exhibit the relatively highest volatility towards the beginning of the sample. The tranquil regime prevails predominantly between the years 2003 and 2006. After computing the variance–covariance matrix for each volatility regime, we reestimate Equation (3). As before, the standard errors of the estimates are computed by bootstrapping.

Based on the pre-2008 sample, we obtain the following estimates for the elements in matrix A and Γ (with the corresponding standard errors in parentheses):

$$\hat{A}_{99-07} = \begin{bmatrix} 1 & \underset{(0.303)}{-0.728} & \underset{(0.112)}{-0.300} \\ \underset{(0.295)}{-0.352} & 1 & \underset{(0.152)}{-0.053} \\ \underset{(0.099)}{-0.144} & \underset{(0.153)}{-0.197} & 1 \end{bmatrix} \quad \text{and}$$

$$\hat{\Gamma}_{99-07} = \begin{bmatrix} 1 \\ \underset{(0.182)}{-1.119} \\ \underset{(0.260)}{-0.341} \end{bmatrix}.$$

The overall contemporaneous effects of the shocks are given by:

$$\hat{A}^{-1}_{99-07} = \begin{bmatrix} \underset{(0.269)}{1.491} & \underset{(0.249)}{1.186} & \underset{(0.071)}{0.511} \\ \underset{(0.299)}{0.542} & \underset{(0.248)}{1.442} & \underset{(0.074)}{0.240} \\ \underset{(0.113)}{0.322} & \underset{(0.127)}{0.455} & \underset{(0.038)}{1.121} \end{bmatrix} \quad \text{and} \quad \hat{\Gamma}^{*}_{99-07} = \begin{bmatrix} \underset{(0.393)}{-0.011} \\ \underset{(0.343)}{-1.154} \\ \underset{(0.253)}{-0.570} \end{bmatrix}.$$

The main results from the previous section also hold true for the pre-crisis sample. We again find no significant direct reaction of the US market to the EA and EM but a strong direct reaction of the EA to the US. In addition, comparing the direct effects given by $\hat{A}_{99-07}$ with the overall effects given by $\hat{A}^{-1}_{99-07}$ emphasizes the importance of indirect spillovers among the three markets.

Some differences between the two sample periods are, however, worth highlighting. First, the EA market shows a stronger reaction to the US market in the pre-2008 sample. Second, we now find a weaker direct effect from the EM to the EA and the US. For the US, the effects are again statistically insignificant. Third, we find only a weak and insignificant direct effect from the EA and the US to the EM. These results suggest that advanced economies have become more sensitive to potential shocks from emerging economies in more recent times, and vice versa. The lower degree of sensitivity to foreign markets in the pre-2008 sample also influences the overall effect of domestic shocks on the domestic market. For instance, the lower rightmost element of $\hat{A}^{-1}_{99-07}$ suggests that the overall effect of an EM shock to the EM group is only slightly greater than 1 since the direct effect is only modestly amplified by indirect spillovers. We also find some differences regarding the reaction of the three markets to the common shock z_t. A common shock that has a direct effect of +1 on y_t^{EA} affects the US market by a coefficient of −1.119. Hence, we find a strong opposite reaction of the EA and the US to common shocks in the pre-2008 sample whereas the results for the post-crisis period (cf. Section 3.2) suggest a rather parallel reaction of the two markets to the common shock.

Finally, we repeat the variance decomposition exercises for the pre-crisis sample (Tables 5 and 6). The small overall effect of the common shock on the EA market is also visible in the variance decomposition into market-specific and common shocks which shows that almost all of the variation in the EA returns can be explained by market-specific shocks. In contrast, about one third of the variation in US returns can be attributed to common shocks. Comparing these results with the results from Section 3.4, indicates that the relative importance of common shocks for the EA and the US has become more similar over time.

A comparison of the relative importance of domestic and foreign shocks between the two samples (Tables 4 and 6) suggests that this importance has changed considerably over time for the EM. While only about 10% of the variation in EM returns can be attributed to foreign shocks in the pre-crisis sample, this share rises to about 40% in the 2008–2017 sample. In contrast, the relative importance of domestic versus foreign market shocks remains broadly stable across the different sample periods for the EA and the US. We find that the proportion of the variance in the EA and US market explained by EM shocks is slightly lower in the pre-2008 sample. This suggests that EM shocks have gained some importance for both advanced economies in more recent times. The differences, however, are comparatively minor. Given our previous finding of a strengthened transmission of shocks not only from advanced to emerging but also from emerging to advanced economies, this implies a smaller variance of EM shocks in the more recent 2008–2017 sample.[14]

Overall, the comparison with the pre-crisis period shows that EA and US shocks have become a more important driver of fluctuations in the EM stock index. EM shocks, however, have become only slightly more important for the EA and US market, despite a strengthened transmission.

5 | CONCLUSIONS

We have examined the contemporaneous relationships among stock markets in the euro area, the US, and a group of emerging economies in recent times. Our main objective has been to analyse and compare the direct and overall spillovers among these three markets that result from domestic, foreign, and common 'global' shocks. We have exploited changes in the volatility of the structural shocks to solve the problem of identification in our model with only a minimum of a priori assumptions and restrictions.

Our results underline the leading role of the US market, but also emphasize that all stock markets are significantly affected by foreign shocks when direct and indirect effects are taken into account. We find that while domestic shocks explain the larger part of the variation in each stock market, a substantial part of the variation is due to shocks that originated in foreign markets. Furthermore, our results suggest that the linkages between advanced and emerging economies have become stronger in more recent years. Particularly, the spillovers from advanced to emerging economies have become much more pronounced.

A thorough quantification of the extent of interdependencies among financial markets is important for policymakers to better assess the vulnerabilities of domestic markets to foreign shocks and, hence, the potential transmission of financial instability from abroad. Our findings suggest that this applies to policymakers in both, advanced and emerging economies, although it might be especially relevant for the latter. In this regard, a more detailed look at the effects of different types of foreign shocks (such as monetary policy shocks, demand shocks, or supply shocks) as well as their different transmission channels could constitute an interesting topic for future research.

ACKNOWLEDGEMENTS

The authors thank Nils Jannsen, Helmut Lütkepohl, Roberto Rigobon, Maik H. Wolters, and two anonymous referees for their helpful comments and suggestions. The authors are also grateful for fruitful discussions with participants at the Rimini Conference in Economics and Finance (RCEF 2018), the VfS Annual Conference 2018, and the 4th International Workshop on 'Financial Markets and Nonlinear Dynamics' (FMND 2019, www.fmnd.fr). Open access funding enabled and organized by Projekt DEAL.

ENDNOTES

[1] The assumption of time-invariant effects of the shocks on the variables is very common in the SVAR or ARCH/GARCH literature and seems justified in our case given that we concentrate on the relatively short period since the financial crisis.

[2] Identification through heteroskedasticity has also been applied in other areas, for example, to study the reaction of monetary policy to the stock market (Rigobon & Sack, 2003) or the effects of monetary policy shocks (Lanne & Lütkepohl, 2008). Herwartz and Plödt (2016) evaluate the accuracy of this statistical identification approach by means of Monte Carlo simulations. Note that the approach proposed by Rigobon (2003) relies on unconditional heteroskedasticity in the data. Several other studies also exploit conditional heteroskedasticity (see, among others, Bouakez & Normandin, 2010; Lanne, Lütkepohl, & Maciejowska, 2010).

[3] Note that our interest is in the typical spillovers among markets which could or could not be contagious. We do not explicitly focus on contagion in the sense of an intensified propagation of shocks during a specific crisis event (Rigobon, 2016). For an analysis of contagion during the 2007–2009 financial crisis see, for example, Bekaert, Ehrmann, Fratzscher, and Mehl (2014).

[4] The MSCI Emerging Markets Index includes the following countries: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, Qatar, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, and the United Arab Emirates.

[5] In the robustness section, we provide additional analyses and also look at subsets of emerging markets.

[6] The economic labelling of the structural shocks in our empirical analysis is discussed in Section 3.1.

[7] Recall that the 20-observations windows are based on 2-day average returns. Our first window, therefore, covers the information

of the 40 trading days from January 1, 2008 to February 25, 2008. Our choice of 20-observations windows is common in the corresponding literature (see, e.g., Ehrmann et al., 2011; Rigobon, 2002).

[8] In Section 3.5, we check the robustness of our results with respect to a change in the classification of volatility regimes.

[9] Recall that the reduced-form residuals are linked to the structural shocks in Equation (2) by $\eta_t = A^{-1}(\Gamma z_t + \varepsilon_t)$. This implies that $\mathrm{Cov}[\eta_t] =: \Omega_t = A^{-1}\Gamma\Sigma_{z,t}\Gamma' A'^{-1} + A^{-1}\Sigma_{\varepsilon,t}A'^{-1}$.

[10] We do not take a stand on whether this is an EA monetary policy shock, demand shock, or supply shock. This, however, would be an interesting question for future research.

[11] Note that if the relative variances were completely constant across all regimes, heteroskedasticity would not identify the model. Very small changes in the relative variances of the shocks would imply a lower accuracy of the estimation results (Herwartz & Plödt, 2016).

[12] The country weight of China in the MSCI EM Index is 33%.

[13] Structural breaks in the three equations around the crisis period are also indicated by Chow-type breakpoint tests.

[14] A similar argument can be made regarding the link between the EA and the US. We find a stronger reaction of the EA to the US in the pre-2008 sample while the relative importance of domestic and foreign shocks remained broadly stable across the two samples. The thereby implied higher variance of US shocks in the 2008–2017 sample seems reasonable as this period covers the aftermath of the global financial crisis.

REFERENCES

Bayoumi, T., & Bui, T. (2012). Global bonding: Do U.S. bond and equity spillovers dominate the financial markets? *IMF Working Paper No. 12/298*. Washington, DC: International Monetary Fund.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., & Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate garch-in-mean analysis. *Emerging Markets Review*, *11*(3), 250–260.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., & Spagnolo, N. (2013). Volatility spillovers and contagion from mature to emerging stock markets. *Review of International Economics*, *21*(5), 1060–1075.

Bekaert, G. (1995). Market integration and investment barriers in emerging equity markets. *The World Bank Economic Review*, *9*(1), 75–107.

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and equity market contagion. *The Journal of Finance*, *69*(6), 2597–2649.

Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *The Journal of Finance*, *50*(2), 403–444.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, *45*, 182–198.

Bouakez, H., & Normandin, M. (2010). Fluctuations in the foreign exchange market: How important are monetary policy shocks? *Journal of International Economics*, *81*(1), 139–153.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), 1177–1199.

Cuadro-Sáez, L., Fratzscher, M., & Thimann, C. (2009). The transmission of emerging market shocks to global equity markets. *Journal of Empirical Finance*, *16*(1), 2–17.

Drehmann, M., Borio, C., & Tsatsaronis, K. (2012). Characterising the financial cycle: Don't lose sight of the medium term! *BIS Working Papers No. 380*. England: Bank for International Settlements.

Ehrmann, M., Fratzscher, M., & Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: Measuring international financial transmission. *Journal of Applied Econometrics*, *26*(6), 948–974.

Fratzscher, M., Schneider, D., & Van Robays, I. (2014). Oil prices, exchange rates and asset prices. *ECB Working Paper Series No. 1689*. Frankfurt am Main: European Central Bank.

Hamao, Y., Masulis, R. W., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies*, *3*(2), 281–307.

Herwartz, H., & Lütkepohl, H. (2014). Structural vector autoregressions with markov switching: Combining conventional with statistical identification of shocks. *Journal of Econometrics*, *183*(1), 104–116.

Herwartz, H., & Plödt, M. (2016). Simulation evidence on theory-based and statistical identification under volatility breaks. *Oxford Bulletin of Economics and Statistics*, *78*(1), 94–112.

IMF. (2016). *Global financial stability report*. Washington, DC: International Monetary Fund.

Kaminsky, G. L., & Reinhart, C. (2003). The center and the periphery: The globalization of financial turmoil. *NBER Working Papers 9479*. Cambridge, MA: National Bureau of Economic Research, Inc.

King, M., Sentana, E., & Wadhwani, S. (1994). Volatility and links between national stock markets. *Econometrica*, *62*(4), 901–933.

Kose, M. A., Prasad, E., Rogoff, K. S., & Wei, S.-J. (2006). Financial globalization: A reappraisal. *NBER Working Papers 12484*. Cambridge, MA: National Bureau of Economic Research, Inc.

Lane, P., & Milesi-Ferretti, G. M. (2008). The drivers of financial globalization. *American Economic Review*, *98*(2), 327–332.

Lane, P., & Milesi-Ferretti, G. M. (2017). International financial integration in the aftermath of the global financial crisis. *IMF Working Paper No. 17/115*. Washington, DC: International Monetary Fund.

Lanne, M., & Lütkepohl, H. (2008). Identifying monetary policy shocks via changes in volatility. *Journal of Money, Credit and Banking*, *40*(6), 1131–1149.

Lanne, M., Lütkepohl, H., & Maciejowska, K. (2010). Structural vector autoregressions with Markov switching. *Journal of Economic Dynamics and Control*, *34*(2), 121–131.

Lin, W.-L., Engle, R. F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies*, *7*(3), 507–538.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2013). International stock return predictability: What is the role of the United States? *The Journal of Finance*, *68*(4), 1633–1662.

Rey, H. (2015). Dilemma not trilemma: The global financial cycle and monetary policy independence. *NBER Working Papers 21162*. Cambridge, MA: National Bureau of Economic Research, Inc.

Rigobon, R. (2002). Contagion: How to measure it?. S. Edwards & J. A. Frankel In *Preventing Currency Crises in Emerging Markets* (pp. 269–334). Chicago: University of Chicago Press.

Rigobon, R. (2003). Identification through heteroskedasticity. *Review of Economics and Statistics*, *85*(4), 777–792.

Rigobon, R. (2016). Contagion, spillover and interdependence. *Bank of England Staff Working Paper No. 607*. England: Bank of England.

Rigobon, R., & Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *Quarterly Journal of Economics*, *118* (2), 639–669.

Stremmel, H. (2015). Capturing the financial cycle in Europe. *ECB Working Paper Series No. 1811*. Frankfurt: European Central Bank.

How to cite this article: Ademmer M, Horn W, Quast J. Stock market dynamics and the relative importance of domestic, foreign, and common shocks. *Int J Fin Econ*. 2022;27:3911–3923. https://doi.org/10.1002/ijfe.2194