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Determinants of stock market correlations. Accounting for model uncertainty and reverse causality in a large panel setting

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Abstract

We examine 22 determinants of stock market correlations in a panel setting with 651 country pairs of developed economies over the 2001-2018 period, while accounting for model uncertainty and reverse causality. On the one hand, we find, that a number of determinants, well established in the literature, e.g. trade, institutional distance, and exchange rate volatility fail the robustness test. On the other hand, we find strong evidence supporting several others: (1) inertia, with current correlation being the best single predictor of the future stock market correlation (2) positive impact of the market size (3) imperative role of the interconnected financial factors: capital mobility, financial development, and portfolio equity flows. With the expected future growth of economies and their capital markets as well as deepening financial liberalization, this paper brings strong support to the hypothesis of diminishing international diversification potential.

Keywords stock market correlations · stock market comovement · financial development · Bayesian model averaging · OECD countries

***JEL codes* G10, G11, G15, F62**

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1 Introduction

Ongoing globalization and financial liberalization leads to increasingly integrated financial markets. With more consolidated financial markets, the question of the degree of correlation of stock market returns is becoming more pressing. On the one hand, the correlation of asset prices is a major component of the Markovitz model and facilitates international risk sharing. On the other hand, and especially since the outbreak of the 2008 Global Financial Crisis (GFC), financial market contagion has become a major issue for policy makers all over the world. Consequently, there is a growing body of research evaluating the degree of stock market correlation and the consequences of contagion (Baig and Goldfajn, 1999; Calvo and Reinhart, 1996; Chiang et al., 2007; Claessens et al., 2011; Corsetti et al., 2005; Forbes and Rigobon, 2002; Goetzmann et al., 2005; Jordà et al., 2019; King and Wadhwani, 1990; Norden and Weber, 2009; Stoupos and Kiohos, 2022; Syllignakis and Kouretas, 2011; de Truchis, 2013; Yang et al., 2003).

Nonetheless, the examination of factors explaining stock market correlations received less attention in the literature. There is a handful of papers where the authors examine a couple of potential determinants at a time (Baele et al., 2010; Beine and Candelon, 2011; Bracker and Koch, 1999; Hwang et al., 2013; Johnson and Soenen, 2002; Liu, 2013; Wälti, 2011). Most of the research concentrates on one or two specific linkages (Aladesanmi et al., 2019; Flavin et al., 2002; Forbes and Chinn, 2004; Guo and Tu, 2021; Lee and Kim, 2020; Quinn and Voth, 2008; Roll, 1992; Viceira and Wang, 2018) or reports an empirical finding in the support of a theoretical model (Anagnostopoulos et al., 2022; Gavazzoni and Santacreu, 2020). However, almost none of the work, thus far, accounts for model uncertainty in a systematic way. Moreover, the research thus far has not addressed the issue of reverse causality, as well as interrelations between different determinants of stock market comovement that are prone to simultaneity bias.

Therefore, this paper examines a comprehensive set of 22 possible determinants of stock market correlations while accounting for model uncertainty and reverse causality with Bayesian model averaging and simultaneous equations, an approach proposed by Moral-Benito (2013, 2016). After a two-stage procedure, we find seven robust variables that can be organized within three categories of factors contributing to tighter stock market synchronization. Firstly, we find that inertia plays a dominant role, and that the current correlation remains the single best predictor of the future correlation of stock markets. Secondly, the economic size of the markets plays an instrumental role in facilitating the comovement between stock markets. Thirdly, three mutually reinforcing factors arise: capital mobility, the development of financial markets, and the magnitude of portfolio equity flows, positively affect stock market correlations. At the same time, we find that some of the variables, firmly rooted in the empirical literature, fail the robustness test, with trade, institutional distance, and exchange rate volatility being the primary examples.

These results demonstrate that expanding economies with growing capital markets that pursue financial liberalization will inevitably create an environment of highly correlated stock markets. This will in turn reduce the possibilities for international portfolio diversification that facilitates risk sharing. Therefore, the results presented in this paper give strong support to the "diminishing international diversification potential" proposed by Lewis (2006) and developed by Christoffersen et al. (2012).

The remainder of this paper is laid out as follows. Section 2 presents the methodology and comprises of two subsections. Subsection 2.1 describes the data, provides the definitions of the examined variables, and places them in the context of the previous theoretical and empirical research. Subsection 2.2 describes the estimation strategy employed in the research. The empirical results are discussed in Section 3. Section 4 concludes.

2 Methodology

2.1 Data and variables under investigation

The main variable of interest is the correlation coefficient of market returns for the main stock market indices in the following 40 economies[1]: Austria, Australia, Belgium, Canada, Switzerland, Chile, Czechia, Germany, Estonia, Spain, Finland, France, Greece, Hong Kong, Hungary, Ireland, Iceland, Italy, Japan, Korea, Lebanon, Lithuania, Luxembourg, Latvia, Malta, Mauritius, Mexico, Netherlands, Norway, New Zealand, Panama, Poland, Portugal, Romania, Sweden, Singapore, Slovakia, Turkey, the UK, and the USA[2]. The choice of the countries is dictated by the data availability of portfolio and direct equity flows described later in this section. With 40 countries, there are 780 bilateral correlation coefficients. The percentiles of the distribution calculated using monthly data on market returns for the 2000-2019 period are depicted in Figure 1. Panel (a) in Figure 1 shows the correlation coefficients calculated for each year separately, while panel (c) presents the correlation coefficients obtained with a twelve-month rolling window. Panels (b) and (d) depict percentiles of the distribution of the changes in annual and monthly correlation coefficients, respectively. The values of stock market indices are expressed in the local currency. The distribution, where all indices are expressed in US dollars, is reported in Appendix B.[3]

Both panels (a) and (c) show that 50% of the correlation coefficients are positive, while 75% of them are positive during the majority of the sample, indicating a strong degree of comovement between stock market indices over the 2000-2019 period. Interestingly, there is no secular movement in any of the moments, indicating that the degree of synchronization between the analyzed stocks was relatively stable. The latter point is reinforced by the results from panels (b) and (d). We observe that 50% of all the changes in the value of the correlation coefficients are tightly wrapped around zero. Looking at extreme values, we see that the highest positive changes are around one, while the smallest negative changes are below negative one[4] in the case of annual correlation coefficients. The interval between the 25th and the 75th percentile, as well as

[1]The group which, using the nomenclature from The Economist, can be called "mostly developed economies".

[2]The list of all stock market indices is presented in Appendix A.

[3]Estimation results with stock market indices expressed in dollars are depicted in Appendix E.

[4]The range of changes is [-2,2], with -2 indicating the change in the value of the correlation coefficient from 1 to -1, and 2 other way around.

between the minimum and the maximum, in the case of the rolling window is, understandably, even smaller with the highest month-to-month changes in a range of 0.5. Consequently, we observe a relatively high degree of persistence in the value of the correlation coefficient that should be accounted for, while evaluating the determinants of stock market comovement. We account for inertia by including a specification with a lagged value of the correlation coefficient, as explained in detail in subsection 2.2. Kim et al. (2005) and Liu (2013) follow a similar reasoning in their argumentation of choices of modelling strategy.

As the correlation coefficient is bounded in the interval $[-1, 1]$, before the estimation, we have applied the Fisher transformation to the correlation coefficients in order to ensure a normal distribution of errors. Consequently, the measure of the stock market comovement is given by:

$$y_{ij,t} = \frac{1}{2} \ln \left(\frac{1 + r_{ij,t}}{1 - r_{ij,t}}\right) \tag{1}$$

where: $r_{ij,t}$ is the correlation coefficient of stock market returns between countries i and j over the period t. In the main results, we present the findings obtained using the stock market indices expressed in the local currency, while the results obtained using stock indices expressed in US dollars are depicted in Appendix E. For estimation purposes, out of the 780 available correlation coefficients, we use 651. Indeed, we are forced to drop 129 pairs due to the unavailability of financial flows data for these country pairs. The full list of country pairs used in the analysis is presented in Appendix C. Moreover, the estimation period covers the years between 2001 and 2018. Hence, with 651 country pairs and 18 years, our balanced panel includes 11718 observations. Finally, data on stock market returns comes from the Bloomberg database.

In addition, we are considering a set of 21 potential determinants of stock market comovement. The first two potential determinants are constructed using the Finflows database (Nardo et al., 2017) which reports country bilateral financial flows. In this context, we consider portfolio and direct equity flows separately. In the main results, we have scaled the size of the flows by the sum of market capitalization in the pair of examined countries. However, the data for market capitalization was combined from two different sources, namely the World Bank and Bloomberg. Consequently, we divided the the flows by the time averages to minimize the bias. Nevertheless, we obtained qualitatively similar results using year by year scaling, as well as bilateral financial flows without scaling. The results for alternative measures of financial flows are reported in Appendix F. Portfolio equity flows between countries i and j, at time t are calculated as[5]:

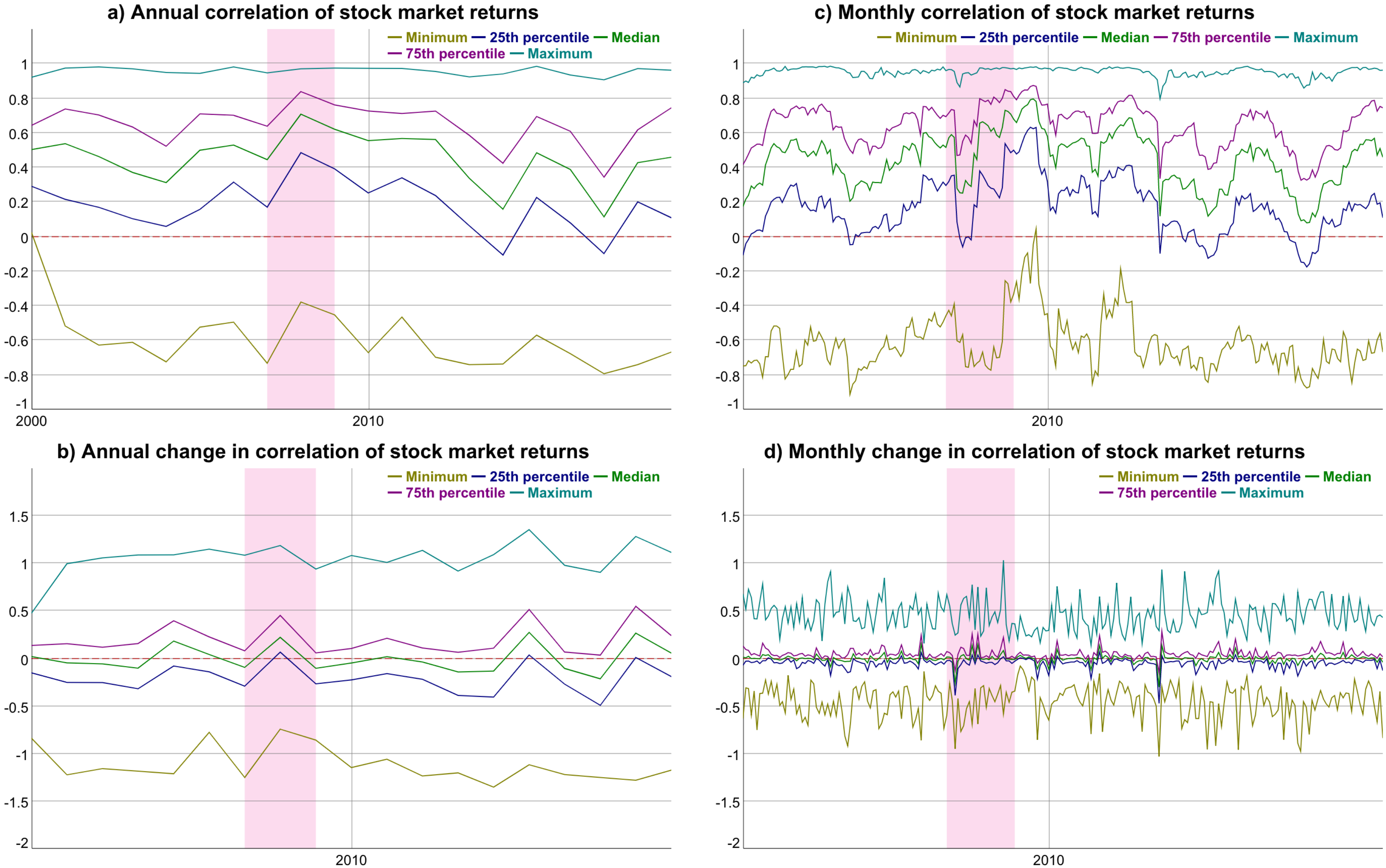
$$PEflows_{ij,t} = \frac{PE_{ij,t} + PE_{ji,t}}{\frac{1}{T}\Sigma_{t=1}^{T}(MC_{i,t} + MC_{j,t})} \tag{2}$$

where $PE_{ij,t}$ and $PE_{ji,t}$ denote portfolio equity flows from country i to country j and from country j to country i, respectively, while $MC_{i,t}$ and $MC_{j,t}$ denote market capitalization in country i and j respectively. Similarly, direct equity flows between countries i and j, at time t are calculated as[6]:

[5]In alternative specifications, portfolio equity flows are defined as: $\frac{PE_{ij,t}+PE_{ji,t}}{MC_{i,t}+MC_{j,t}}$ and $PE_{ij,t} + PE_{ji,t}$.

[6]In alternative specifications, portfolio equity flows are defined as: $\frac{DE_{ij,t}+DE_{ji,t}}{MC_{i,t}+MC_{j,t}}$ and $DE_{ij,t} + DE_{ji,t}$.

Figure 1: Correlation of stock market returns, local currency



$$DEflows_{ij,t} = \frac{DE_{ij,t} + DE_{ji,t}}{\frac{1}{T}\Sigma_{t=1}^{T}(MC_{i,t} + MC_{j,t})} \tag{3}$$

where $DE_{ij,t}$ and $DE_{ji,t}$ denote direct equity flows from country i to country j and from country j to country i, respectively. None of the related existing studies, thus far, considered the role of portfolio capital flows on stock market market comovement. However, the role of FDI was considered by Johnson and Soenen (2002) and Anagnostopoulos et al. (2022).

The next potential determinant of stock market comovement is the degree of capital mobility. To construct this variable, we utilized the Chinn and Ito (2006) database on de jure measures of financial openness. The measure of financial openness in this database (FO_{it}) for a given country i takes values from 0 (indicating no capital mobility) to 1 (indicating perfect capital mobility). As the capital mobility between pairs of countries depends on the degree of controls in both countries, we define the bilateral measure of capital controls as:

$$CapMob_{ij,t} = FO_{i,t} * FO_{j,t} \tag{4}$$

The advantage of using a product measure lies in the fact that the measure is bound between 0 and 1, and can take the value of 0, even if one of the countries is characterized by perfect capital mobility, while the other imposes prohibitive capital controls. Capital mobility was considered in various analyses as an incentive of stock market correlations (Anagnostopoulos et al., 2022; Bracker and Koch, 1999; Quinn and Voth, 2008; Viceira and Wang, 2018; Wälti, 2011).

To assess the impact of the development of the financial markets we use the database on financial market development created by Svirydzenka (2016). The database provides financial development indices ($FD_{i,t}$) that evaluate financial markets in terms of their depth, access, and efficiency. The index takes values ranging from 0 to 1, with values closer to 1 indicating higher degree of financial development. We use two variables in the examination. The first is the product of financial development between two analyzed countries:

$$FDprod_{ij,t} = FD_{i,t} * FD_{j,t} \tag{5}$$

while the second is the absolute value of the difference:

$$FDdif_{ij,t} = |FD_{i,t} - FD_{j,t}|. \tag{6}$$

To the best of our knowledge, the impact of financial development on the degree of stock market correlation has not been examined in the literature, thus far.

We also examine the impact of exchange rate volatility on stock market comovement,and we use the data on monthly bilateral nominal exchange rates from the IMF International Financial Statistics. Hence, we have calculated the measure of exchange rate volatility as:

$$Exchange_{ijt} = \frac{SD(BiER_{ijt})}{M(BiER_{ijt})} \tag{7}$$

where, SD and M denote, standard deviation and mean, while $BiER_{ijt}$ is a series of monthly bilateral nominal exchange rates between country i and country j, in year t. The division of the standard deviation by the mean has the advantage of expressing the volatility as a percentage deviation from the mean, thus facilitating better comparisons between pairs of countries with high and low absolute levels of bilateral exchange rates. The effect of exchange rate volatility on stock market comovement is found to have rather mixed results in the literature. Roll (1992) and Hwang et al. (2013) report positive effects, Wälti (2011) negative effects, while Aladesanmi et al. (2019) find no effects on stock market synchronization. Beine and Candelon (2011) find no relationship between the exchange rate regime and stock market correlations.

The impact of economic size is proxied by two variables for which data was obtained from the PWT (Feenstra et al., 2015) . The first is the natural logarithm of the product of real GDP

$$GDPprod_{ij,t} = \ln\left(GDP_{i,t} * GDP_{j,t}\right) \tag{8}$$

and the second is the natural logarithm of the absolute value of the difference of real GDP

$$GDPdif_{ij,t} = \ln\left|GDP_{i,t} - GDP_{j,t}\right| \tag{9}$$

where $GDP_{i,t}$ and $GDP_{j,t}$ denotes real GDP at time t in country i and j, respectively. The impact of economic size on stock market correlation has been extensively studied in the prior research (Flavin et al., 2002; Guo and Tu, 2021; Lee and Kim, 2020; Liu, 2013).

Using data from the PWT we also examine the role of the difference in the level of economic development using the natural logarithm of the absolute value of the difference of the real GDP per capita:

$$GDP_{pc}dif_{ij,t} = \ln\left|GDPpc_{i,t} - GDPpc_{j,t}\right| \tag{10}$$

where $GDPpc_{i,t}$ and $GDPpc_{j,t}$ denotes real GDP per capita at time t in country i and j, respectively. The role of the differences in the level development for stock market comovement was previously stressed by Beine and Candelon (2011) and Liu (2013).

We also considered differences in institutions between the examined economies using the six categories of the World Bank Worldwide Governance Indicators database. Consequently, we obtain six institutional differences defined as:

$$Xdif_{ij,t} = |X_{i,t} - X_{j,t}| \tag{11}$$

where $X_{i,t}$ and $X_{j,t}$ are values of the index for countries i and j, respectively. The six indices are as follows. $Voice_{ij,t}$ represents difference in the Voice and Accountability index, which besides freedom of expression and freedom of association, captures the availability of information to citizens. The availability of information appears to be especially important in the decision of economic agents to engage in a given market, as stressed by the literature on rational inattention (Sims, 2003, 2006) and costly information acquisition (Chambers et al., 2020). This is also shown in the research stressing the role of information availability on the performance of financial markets (Portes et al., 2001; Portes and Rey, 2005; Choi et al., 2014). $Stability_{ij,t}$ relates to differences in Political Stability and Absence of Violence index that represents the stability of the political system. $GovEffectivness_{ij,t}$ is based on the difference in the Government Effectiveness indicator, which evaluates quality of public services, as well as policy formulation and implementation. $Regulatory_{ij,t}$ reflects differences in the Regulatory Quality index that captures perceived quality of legislation. $RuleofLaw_{ij,t}$ represents difference in the Rule of Law index, which assesses quality of contract enforcement, property rights, and the courts. $Corruption_{ij,t}$ captures differences in the Control of Corruption measure that appraises the extent to which public power is exercised for private gain. The study by Guo and Tu (2021) is the only one examining the role of institutional distances on stock market comovement.

To establish the role of trade linkages in determining the degree of stock market correlation we calculate the measure of bilateral trade defined as:

$$Trade_{ij,t} \frac{Exports_{ij,t} + Imports_{ij,t}}{GDP_{i,t} + GDP_{j,t}} \tag{12}$$

where $Exports_{ij,t}$ and $Imports_{ij,t}$ denote exports and imports, respectively, from country i to country j at time t. The sum of exports and imports are scaled by the sum of GDP in the trading countries. Data on bilateral trade comes from the IMF Directions of Trade. The results on the impact of trade linkages in stock market comovement in the existing literature is mixed. Most of the authors report it as being significant (Forbes and Chinn, 2004; Gavazzoni and Santacreu, 2020; Guo and Tu, 2021; Liu, 2013; Wälti, 2011), while in other studies it depends on the specification (Anagnostopoulos et al., 2022; Beine and Candelon, 2011) or has no impact on stock market synchronization (Viceira and Wang, 2018).

We explore the role of the difference in the government debt ratios, by calculating the following variable:

$$DEBTdif_{ij,t} = \ln |Debt_{i,t} - Debt_{j,t}| \tag{13}$$

where $Debt_{i,t}$ and $Debt_{j,t}$ are the debt-to-GDP ratios in country i and country j, respectively, in year t.

We examine the role sovereign ratings following the approach of Afonso et al. (2014) who created a scale from 1 (lowest quality) to 17 (highest quality, AAA) to categorize the respective qualitative ratings from the three main rating agencies (Moody's, Standard Poors, and Fitch). The average for the three agencies is used to create an overall measure of a given country rating $R_{i,t}$. Consequently, the variable indicating the difference in the ratings is given by:

$$Rating_{ij,t} = |R_{i,t} - R_{j,t}|. \tag{14}$$

Neither differences in debt, nor the differences in sovereign rating have been examined in the existing literature. However, Hwang et al. (2013) reports a significant impact of CDS spreads of returns on government bonds.

The last three measures for possible determinants are based on the monthly time series of stock market returns taken from Bloomberg. Firstly, we consider the natural logarithm of the absolute value of the difference in mean returns is defined as:

$$Return_{ij,t} = \ln |MR_{i,t} - MR_{j,t}| \tag{15}$$

where: $MR_{i,t}$ and $MR_{j,t}$ are mean monthly returns calculated over a 12 month period, between stock indices in country i and country j, respectively, in year t. The second measure is the natural logarithm of the absolute value of the difference in standard deviations:

$$SD_{ijt} = \ln|SDR_{i,t} - SDR_{j,t}| \tag{16}$$

where: $SDR_{i,t}$ and $SDR_{j,t}$ are standard deviations of monthly returns calculated over the 12 month period, between stock indices in country i and country j, respectively, in year t. The third one is the natural logarithm of the absolute value of the difference of the Sharpe ratios:

$$Sharpe_{ij,t} = ln\left|\frac{MR_{i,t} - TB_t}{SDR_{i,t}} - \frac{MR_{j,t} - TB_t}{SDR_{j,t}}\right| \tag{17}$$

where TB denotes the interest rate on a Treasury bill at time t. Data on returns on treasury bills comes from the FRED database[7]. Aladesanmi et al. (2019); Hwang et al. (2013); Wälti (2011) find that volatility impacts stock market comovement, while Lee and Kim (2020) report otherwise. Wälti (2011) reports a significant role of the differences in returns, while the role of the Sharpe ratio has not been examined, thus far.

All the examined variables were standardized before estimation for two main reasons. Firstly, standardized coefficients allow the comparison of the relative impact of the determinants on the degree of stock market comovement. Secondly, in the second stage of the analysis the likelihood function is maximized numerically, and standardization facilities an easier and faster achievement of the maximum.

2.2 Estimation strategy

In order to establish a set of robust determinants of stock market correlations, we employ estimation strategies based within the framework of Bayesian model averaging (BMA). Firstly, we set up an equation:

$$y_{ij,t} = \alpha y_{ij,t-1} + \beta x_{ij,t} + \eta_{ij} + \zeta_t + \nu_{ij,t} \tag{18}$$

where $y_{i,j,t}$ is a measure of stock market comovement between country i and country j at time t, $x_{ij,t}$ is a vector of potential stock market correlation determinants (described in subsection 2.1), β is a parameter vector, η_{ij} is a country-pair specific fixed effect, ζ_t is period-specific shock and

[7]There is a warranted concern that there is a positive bias in case of the variables return differences, standard deviation differences, and Sharpe ratio differences as they contain similar elements with those used to construct the correlation coefficient. However, none of these variables turned out to be robust, so even if the bias exists, it is not strong enough to affect the results

$\nu_{ij,t}$ is a shock to stock market synchronization. Within this setting, t=0,1,2,...,18 for $y_{ij,t}$, while t=1,2,...,18 for the determinants in $x_{ij,t}$.

In the first stage of the analysis we estimate all the possible variants of (18) with the changing composition of vector $x_{ij,t}$, from the model without any variables to the model with all $K = 21$ considered regressors. This constitutes a model space with $2^K = 2097152$ elements. Once estimated, each model is assigned a posterior model probability (PMP) given by the Bayes rule:

$$PMP_m = \frac{L(data|M_m) \times P(M_m)}{\sum_{m=1}^{2^K} L(data|M_m) \times P(M_m)} \tag{19}$$

where $L(data|M_m)$ is the value of the likelihood function for model m (M_m), and $P(M_m)$ is the prior probability of model m. Using the PMPs in the role of weights allows for the calculation of the posterior mean (PM) and standard deviation of the coefficient β_k ($k = 1, \ldots, 21$). The PM of the coefficient β_k, is given by

$$PM_k = \sum_{m=1}^{2^K} \widehat{\beta}_{k,m} \times P(M_m|data) \tag{20}$$

where $\widehat{\beta}_{k,m}$ is the value of the coefficient β_k estimated for model m and k indexes the regressor. The posterior standard deviation (PSD) is equal to

$$PSD_k = \sqrt{\sum_{m=1}^{2^K} V(\beta_{k,m}|data, M_m) \times PMP_m + \sum_{m=1}^{2^K} [\widehat{\beta}_{k,m} - PM_k]^2 \times PMP_m} \tag{21}$$

where $V(\beta_{k,m}|data, M_j)$ denotes the conditional variance of the parameter in the model M_m.

The application of Bayesian model averaging requires the specification of the model prior and it is common to use g prior on the parameter space. The benchmark rule (Fernández et al., 2001) dictates the choice of unit information prior (UIP) on coefficients proposed by Kass and Wasserman (1995). The combination of UIP with the uniform model prior (equal probabilities of all considered models) is advocated by Eicher et al. (2011), while Ley and Steel (2009) recommend a binomial-beta model prior (equal probabilities on all considered model sizes). Therefore, in all the estimations presented here, the UIP is combined with uniform and binomial-beta priors on the model space.

The robustness of the determinants is assessed with the absolute value of the ratio of the PM to PSD. Raftery (1995) considers a variable robust if this ratio is higher than 1, indicating that the inclusion of the variable improves the power of the model. Masanjala and Papageorgiou (2008) advocate a critical value of 1.3 for a 90% confidence interval based on the frequentist approach, while Sala-I-Martin et al. (2004) advise a value of 2 corresponding to a 95% confidence interval.

To assure the robustness of the results we examined the stability of the reported outcomes to changes in the prior specification. In order to account for potential multicollinearity between regressors, we implement two alternative strategies. Firstly, we implement a dilution prior. Accordingly, a uniform model prior is supplemented with a function accounting for multicollinearity (George, 2010) to obtain prior model probabilities:

$$P(M_m) \propto |R_m|^{0.5}(\frac{1}{2})^K, \tag{22}$$

where $(|R_j|)$ is the determinant of the correlation matrix for all the regressors in the model j. The uniform model prior implies equal probabilities assigned to all the models, so the $(|R_j|)$ component of (22) determines the distribution of the prior probability mass. The higher the multicollinearity between the variables, the closer the value of $(|R_j|)$ to 0 and the lower the prior ascribed to a given model. Secondly, dilution is implemented through the MC^3 Madigan et al. (1995) search. Tessellation is achieved through the "Spinner Process", which uses the following method of sampling from a subspace of models $P_V(M_j)$ (George, 2010):

1) sample the model size k from K,

2) simulate Y^* $N_n(0, I)$, where Y^* could be thought of as an 'imaginary data',

3) select the matrix of covariates with $k_j = k$ that is 'closest' to Y^* – select j for which R^2 is the highest in the regression of Y^* on the matrix of covariates.

The tessellation prior is combined with both uniform and binomial-beta model priors in turn. Next, we used the risk inflation criterion (RIC) g prior proposed by Foster and George (1994) combined with uniform and binomial-beta model prior. The results for dilution priors and and RIC prior are reported in Appendix D, and are virtually the same as the ones reported in the main text.

We also obtained virtually the same results using g prior that mimics Hannan-Quinn information criterion, empirical Bayesian local g prior (George and Foster, 2000; Hansen and Yu, 2001) and hyper-g prior (Liang et al., 2008; Feldkircher and Zeugner, 2009). We do not report the results for brevity but they are available upon request from the authors.

BMA is a very powerful tool that deals with model uncertainty, and consequently is best fitted for carrying out the research in the areas where there is a high number of potential determinants and very little prior empirical research on the subject. However, within the framework described above all the regressors are assumed strictly exogenous. In other words, the framework cannot account for reverse causality. To overcome this issue, in the second stage of the analysis we employ a framework developed by Moral-Benito (2013, 2016); Moral-Benito et al. (2019) that deals with model uncertainty and reverse causality at the same time. Following Moral-Benito et al. (2019) we adopt the assumption of weak exogeneity that can be formalized as

$$E(v_{ij,t}|y_{ij}^{t-1}, x_{ij}^{t}, \eta_{ij}) = 0 \tag{23}$$

where $y_{ij}^{t-1} = (y_{ij,0}, ..., y_{ij,t-1})'$ and $x_t = (x_{ij,0}, ..., x_{ij,t})'$. Accordingly, weak exogeneity implies that the current values of the regressors, lagged dependent variable, and fixed effects are uncorrelated with the current shocks, while they are all allowed to be correlated with each other at the same time. Following Moral-Benito (2013) equation (18) is augmented with a reduced-form equation capturing the unrestricted feedback process:

$$x_{ij,t} = \gamma_{t,0} y_{ij,0} + ... + \gamma_{t,t-1} y_{ij,t-1} + \Lambda_{t,1} x_{ij,1} + ... + \Lambda_{t,t-1} x_{ij,t-1} + c_t \eta_{ij} + v_{ij,t} \tag{24}$$

where $t = 1, \ldots, T$; c_t is the $k \times 1$ vector of parameters. For $h < t$, $\gamma_{t,h}$ is a $k \times 1$ vector $(y_{th}^1, \ldots, y_{th}^k)'$ $h = 0, \ldots, T-1$; Λ_{th} is a $k \times k$ matrix of parameters, and $v_{i,j,t}$ is a $k \times 1$ of prediction errors. The mean vector and the covariance matrix of the joint distribution of the initial observations ($y_{i,j,0}$ and $x_{i,j,1}$) and the individual effects $\eta_{i,j}$ are unrestricted, and consequently:

$$y_{ij0} = c_0 \eta_{ij} + \nu_{ijt} \tag{25}$$

$$x_{ij1} = \gamma_{10} y_{ij0} + c_1 \eta_{ij} + v_{ijt} \tag{26}$$

where c_0 is a scalar, and c_1 and $\gamma_{1,0}$ are $k \times 1$ vectors. Given the model setup in equations (18) and (24-26), the natural logarithm of the likelihood function under Gaussian errors can be expressed as (Moral-Benito, 2016)

$$\log f(data|\theta) \propto \frac{N}{2} \log det(B^{-1} D \Sigma D' (B')^{-1}) - \frac{1}{2} \sum_{ij=1}^{N} [R_{ij}' (B^{-1} D \Sigma D' (B')^{-1})^{-1} R_{ij}] \tag{27}$$

where $R_{ij} = (y_{ij,0}, x'_{ij,1}, ..., x'_{ij,T}, y_{ij,T})'$ is a vector of observable variables, $\Sigma = diag[\sigma^2_\eta, \sigma^2_{\nu_0}, \Sigma_{\nu_1}, \sigma^2_{\nu_1}, ..., \Sigma_{\nu_T}, \sigma^2_{\nu_T}]$ is the block-diagonal variance-covariance matrix of $U_{ij} = (\eta_{ij}, \nu_{ij,0}, \upsilon'_{ij,1}, \nu_{ij,1}, ..., \upsilon'_{ij,T}, \nu_{ij,T})$, and B is a matrix of coefficients given by

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ -\gamma_{1,0} & I_k & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ -\alpha & -\beta' & 1 & 0 & 0 & \dots & 0 & 0 & 0 \\ -\gamma_{2,0} & -\Lambda_{2,1} & -\gamma_{2,1} & I_k & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & -\alpha & -\beta' & 1 & \dots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 & 0 & 0 \\ -\gamma_{T,0} & -\Lambda_{T,1} & -\gamma_{T,1} & -\Lambda_{T,2} & -\gamma_{T,2} & \dots & -\gamma_{T,t-1} & I_k & 0 \\ 0 & 0 & 0 & 0 & 0 & \dots & -\alpha & -\beta' & 1 \end{bmatrix} \tag{28}$$

and D is a matrix of coefficients given by[8]

$$D = \begin{bmatrix} (c_0 & c'_1 & 1 & c'_2 & 1 & \dots & c'_T & 1)' & I_{T(k+1)+1} \end{bmatrix}. \tag{29}$$

Given the likelihood function for the model setup in equations (18) and (24-26), it is possible to use BMA within this framework. Nevertheless at this point, we depart from the Moral-Benito (2016) framework, which is based on the notion that to ensure the comparability of the likelihood function all the examined models are nested in the full specification. Comparisons within BMA are based on the restricted version of the full specification where some subset of coefficients on the regressors in equation (18) are set to zero. This framework has the disadvantage of placing overwhelming weight on the full specification, which biases the results towards estimates from that model[9]. To avoid this bias we follow the non-nested approach proposed by Beck and Wyszyński (2022)[10]. Beck and Wyszyński (2022) consider all versions of the model given by equations (18) and (24-26) where each of the possible specifications is different in the number of considered regressors in vector $x_{ij,t}$. To ensure comparability between models Beck and Wyszyński (2022) propose the introduction of the

[8]The expression for D in Moral-Benito (2016) is different; however, here, we present the corrected version.
[9]Additionally, the nested approach of Moral-Benito with the number of observations in our sample is computationally unfeasible.
[10]Even in the case of the non-nested approach the estimations have taken over eight days.

normalizing constant, which gives the following expression for the model specific likelihood:

$$\log \hat{f}(data|\theta)_m \propto \log f(data|\theta)_m - \frac{N(T + (T-1)k)}{2} \cdot \log 2\pi. \tag{30}$$

Due to computational infeasibility of the estimation of the setup (18) and (24-26) within the BMA framework[11], especially given the large number of observations, in the second stage we examine only the regressors that were robust in the first stage of estimations. The evaluation of the robustness of the examined variables under the assumption of weak exogenity is performed using the same BMA statistics (20-21), giving again very strict assessment criteria.

3 Empirical Results

The results of Bayesian model averaging under uniform and binomial-beta model prior are depicted in Table 1. Figure 2 and Figure 3 depict the corresponding posterior densities of the standardized coefficients for the the transformed lagged correlation coefficient and the remaining regressors, respectively. The results provide an extremely clear division with eight (including lagged transformed correlation coefficient) and remaining fourteen being fragile. This outcome is strongly supported by the significant number of robustness checks presented in appendices D, E, and F[12]. In the case of the variables $y_{ij,t-1}$, GDPdif, GDPprod, PEflows, CapMob, Exchange, FDdif, and FDprod, they are all characterized by an absolute value of the ratio of the posterior mean to posterior standard deviation above two indicating strong robustness to changes in model specification. All the remaining regressors have the absolute values of the aforementioned ratio below one, which points to the strong fragility of all these variables. The values of the posterior means of the standardized coefficients for models under uniform and binomial-beta model prior are very stable and differ only by less than 0.001.

The posterior mean for the transformed lagged correlation coefficient ($y_{ij,t-1}$) is 0.278 and it is the highest among all the considered regressors. This indicates that the past value of the correlation coefficient of stock market returns is the best predictor of the future value of the correlation, and

[11] After nearly two months of estimations less than 10% of the total model space was estimated for the case of 21 regressors. Moreover, the models already estimated were the smallest ones with the lowest computational load.

[12] The only exception is $GDP_{pc}dif$ which appears robust in some specification and not in others. Consequently, we classify difference in economic development as fragile along the outcomes presented in the main results.

Table 1: Posterior means and posterior standard deviations (in parentheses) on transformed stock market correlations determinants under different prior model probability distributions

Model prior	Uniform	Binomial-beta
$y_{ij,t-1}$	0.278***	0.278***
	(0.009)	(0.009)
GDPdif	-0.112***	-0.111***
	(0.008)	(0.008)
GDPprod	0.163***	0.163***
	(0.010)	(0.010)
PEflows	0.065***	0.065***
	(0.008)	(0.008)
CapMob	0.069***	0.069***
	(0.008)	(0.008)
Exchange	0.056***	0.056***
	(0.008)	(0.008)
FDdif	-0.099***	-0.099***
	(0.010)	(0.010)
FDprod	0.126***	0.126***
	(0.011)	(0.011)
Sharpe	0.001	0.000
	(0.004)	(0.003)
$GDP_{pc}dif$	-0.000	-0.000
	(0.003)	(0.002)
RuleofLaw	-0.000	-0.000
	(0.002)	(0.002)
Return	0.000	0.000
	(0.002)	(0.002)
Corruption	-0.000	-0.000
	(0.002)	(0.001)
Stability	-0.000	-0.000
	(0.002)	(0.001)
GovEffectivness	-0.000	-0.000
	(0.002)	(0.001)
Voice	0.000	0.000
	(0.002)	(0.001)
Regulatory	-0.000	-0.000
	(0.001)	(0.001)
SD	-0.000	-0.000
	(0.001)	(0.001)
Trade	0.000	0.000
	(0.001)	(0.001)
Rating	-0.000	-0.000
	(0.001)	(0.001)
DEBTdif	0.000	0.000
	(0.001)	(0.001)
DEflows	0.000	0.000
	(0.001)	(0.001)

*/**/*** denote the ratio of PM to PSD above 1/1.3/2.0; posterior standard deviations are in parentheses.

thus, it captures the stability of correlations we see in Figure 1. These results corroborate the findings of Kim et al. (2005) and Liu (2013) who list the lagged correlation as the main driver of the stock market comovement. The value of the posterior mean for the difference in GDP (GDPdif) is -0.112 and -0.111 for the uniform and the binomial-beta model prior, respectively. The posterior mean for product of the two GDPs (GDPprod) is 0.163 under both model priors. On the one hand, the signs of the posterior means indicate that bigger economies are characterized by higher stock market comovement. On the other hand, comovement is higher between economies of similar sizes in comparison with the ones that have a very different sizes. This, contrasts with the hypothesis of the contagion of small markets by the large ones. Nevertheless, this outcome should be attributed to fixed time effects that account for the effects of contagion during major economic downturns. Our results on the effect of the economic size are in line with Flavin et al. (2002); Guo and Tu (2021); Liu (2013), but are in contrast to Lee and Kim (2020) who do not report a significant impact of the differences in market size.

The portfolio equity flows (PEflows) determinant has a posterior mean equal to 0.065 in both model prior specifications. This outcome puts it in the second tier of the stock market synchronization determinants. However, this relatively small effect should not be overstated, as there are three other variables that can capture the role of financial flows on the comovement of market returns. This result can be contrasted with the fragility of direct investment flows (DEflows) characterized by the value of posterior mean below 0.001[13], and differs from prior research that reports significant role for FDI flows in stock market correlations (Anagnostopoulos et al., 2022; Johnson and Soenen, 2002). The difference between our results and previous related studies could be linked to the fact that such research did not account for model uncertainty, and did not include portfolio flows in their specification. The correlation coefficients between portfolio and direct flows in our sample is 0.32, which shows that FDI in previous research could be picking up portfolio equity flows. To explain why portfolio equity flows are in fact the ones that determine stock market correlations we examined the average ratio of the two. It turns out that average portfolio equity flow is only 16% higher than direct equity flow. Consequently, it is hard to assign the difference in their impact on stock market synchronization to the relative size alone. Instead, the reason between those differences can be attributed to the motives behind those types of investment. In the case of direct flows, long-run gains

[13] As demonstrated in Appendix D, this outcome cannot be attributed to multicolinearity.

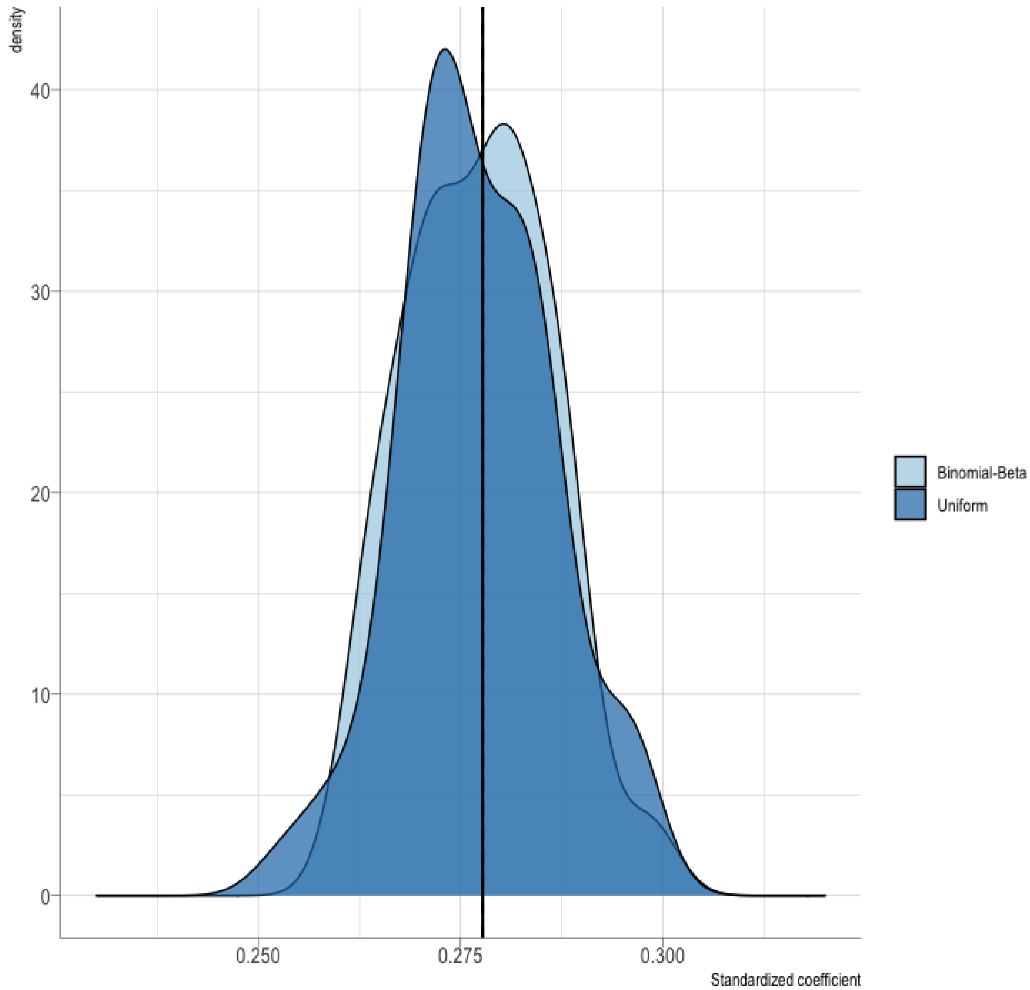


Figure 2: Posterior densities of the standardized coefficients on the transformed lagged correlation coefficient ($y_{ij,t-1}$).

Notes: solid (dashed) horizontal line represents the posterior mean under uniform (binomial-beta) model prior and even taking some part in controlling the company motivates economic agents. Consequently, their decision might not be driven by short run considerations. Portfolio equity movements, on the other hand, are driven by short-run economic incentives, resulting in flows affecting the short-run behavior of the markets.

Capital mobility (CapMob) is, thus far, the most highly acknowledged determinant of stock market correlations (Anagnostopoulos et al., 2022; Bracker and Koch, 1999; Quinn and Voth, 2008; Viceira and Wang, 2018; Wälti, 2011). The posterior mean on CapMob is 0.069, under both prior specification, which translates to the second tier of the determinants in terms of their impact on market returns comovement. However, the small size of the standardized coefficient means that the result should be taken with caution. The effect of capital mobility in studies, which do not consider portfolio and direct equity flows and the degree of financial development, might be overestimated as capital mobility goes hand in hand with intensified flows and deeper financial markets.

The posterior mean on the difference in degree of financial development (FDdif) is -0.099, while on financial development product (FDprod) is 0.126, regardless of the applied prior model probability distribution. These results put financial development in the first tier of the determinants of stock market synchronization in terms of the magnitude of influence. On the one hand, the more financial markets are developed in two given countries, the higher is the degree of the stock market comovement. On the other hand, the bigger is the difference in the financial development, the smaller is the comovement. Taken together this result indicates that deepening financial development fosters higher stock market synchronization. Nevertheless, there can be a potential issues with multicolinearity and endogeneity between PEflows, CapMob, FDdif, and FDprod. However, as demonstrated in Appendix D, multicolinearity is not affecting the results. The issue of interdependence between the regressors is tackled later in the analysis with the use of the Moral-Benito (2013, 2016) approach.

The last robust variable, with the lowest absolute value of the standardized coefficient is the exchange rate volatility (Exchange) with the posterior mean equal to 0.056. Similar to Roll (1992) and Hwang et al. (2013), we report a positive effect of exchange rate volatility on the synchronization of stock markets.

The remaining variables are all fragile. In contrast to results reported by Forbes and Chinn (2004); Gavazzoni and Santacreu (2020); Guo and Tu (2021); Liu (2013); Wälti (2011), we find that trade intensity (Trade) is not influencing stock market comovement. However, we note that these authors

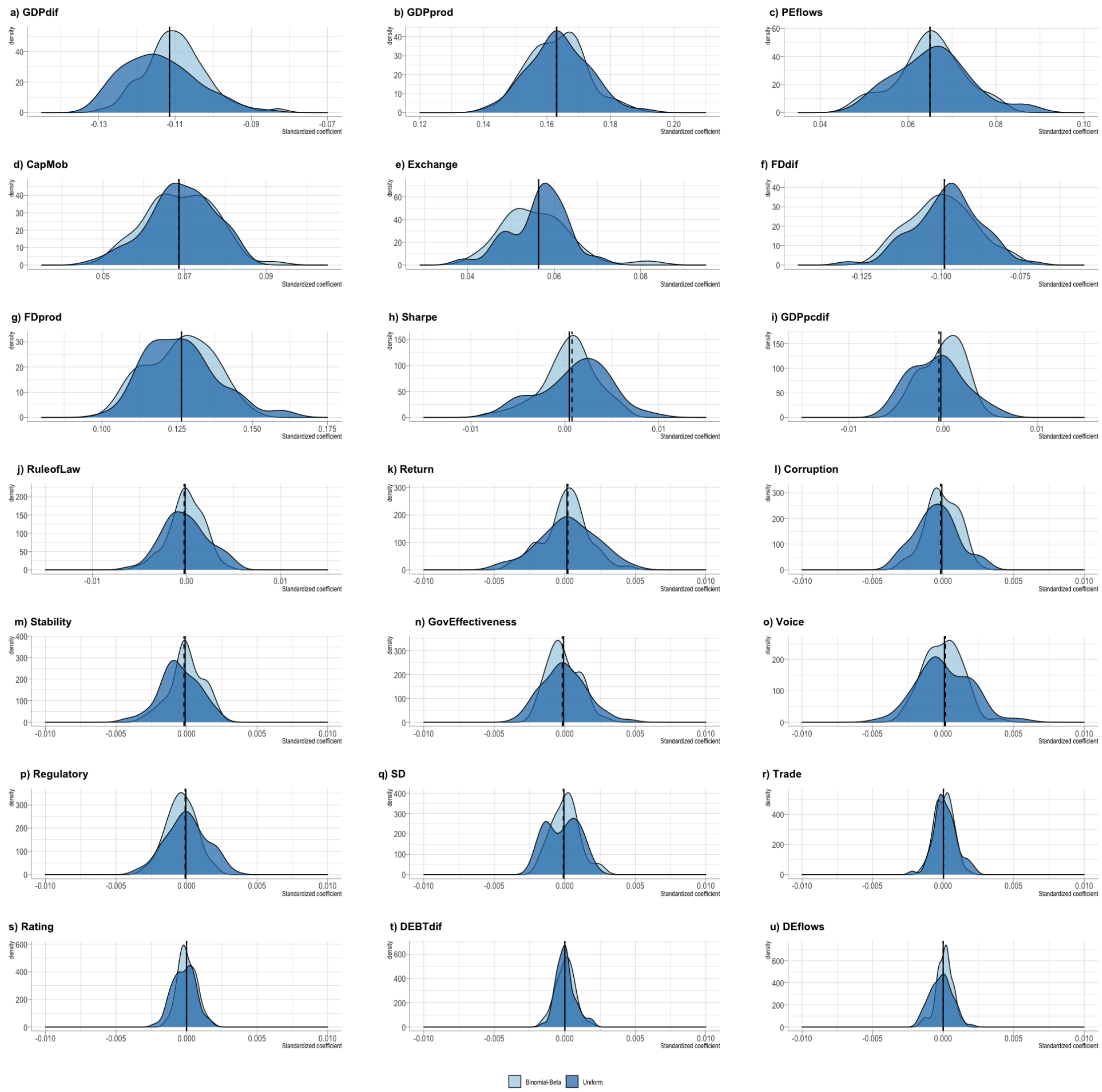


Figure 3: Posterior densities of the standardized coefficients on the examined regressors.
Notes: solid (dashed) horizontal line represents the posterior mean under uniform (binomial-beta) model prior. However, the two lines overlap.

are not investigating robustness to changes in model specification. Consequently, our results are in line with Anagnostopoulos et al. (2022); Beine and Candelon (2011) who find that trade is significant only in some specifications, as well as Viceira and Wang (2018) who reports a non-significant coefficient. We also find all that all six institutional distance variables (RuleofLaw, Corruption, Stability, GovEffectiveness, Voice, and Regulatory) are classified as fragile. These results are different to that reported by Guo and Tu (2021), who were also not checking the robustness with respect to changes in model specification.

Additionally, and contrary to Aladesanmi et al. (2019); Hwang et al. (2013); Wälti (2011) we find that the difference in volatility (SD) has no bearing on stock market comovement, the result previously reported by Lee and Kim (2020). Contrary, to Wälti (2011) we find that the differences in returns (Return) are not influencing stock market correlation, and we obtain the same outcome for the differences in Sharpe ratio (Sharpe). In other words, our findings show that the stock market returns correlation are independent from two other key components of the Markovitz model. In contrast with Beine and Candelon (2011) and Liu (2013) we find no relationship between the level of development ($GDP_{pc}dif$) and synchronization of stock markets. This outcome could be attributed to the lack of control for financial development that is inherently associated with the degree of economic development in these papers. Finally, we find no relationship between the difference in public debt (DEBTdif) nor in the sovereign ratings (Rating). This outcome stands in contrast with Hwang et al. (2013) who reports a significant impact of CDS spreads on government bonds.

BMA enables dealing with model uncertainty in a systematic way, however, it relies on the assumption of strictly exogenous regressors. As mentioned earlier, this assumption might not be fulfilled with the considered set of variables. Moreover, variables under analysis might be correlated with each other, as exemplified by PEflows, CapMob, FDdif, and FDprod. To deal with these issues we employed BMA within the framework proposed by Moral-Benito (2013, 2016). The results under the uniform and binomial-beta model prior are shown in Table 2, while Figure 4 depicts the corresponding posterior densities of the standardized coefficients for the transformed lagged correlation coefficient and the remaining regressors, respectively.

The results show that after controlling for reverse causality, and capturing the intermediate channel between the regressors one more variable turned out to be fragile. Indeed, exchange rate volatility, with a PM equal to 0.045 is not robust, confirming the results reported by Aladesanmi et al. (2019)

Table 2: Posterior means and posterior standard deviations (in parentheses) on transformed stock market correlation determinants under different prior model probability distributions. Results for Moral-Benito approach.

Model prior	Uniform	Binomial-beta
$y_{ij,t-1}$	0.321***	0.319***
	0.028	0.028
GDPdif	-0.121**	-0.122**
	(0.062)	(0.062)
GDPprod	0.131***	0.129***
	(0.047)	(0.047)
PEflows	0.067***	0.067***
	(0.025)	(0.025)
CapMob	0.171***	0.172***
	(0.057)	(0.057)
Exchange	0.045	0.045
	(0.068)	(0.069)
FDdif	-0.112***	-0.111***
	(0.051)	(0.051)
FDprod	0.049**	0.050**
	(0.027)	(0.029)

*/**/*** denote the ratio of PM to PSD above 1/1.3/2.0; posterior standard deviations are in parentheses.

and Beine and Candelon (2011). Additionally, the difference in GDP and product of financial development no longer have an absolute value of posterior mean to posterior standard deviation ratio above two. However, both variables are still robust, as the absolute value of the aforementioned ratio is above the critical value of 1.3 in both cases. The absolute values of the ratios are 1.95 and 1.97 for GDPdif, and 1.82 and 1.72 for FDprod for uniform and binomial-beta model prior, respectively. Consequently, the ratios are fairly close to the most stringent critical value of two, making interference on the obtained posterior mean firmly reliable.

The posterior mean on the lagged transformed correlation coefficient is 0.321 and 0.319 for uniform and binomial-beta prior, respectively. This indicates even a higher degree of inertia than the results reported in Table 1. The magnitude of the posterior mean, once again, indicates that today's correlation is the best individual predictor of future correlation of stock markets.

The absolute value of the posterior mean on GDP difference is slightly higher; increasing from 0.112 to 0.121 and from 0.111 to 1.22 for the uniform and for the binomial-beta prior, respectively. On the other hand, the values of standardized posterior mean drops for the GDP product from 0.163 to 0.131 and 0.129 for uniform and binomial-beta prior respectively. However, the main conclusion about the role of the economic size on the degree of stock market comovement can be maintained.

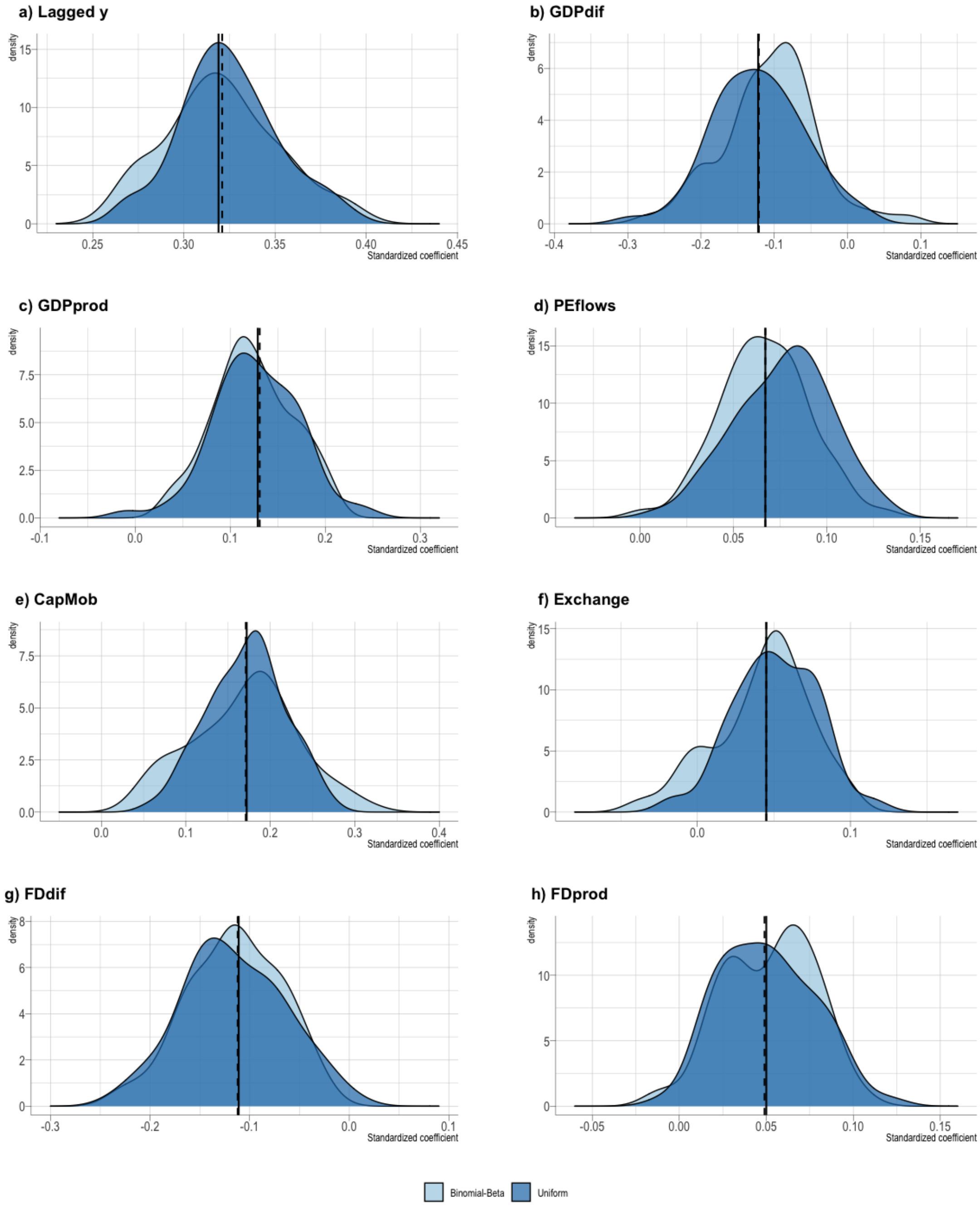


Figure 4: Posterior densities of the standardized coefficients on the examined regressors and transformed lagged correlation coefficient ($y_{ij,t-1}$). Results for Moral-Benito approach.

Notes: solid (dashed) horizontal line represents the posterior mean under uniform (binomial-beta) model prior

The posterior mean of portfolio equity flows increases slightly from 0.065 to 0.067 for both priors making it the most stable estimate in the sample. Contrarily, the degree of capital mobility records the most significant increase in the value of the posterior mean from 0.069 to 0.171 and 0.172 for uniform and binomial-beta model prior, respectively. This places capital mobility as the most important determinant of stock market comovement in terms of magnitude, with the exception of the past correlation, in line with the results reported by (Anagnostopoulos et al., 2022; Bracker and Koch, 1999; Quinn and Voth, 2008; Viceira and Wang, 2018; Wälti, 2011).

The notable increase in the value of the posterior mean for capital mobility coincides with the considerable drop in the value of the posterior mean on financial development product from 0.126 to 0.049 and 0.050 for uniform and binomial-beta model prior, respectively. The absolute value of the posterior mean for the difference in financial development increased slightly from 0.099 to 0.112 and 0.111 for uniform and binomial-beta model prior, respectively. The conclusion about the role of financial development on stock market synchronization can be maintained. However, controlling for the intermediate relationships further highlights the relevant role of capital mobility that was more suppressed within the framework that assumed exogenous regressors.

4 Conclusions

In this paper we have applied a methodological framework that accounts for model uncertainty and reverse causality, to a large panel of 651 country pairs over the 2001-2018 period, in order to identify the robust determinants of stock market correlations. Out of twenty-two examined regressors, seven are classified as the main drivers of of stock market synchronization. We report a high degree of persistence in stock market correlations and show that current correlation is the best single predictor of future correlation. Therefore, this implies that while creating an optimal portfolio the agent can reliably use past correlation as a guide.// The other robust determinants of stock market comovement can be divided into two categories. The first category refers to the size of the market. We report that bigger markets are tied by a stronger degree of synchronization of returns, along the lines of standard gravity models. However, we also report that markets of similar size are characterized by a higher degree of stock market comovement. Overall, we can expect that growing economies, and along with them capital markets, will increase their gravity pull resulting in higher stock market correlations.

The second category refers to financial liberalization. We find that increasing capital mobility, financial development, and portfolio equity flows contribute to higher stock market comovement. Progressing financial liberalization, associated with decreasing barriers to capital movement, and the deepening of financial markets facilitates higher portfolio equity flows. On the other hand, the development of financial markets enables capital mobility and vice versa. Consequently, we identify reinforcing factors that facilitate higher stock market correlations.

The two aforementioned categories of determinants paint a very clear picture of the possible future of stock market comovement. Expanding economies with growing capital markets that pursue financial liberalization will inevitably create an environment of highly correlated stock markets. This in turn will reduce the possibilities for international portfolio diversification that facilitates risk sharing. Therefore, the results presented in this paper give strong support to the "diminishing international diversification potential" proposed by Lewis (2006) and developed by Christoffersen et al. (2012).

Finally, we find that institutional distance (Guo and Tu, 2021), differences in volatility (Aladesanmi et al., 2019; Hwang et al., 2013; Wälti, 2011) and returns (Wälti, 2011), and trade (Forbes and Chinn, 2004; Gavazzoni and Santacreu, 2020; Guo and Tu, 2021; Liu, 2013; Wälti, 2011), that were found to be significant in prior research, were not able to withstand a rigorous accounting for model uncertainty within the Bayesian model averaging framework. Similarly, the exchange rate volatility found significant in Hwang et al. (2013); Roll (1992); Wälti (2011) turned out to be fragile in the approach accounting for reverse causality. Nevertheless, the negative outcomes and fragility of some examined variables brings about important information concerning the behavior of stock market correlation. Firstly, we report that it is not directly related to two other parts of the Markovitz model, namely mean and standard deviations of returns. Consequently, we see that covariances are driving the correlations between stock market returns. Secondly, the fragility of all the institutional distances shows the dominant role of the financial institutions in explaining stock market correlations.

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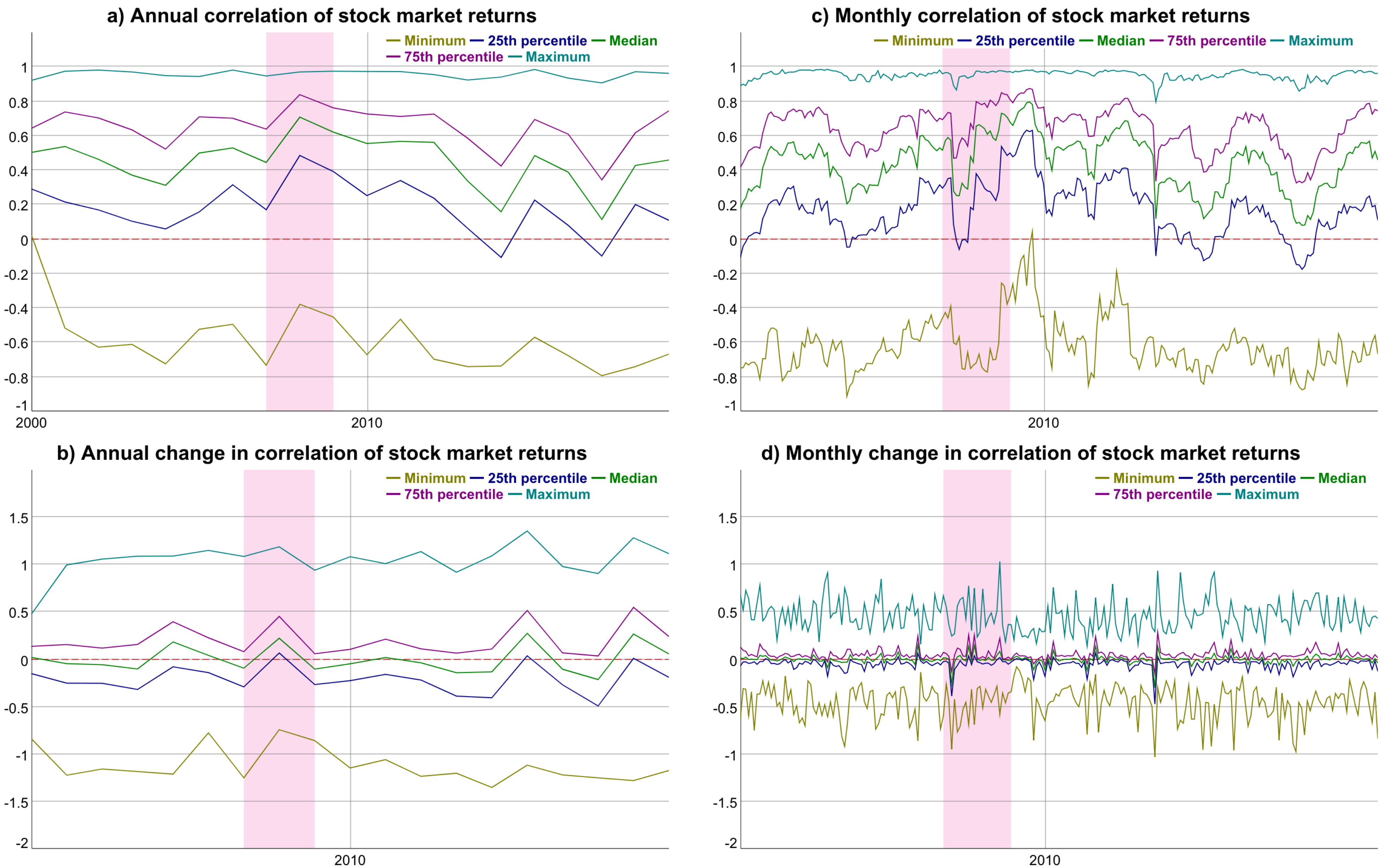
Country	Index	Country	Index	Country	Index	Country	Index	Country	Index
Australia	AS51	France	CAC	Japan	NKY	Mexico	MEXBOL	Singapore	STI
Austria	ATX	Germany	DAX	Korea	KOSPI	Netherlands	AEX	Slovakia	SKSM
Belgium	BEL20	Greece	ASE	Latvia	RIGSE	New Zealand	NZSE	Spain	IBEX
Canada	SPTSX	Hong Kong	HSI	Lebanon	BLOM	Norway	OBX	Sweden	OMX
Chile	IGPA	Hungary	BUX	Lithuania	VILSE	Panama	BVPS	Switzerland	SMI
Czechia	PX	Iceland	ICEXI	Luxembourg	LUXXX	Poland	WIG	Turkey	XU100
Estonia	TALSE	Ireland	ISEQ	Malta	MALTEX	Portugal	PSI20	UK	UKX
Finland	HEX25	Italy	FTSEMIB	Mauritius	SEMDEX	Romania	BET	USA	SPX

Appendix A: List of countries and stock indices

Appendix B: Correlation of stock market returns, US Dollars



a) Annual correlation of stock market returns
Minimum 25th percentile Median
75th percentile Maximum
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2000
2010
c) Monthly correlation of stock market returns
Minimum 25th percentile Median 75th percentile Maximum
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2010
b) Annual change in correlation of stock market returns
Minimum 25th percentile Median
75th percentile Maximum
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2010
d) Monthly change in correlation of stock market returns
Minimum 25th percentile Median
75th percentile Maximum
1.5
1
0.5
0
-0.5
-1
-1.5
-2
2010

Appendix C: List of country pairs under investigation

AU-AT	BE-IR	CL-BE	FI-SG	DE-FI	GR-SK	IT-CL	JP-LT	KR-SK	NL-AT	PL-GR	RO-LT	ES-PL	TR-FI	UK-NO	US-SK
AU-BE	BE-LV	CL-CZ	FI-SK	DE-FR	GR-SE	IT-CZ	JP-LU	KR-ES	NL-BE	PL-HK	RO-LU	ES-PT	TR-FR	UK-PA	US-ES
AU-CL	BE-LB	CL-EE	FR-AU	DE-GR	GR-CH	IT-EE	JP-MU	KR-SE	NL-CL	PL-HU	RO-NL	ES-RO	TR-GR	UK-PL	US-SE
AU-CZ	BE-LT	CL-FI	FR-AT	DE-HK	HK-FI	IT-FI	JP-MX	KR-CH	NL-CZ	PL-IS	RO-NO	ES-SG	TR-HK	UK-PT	US-CH
AU-FI	BE-LU	CL-GR	FR-BE	DE-HU	HK-IS	IT-GR	JP-NL	LV-EE	NL-EE	PL-IR	RO-PT	ES-SK	TR-HU	UK-RO	US-TR
AU-GR	BE-MT	CL-HK	FR-CA	DE-IS	HK-IR	IT-HK	JP-NZ	LV-LU	NL-FI	PL-LV	RO-SK	ES-SE	TR-IR	UK-SG	US-UK
AU-HK	BE-MU	CL-HU	FR-CL	DE-IR	HK-LT	IT-HU	JP-NO	LB-LU	NL-GR	PL-LT	RO-SE	ES-CH	TR-IT	UK-SK	
AU-HU	BE-NZ	CL-IS	FR-CZ	DE-IT	HK-LU	IT-IS	JP-PL	LB-MU	NL-HK	PL-LU	RO-CH	SE-AT	TR-KR	UK-ES	
AU-IS	BE-NO	CL-IR	FR-EE	DE-KR	HK-MU	IT-IR	JP-PT	LT-EE	NL-HU	PL-MT	SG-IR	SE-EE	TR-LB	UK-SE	
AU-IR	BE-PA	CL-LU	FR-FI	DE-LV	HK-NZ	IT-KR	JP-RO	LT-IS	NL-IS	PL-NL	SG-LT	SE-FI	TR-LU	UK-CH	
AU-LU	BE-PT	CL-NO	FR-GR	DE-LB	HK-NO	IT-LV	JP-SG	LT-LV	NL-IR	PL-NO	SG-LU	SE-HK	TR-NL	US-AU	
AU-MU	BE-SG	CL-PA	FR-HK	DE-LT	HK-PA	IT-LB	JP-SK	LT-LU	NL-LV	PL-PA	SG-MU	SE-IS	TR-NO	US-AT	
AU-NL	BE-SK	CL-PT	FR-HU	DE-LU	HK-SG	IT-LT	JP-ES	LT-MT	NL-LB	PL-PT	SG-NZ	SE-IR	TR-PL	US-BE	
AU-NZ	BE-SE	CL-SE	FR-IS	DE-MT	HU-AT	IT-LU	JP-SE	LU-IS	NL-LT	PL-RO	SG-NO	SE-LV	TR-PT	US-CA	
AU-NO	BE-CH	CL-CH	FR-IR	DE-MU	HU-EE	IT-MT	JP-CH	LU-MT	NL-LU	PL-SG	SG-PA	SE-LT	TR-RO	US-CL	
AU-PT	CA-AU	CZ-AT	FR-IT	DE-NL	HU-FI	IT-MU	JP-TR	LU-NZ	NL-MT	PL-SK	SK-EE	SE-LU	TR-SG	US-CZ	
AU-SG	CA-AT	CZ-EE	FR-KR	DE-NZ	HU-HK	IT-NL	JP-UK	MU-LU	NL-MU	PL-SE	SK-IS	SE-MT	TR-ES	US-EE	
AU-SK	CA-BE	CZ-FI	FR-LV	DE-NO	HU-IS	IT-NZ	KR-AU	MU-MT	NL-NZ	PL-CH	SK-IR	SE-MU	TR-SE	US-FI	
AU-SE	CA-CL	CZ-HK	FR-LB	DE-PA	HU-IR	IT-NO	KR-AT	MX-AU	NL-NO	PT-AT	SK-LV	SE-NZ	TR-CH	US-FR	
AU-CH	CA-CZ	CZ-HU	FR-LT	DE-PL	HU-LV	IT-PA	KR-BE	MX-AT	NL-PA	PT-CZ	SK-LT	SE-NO	TR-UK	US-DE	
AT-EE	CA-EE	CZ-IS	FR-LU	DE-PT	HU-LT	IT-PL	KR-CA	MX-BE	NL-PT	PT-EE	SK-LU	SE-SG	UK-AU	US-GR	
AT-FI	CA-FI	CZ-IR	FR-MT	DE-RO	HU-LU	IT-PT	KR-CL	MX-CA	NL-SG	PT-FI	SK-MT	SE-SK	UK-AT	US-HK	
AT-HK	CA-GR	CZ-LV	FR-MU	DE-SG	HU-MT	IT-RO	KR-CZ	MX-CL	NL-SK	PT-HK	SK-NO	SE-CH	UK-BE	US-HU	
AT-IR	CA-HK	CZ-LT	FR-NL	DE-SK	HU-MU	IT-SG	KR-EE	MX-FI	NL-SE	PT-HU	ES-AU	CH-EE	UK-CA	US-IS	
AT-LV	CA-HU	CZ-LU	FR-NZ	DE-ES	HU-NO	IT-SK	KR-FI	MX-FR	NL-CH	PT-IR	ES-AT	CH-FI	UK-CL	US-IR	
AT-LT	CA-IS	CZ-MT	FR-NO	DE-SE	HU-PA	IT-ES	KR-GR	MX-DE	NO-EE	PT-LV	ES-BE	CH-HK	UK-CZ	US-IT	
AT-LU	CA-IR	CZ-NO	FR-PA	DE-CH	HU-SG	IT-SE	KR-HK	MX-GR	NO-IS	PT-LT	ES-CA	CH-IS	UK-EE	US-JP	
AT-MT	CA-LV	CZ-SG	FR-PL	DE-TR	HU-SK	IT-CH	KR-HU	MX-HK	NO-IR	PT-LU	ES-CL	CH-IR	UK-FI	US-KR	
AT-MU	CA-LT	CZ-SK	FR-PT	DE-UK	HU-SE	JP-AU	KR-IS	MX-IS	NO-LV	PT-MT	ES-CZ	CH-LV	UK-GR	US-LV	
AT-NZ	CA-LU	CZ-SE	FR-RO	GR-AT	HU-CH	JP-AT	KR-IR	MX-IR	NO-LT	PT-NZ	ES-EE	CH-LB	UK-HK	US-LB	
AT-NO	CA-MT	CZ-CH	FR-SG	GR-CZ	IR-EE	JP-BE	KR-LB	MX-IT	NO-LU	PT-NO	ES-FI	CH-LT	UK-HU	US-LT	
AT-PA	CA-MU	EE-IS	FR-SK	GR-FI	IR-IS	JP-CA	KR-LT	MX-KR	NO-MT	PT-PA	ES-GR	CH-LU	UK-IS	US-LU	
AT-SG	CA-NL	EE-LU	FR-ES	GR-HK	IR-LV	JP-CZ	KR-LU	MX-LU	NO-NZ	PT-SG	ES-HK	CH-MU	UK-IR	US-MT	
AT-SK	CA-NZ	EE-MT	FR-SE	GR-HU	IR-LT	JP-EE	KR-MT	MX-NL	NO-PA	PT-SK	ES-HU	CH-NZ	UK-IT	US-MU	
AT-CH	CA-NO	FI-EE	FR-CH	GR-IS	IR-LU	JP-FI	KR-MU	MX-NO	PA-LU	PT-SE	ES-IS	CH-NO	UK-KR	US-MX	
BE-AT	CA-PA	FI-IS	FR-UK	GR-IR	IR-MT	JP-FR	KR-NL	MX-PA	PL-AU	PT-CH	ES-IR	CH-PA	UK-LV	US-NL	
BE-CZ	CA-PT	FI-IR	DE-AU	GR-LV	IR-MU	JP-DE	KR-NZ	MX-PT	PL-AT	RO-AT	ES-LV	CH-SG	UK-LB	US-NZ	
BE-EE	CA-RO	FI-LV	DE-AT	GR-LT	IR-NZ	JP-GR	KR-NO	MX-SG	PL-BE	RO-BE	ES-LT	CH-SK	UK-LT	US-NO	
BE-FI	CA-SG	FI-LT	DE-BE	GR-LU	IR-PA	JP-HK	KR-PA	MX-ES	PL-CA	RO-CZ	ES-LU	TR-AU	UK-LU	US-PA	
BE-GR	CA-SK	FI-LU	DE-CA	GR-NZ	IT-AU	JP-HU	KR-PL	MX-SE	PL-CL	RO-FI	ES-MT	TR-AT	UK-MT	US-PL	
BE-HK	CA-SE	FI-MT	DE-CL	GR-NO	IT-AT	JP-IR	KR-PT	MX-CH	PL-CZ	RO-GR	ES-NL	TR-BE	UK-MU	US-PT	
BE-HU	CA-CH	FI-NZ	DE-CZ	GR-PT	IT-BE	JP-IT	KR-RO	MX-TR	PL-EE	RO-HU	ES-NO	TR-CA	UK-NL	US-RO	
BE-IS	CL-AT	FI-NO	DE-EE	GR-SG	IT-CA	JP-KR	KR-SG	MX-UK	PL-FI	RO-IR	ES-PA	TR-CL	UK-NZ	US-SG	

Country codes: Australia - AU; Austria - AT; Belgium - BE; Canada - CA; Chile - CL; Czechia - CZ; Estonia - EE; Finland - FI; France - FR; Germany - DE; Greece - GR; Hong Kong - HK; Hungary - HU; Iceland - IS; Ireland - IE; Italy - IT; Japan - JP; Latvia - LV; Lebanon - LB; Lithuania - LT; Luxembourg - LU; Malta - MT; Mauritius - MU; Mexico - MX; Netherlands - NL; New Zealand - NZ; Norway - NO; Panama - PA; Poland - PL; Portugal - PT; Romania - RO; Singapore - SG; Slovakia - SK; Spain - ES; South Korea - KR; Sweden - SE; Switzerland - CH; Turkey - TR; United Kingdom - UK; USA - US.

Appendix D: Results under alternative priors

Table 3: Posterior means and posterior standard deviations (in parentheses) on transformed stock market correlations determinants under different prior model probability distribution.

g prior model prior MC^3	UIP Dillution No	RIC Uniform No	RIC Binomial-beta No	UIP Uniform Tessellation	UIP Binomial-beta Tessellation
$y_{ij,t-1}$	0.278***	0.278***	0.277***	0.278***	0.278***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
GDPdif	-0.111***	-0.112***	-0.112***	-0.111***	-0.111***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
GDPprod	0.163***	0.163***	0.162***	0.163***	0.163***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
PEflows	0.065***	0.065***	0.065***	0.065***	0.065***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
CapControls	0.069***	0.068***	0.068***	0.069***	0.069***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Exchange	0.056***	0.056***	0.056***	0.056***	0.056***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
FDdif	-0.099***	-0.098***	-0.098***	-0.099***	-0.099***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
FDprod	0.126***	0.126***	0.126***	0.126***	0.126***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Sharpe	0.000	0.004	0.003	0.000	0.000
	(0.003)	(0.008)	(0.007)	(0.003)	(0.004)
$GDP_{pc}dif$	-0.000	-0.002	-0.001	-0.000	-0.000
	(0.003)	(0.006)	(0.005)	(0.002)	(0.003)
Return	0.000	0.001	0.001	0.000	0.000
	(0.002)	(0.004)	(0.003)	(0.001)	(0.002)
Stability	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.002)	(0.004)	(0.004)	(0.001)	(0.002)
Corruption	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.002)	(0.004)	(0.004)	(0.001)	(0.002)
GovEffectivness	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)
Voice	0.000	-0.001	-0.001	0.000	0.000
	(0.002)	(0.007)	(0.005)	(0.002)	(0.002)
SD	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.004)	(0.003)	(0.001)	(0.002)
Regulatory	-0.000	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
RuleofLaw	-0.000	-0.002	-0.001	-0.000	-0.000
	(0.002)	(0.006)	(0.005)	(0.002)	(0.002)
DEBTdif	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Rating	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
DEflows	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Trade	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)

*/**/*** denote the absolute value of the ratio of PM to PSD above 1/1.3/2.0; posterior standard deviations are in parentheses.

Appendix E: Results with stock market indices expressed in dollars

Table 4: Posterior means and posterior standard deviations (in parentheses) on transformed stock market correlation determinants under different prior model probability distribution.

Model prior	Uniform	Binomial-beta
$y_{ij,t-1}$	0.342***	0.342***
	(0.009)	(0.009)
GDPdif	-0.113***	-0.113***
	(0.008)	(0.008)
$GDP_{pc}dif$	-0.059***	-0.059***
	(0.009)	(0.009)
GDPprod	0.114***	0.114***
	(0.010)	(0.010)
PEflows	0.071***	0.071***
	(0.008)	(0.008)
CapMob	0.089***	0.089***
	(0.008)	(0.008)
Exchange	0.083***	0.083***
	(0.008)	(0.008)
FDprod	0.126***	0.126***
	(0.011)	(0.011)
FDdif	-0.055***	-0.055***
	(0.011)	(0.011)
SD	-0.001	-0.001
	(0.005)	(0.004)
Corruption	-0.000	-0.000
	(0.002)	(0.002)
RuleofLaw	-0.000	-0.000
	(0.002)	(0.002)
Stability	-0.000	-0.000
	(0.002)	(0.002)
Trade	0.000	0.000
	(0.002)	(0.002)
GovEffectiveness	-0.000	-0.000
	(0.002)	(0.002)
Regulatory	-0.000	-0.000
	(0.001)	(0.001)
Voice	0.000	0.000
	(0.001)	(0.001)
Sharpe	0.000	0.000
	(0.001)	(0.001)
Return	0.000	0.000
	(0.001)	(0.001)
DEBTdif	-0.000	-0.000
	(0.001)	(0.001)
DEflows	-0.000	-0.000
	(0.001)	(0.001)
Rating	-0.000	-0.000
	(0.001)	(0.001)

*/**/*** denote the ratio of PM to PSD above 1/1.3/2.0; posterior standard deviations are in parentheses.

Appendix F: Results with different measures of portfolio and direct equity flows

Table 5: Posterior means and posterior standard deviations (in parentheses) on transformed stock market correlation determinants under different prior model probability distribution.

Equity flows model prior	A Uniform	A Binomial-beta	B Uniform	B Binomial-beta
$y_{ij,t-1}$	0.281***	0.281***	0.277***	0.277***
	(0.009)	(0.009)	(0.009)	(0.009)
GDPdif	-0.119***	-0.119***	-0.112***	-0.111***
	(0.008)	(0.008)	(0.008)	(0.008)
GDPprod	0.139***	0.139***	0.164***	0.164***
	(0.010)	(0.010)	(0.010)	(0.010)
PEflows	0.056***	0.056***	0.074***	0.074***
	(0.009)	(0.009)	(0.008)	(0.008)
CapMob	0.067***	0.068***	0.069***	0.069***
	(0.008)	(0.008)	(0.008)	(0.008)
Exchange	0.054***	0.054***	0.056***	0.056***
	(0.008)	(0.008)	(0.008)	(0.008)
FDdif	-0.099***	-0.099***	-0.099***	-0.099***
	(0.010)	(0.010)	(0.010)	(0.010)
FDprod	0.124***	0.124***	0.127***	0.127***
	(0.012)	(0.012)	(0.011)	(0.011)
DEflows	0.001	0.000	0.000	0.000
	(0.003)	(0.003)	(0.001)	(0.001)
Sharpe	0.000	0.000	0.001	0.001
	(0.003)	(0.002)	(0.004)	(0.003)
Return	0.000	0.000	0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.001)
RuleofLaw	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Voice	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)
Stability	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)
Corruption	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)
Regulatory	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
GovEffectiveness	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)
$GDP_{pc}dif$	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.003)	(0.001)
SD	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Rating	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Trade	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
DEBTdif	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)

*/**/*** denote the absolute value of the ratio of PM to PSD above 1/1.3/2.0; posterior standard deviations are in parentheses.

A: $PEflows = PE_{ij,t} + PE_{ji,t}$ and $DEflows = DE_{ij,t} + DE_{ji,t}$.

B: $PEflows = \frac{PE_{ij,t}+PE_{ji,t}}{MC_{i,t}+MC_{j,t}}$ and $DEflows = \frac{DE_{ij,t}+DE_{ji,t}}{MC_{i,t}+MC_{j,t}}$.