Emerging Markets are Catching Up: Economic or Financial Integration?

Amir Akbari, Lilian Ng, and Bruno Solnik[1]

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[1]Akbari is from University of Ontario Institute of Technology, Ng is from Schulich School of Business at York University, and Solnik is from HEC Paris and Hong Kong University of Science and Technology. Authors' Contact Information: Akbari: amir.akbari@uoit.ca, Tel: (905) 721-8668; Ng: lng@schulich.yorku.ca, (416) 736-2100; Solnik: solnik@ust.hk, Tel: (852) 2358-7666. We thank Kee-Hong Bae, Alexander Barinov, Geert Bekaert, Long Chen, Ric Colacito, Zhi Da, Chuan-Yang Hwang, Zsuzsa Huszar, Andrew Karolyi, Jun Sik Kim, Sie Ting Lau, Yan Li, Qianqiu Liu, David Ng, Richard Roll, Konark Saxena, Stephan Siegel, Rien Wagenvoort, Terry Walter, Qinghai Wang, Xiaoyan Zhang, and participants at the Asian-Finance Association Meetings in Tokyo, Conference of Asia-Pacific Financial Markets in Seoul, China International Conference in Finance in Tianjin, China, Finance Down Under in Melbourne, Financial Management Association (FMA) Meetings in San Diego, FMA-Asia Pacific Conference in Hong Kong, Hong Kong University of Science and Technology, University of Ontario Institute of Technology, for many helpful comments and suggestions. We especially thank Eliza Wu and Bohui Zhang for providing an early motivation of our paper. This paper is a substantial revision of an earlier version entitled, "Integrated Markets: Economic or Financial Integration?" We are grateful to Asian Finance Association for the 2018 best paper award.

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ABSTRACT

We propose a simple metric to measure two aspects of market integration, namely economic integration (defined as a common cash flow dynamic) and financial integration (defined as a common risk pricing dynamic) and then examine their evolution through time while controlling for volatility. We find that developed (DEV) countries exhibit greater degrees of financial and economic integration than emerging (EMG) markets. While the financial integration gap between these markets remains large throughout the sample period, the EMG economies are catching up with their DEV counterparts in recent years – their level of economic integration has reached that of DEV countries.

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JEL Classification Number: F15, F30, G15, E44

I. Introduction

There has been a distinct increase in market integration among developed (DEV) countries in the 1980s, followed by emerging (EMG) markets in the 1990s.[1] Extant studies have widely attributed this increase in market integration to the rise in risk sharing among world economies but seemed to ignore the existence of their real economic activity.[2] However, with increased international trade and foreign investment, which in turn resulted in high interconnection of firms' cash flows in the global economy,[3] one would expect economic convergence among DEV and EMG economies. Therefore, ignoring the real economic channel would inevitably distort the interpretation of market integration. For example, even as the second largest economy behind the United States, China is still largely financially segmented from the world market. On the other hand, Ireland, one of the world's largest offshore financial centers, contributes little to global economic growth but is shown to be highly integrated financially. It is plausible that the institutional and economic differences between China and Ireland would suggest that these two countries exhibit dissimilar degrees of financial and economic integration, possibly resulting in China being more economically integrated with the global market, while Ireland being more financially integrated. But, thus far, there is little research that attempts to disentangle economic and financial integration across countries worldwide.[4] Without distinguishing the two forms of integration, one might not be able to determine whether the increased market integration is derived from the liberalization of financial markets that allows for better risk sharing, or from the growing real economic integration of companies worldwide. Hence, the goal of our study is to introduce a simple metric that would allow us to differentiate between economic and financial integration and examine their respective evolution through time.

Our metric is derived using a return decomposition approach, where economic integration is defined as a common cash flow dynamic and financial integration is defined as a common risk pricing dynamic. In the absence of a general theoretical model for economic and/or financial integration, we employ a standard global asset pricing formulation (global CAPM) under the assumption of complete markets and perfect financial integration.[5] In the global CAPM, there is a unique stochastic discount factor that prices all assets, irrespective of their location (see, for e.g., Solnik, 1974; Stulz, 1981), and the model holds for any currency employed as a numeraire. This asset pricing framework allows a clean separation between the present value of cash flows, discounted at the riskfree rate, and an adjustment due to risk pricing in financial markets. That is, stock returns

[1]See, for e.g., Bekaert and Harvey (1995); Phylaktis and Ravazzolo (2002); Carrieri et al. (2007); Pukthuanthong and Roll (2009); Bekaert et al. (2011); Eiling and Gerard (2015).

[2]Exceptions are the studies by Ammer and Mei (1996), Baele and Soriano (2010), and Bekaert et al. (2013).

[3]Based on the information from World Development Indicators, International Monetary Fund, and United Nations Conference on Trade and Development, international trade (e.g., merchandise trade), foreign direct investments inflows, and GDP have grown at a rapid pace for EMG markets relative to DEV countries.

[4]Exceptions are the studies by Ammer and Mei (1996), Baele and Soriano (2010), and Bekaert et al. (2013).

[5]While global equilibrium models, including the real and financial sectors, would provide a richer theoretical framework, they are non-tractable.

can be decomposed into revisions in cash flow expectations and revisions in risk pricing, where the revisions in cash flow expectations are driven solely by country/firm economic fundamentals and the revisions in risk pricing reflect adjustments of risk pricing in the financial market.

A country's economic (financial) integration with the global market is gauged by the reactions of cash flows (risk pricing) to global shocks. If markets have gained complete financial integration in terms of risk pricing, we should expect strong correlations in pricing valuation between countries.[6] However, in financially segmented markets, countries adjust their local risk pricing quite independently. Thus, a country's degree of financial integration with the global market is measured by the extent of comovements in risk pricing adjustments between the country and world market – the proportion of the country's risk pricing revision that is influenced by world risk pricing revision (i.e., the R-square). Similarly, if markets have attained full economic integration, a common shock would have a similar impact on economic output and growth, and in turn, on expected corporate cash flows in different countries. Accordingly, a country's real economic integration is determined by the proportion of its cash flow news influenced by the world cash flow news. If a country is totally segmented from the global market, then the values of both economic and financial integration metrics would be small (see, e.g., Pukthuanthong and Roll, 2009). In the case of the so-called mild segmentation, market integration falls in between the two aforementioned extreme cases of complete segmentation and full integration (Errunza and Losq, 1985).

While our proposed correlation or R-square approach is simple and not original (see Pukthuanthong and Roll, 2009), it disentangles the effect due to corporate cash flow correlation from the effect due to risk pricing correlation, as opposed to other studies that simply look at financial integration linked to return correlation. More importantly, our analysis examines the short- and long-run dynamics of economic and financial integration using a smooth-transition dynamic conditional correlation (STDCC) model of Ohashi and Okimoto (2016) that allows for trends in correlation while controlling for volatility. STDCC also permits us to investigate the behavior of integration during and around financial crises. Interestingly, our analyses present contrasting results from those reported in previous research.

Similar to the US study by Chen, Da, and Zhao (2013), we use firm-level analyst earnings forecasts to extract cash flows news (CF) and risk pricing adjustments (RP). In contrast, our decomposition of asset returns is motivated by the aforementioned global asset pricing model. For each country, we compute the monthly value-weighted averages of firm-level CFs and RPs, which are employed as proxies for their respective country-level measures. Firm-level analyst earnings forecasts are timely reactions of investors' cash flow expectations, and they incorporate forward-looking information. Our method also has several advantages over the variance decomposition approach of Campbell and Shiller (1988) and Campbell (1991) employed in Ammer and Mei (1996) and Baele and Soriano (2010). Unlike our methodology, the variance decomposition approach

[6] In the global CAPM, a security's risk premium is linearly related to the world premium. Assuming no changes in expected cash flows, a shock to the stochastic discount factor will solely affect risk premium adjustments with full correlation across all securities.

needs to resort to predictive regressions and to the selection of instruments when estimating CF and RP.[7] However, in the international setting, the choice of instruments is further constrained by the availability of country-specific variables. Furthermore, Ammer and Mei (1996) and Baele and Soriano (2010) employ country-level variables in estimating their models over the whole sample period, whereas we focus on individual firm-level expected earnings at the time the stock is priced. Thus, our methodology allows us to generate the time-series dynamics of integration and to draw the comparison between DEV and EMG countries.[8]

Studies of financial integration have primarily used two main integration measures, namely the R-square and earnings yield differentials. Carrieri, Errunza, and Hogan (2007), Pukthuanthong and Roll (2009) (hereafter PR),[9] Lehkonen (2014), and Eiling and Gerard (2015) focus on country or industry index returns and employ the R-square as a measure of global financial integration, but they do not measure economic integration. In particular, PR's R-square measure, while simple and easy to estimate, fails to account for the spurious link between correlation and volatility. As it is widely recognized, an increase in volatility can induce an increase in estimated correlation, and therefore, their R-square may be erroneously interpreted to reflect increased integration. In contrast, our study conducts an empirical analysis that adjusts for time-varying volatility. Bekaert, Harvey, Lundblad, and Siegel (2011) (BHLS, 2011), on the other hand, introduce a different integration metric based on the earnings yield (inverse of the price to earnings ratio) and postulate equality of earnings yields under the null of full integration. Their segmentation measure, "SEG", is defined as the weighted sum of the absolute country-global industry valuation differentials. If countries are financially integrated, the stock price valuation of current earnings should be identical (within an industry) across countries; hence, SEG should be low for integrated markets. Unlike our integration measures that employ forward-looking cash flows, SEG depends on the construction of the earnings yield, which uses backward-looking earnings as the numerator and the current and forward-looking equity price as the denominator. We relegate the detailed comparison of our measures with PR's R-Square and BHLS's SEG to Section II.C and highlight some empirical differences in Sections IV.C below.

We use data on a sample of 39,202 firms from 41 countries worldwide for the 1989-2015 period. Results show that integration measures vary across countries and over time, and that DEV countries tend to be more globally integrated, both economically and financially, than their EMG counterparts. For the China-Ireland example, China's integration with the world market is mainly through economic (i.e., 41.9%) rather than through financial integration (i.e., 10.9%). On the other hand, the extent of Ireland's financial integration (i.e., 40.0%) relative to that of its economic inte-

[7] Chen, Da, and Zhao (2013) provide a critical review of the use of predictive regressions approach in return decomposition.

[8] Ammer and Mei (1996) examine 15 industrialized countries, whereas Baele and Soriano (2010) look at the exposure of 21 local European equity markets to the US market.

[9] They state, "A sensible intuitive quantitative measure of financial market integration is the proportion of a country's returns that can be explained by global factors. If that proportion is small, the country is dominated by local or regional influences (p. 214)."

gration (i.e., 23.3%) reflects a stronger linkage between Ireland's offshore financial activity and the world market's rather than between its economic fundamentals and the world's.

A major contribution of our study is to look at the dynamics of integration. We show that both forms of integration have been increasing across all countries since the start of the sample period, but have fallen after the global financial crisis. Since the recent global crisis, the gap in economic integration between EMG and DEV countries has narrowed dramatically, but their gap in financial integration remains fairly stable. Differences in cross-country factors, such as monetary and fiscal policies, political issues, trade policies, market sentiments or other behavioral biases, institutional constraints, restrictions on capital flows, and other implicit and explicit financial barriers, potentially drive the risk pricing differences between these markets. However, even when their financial markets are quite segmented, the integration dynamics may indicate that economic integration of DEV and EMG countries has converged toward the end of 2015, suggesting that the driver of market integration for EMG countries is economic rather than financial. Overall, these results contrast markedly with those of prior studies that do not explicitly account for time-varying volatility in the correlation estimation and hence, suffer from the volatility bias or other technical biases.[10]

The paper is organized as follows. Section II presents a simple model in which we develop the measures of economic and financial integration. Section III describes the construction and estimation of the two integration measures. Section IV investigates the dynamics of economic and financial integration through time, and Section V concludes.

II. A Measure of Global Integration

Our measure of global integration is based on the pricing formula of a firm's expected cash flows in a global capital asset pricing model under the null of full financial integration.[11] This specification allows a clean pricing separation of the present value of cash flows discounted at the riskfree rate (cash flows effects), and the adjustment due to risk pricing in financial markets (risk pricing effects). We then introduce economic and financial integration metrics based on a particular form of integration. Theory suggests that if markets are financially integrated with the same pricing kernel, country-specific risk premiums should move in tandem across the world. Similarly, we postulate that in an economically integrated world economy, country-level cash flow news should move in tandem with global cash flow news. In this section, we derive a measure of each form of market integration within the pricing framework and then show how we estimate the

[10] It has been shown that increased volatility in subsamples could affect correlation estimation when the time-series dynamics of correlation and volatility are not directly modeled (see, for e.g., Boyer, Gibson, and Loretan, 1997; Longin and Solnik, 2001; Forbes and Rigobon, 2002). The nature of this potential bias is often misunderstood, and these papers provide a discussion of this issue.

[11] Using the null of full financial integration, and studying deviations thereof, are the standard practice in the literature. Working under the null of segmentation requires selecting arbitrarily a specific form of segmentation, and modeling it into an equilibrium framework is seldom feasible.

measure using firm-level cash flow forecasts.

A. Stochastic discount factor under full integration

In integrated markets, one pricing kernel (or stochastic discount factor) governs asset prices across the world.[12] Since Solnik (1974), it is widely accepted that a single stochastic discount factor (SDF) applies to all cash flows when using a given base currency (the US dollar in our empirical application), irrespective of their location.

The price of a security is derived based on its expected cash flows and their covariance with the stochastic discount factor.[13] For example, Cochrane (2005, p. 27) states the price of a security as

$$P_t = \sum_{j=1}^{\infty} \frac{E_t d_{t+j}}{(1+r_{f,t+j})^j} + \sum_{j=1}^{\infty} Cov_t(m_{t+j}, d_{t+j}), \tag{1}$$

where d is the dividend, r_f is the riskfree rate, and m is the pricing kernel. From Eq. (1), the price of a firm's security can be decomposed into two components: $P = PV + RA$. PV, the first term on the right hand side of expression (1), is the present value of expected future cash flows, discounted at the term structure of riskfree rates, and it depends solely on the economic fundamentals of the firm. RA, the second term, captures the adjustment of risk pricing (i.e., the risk premium adjustment) in the financial market. Contingent claims with the same risk properties should receive the same price, independent of the location of their trade.

From Eq. (1), the return on a security can be decomposed as follows:

$$\begin{aligned} R &= \frac{P_t - P_{t-1}}{P_{t-1}} \\ &= \frac{PV_t - PV_{t-1}}{P_{t-1}} + \frac{RA_t - RA_{t-1}}{P_{t-1}} \\ &= CF + RP, \end{aligned} \tag{2}$$

where R is the rate of return on a security, CF is the percentage price effect of a revision in cash flow expectations, and RP is the percentage price effect due to risk pricing adjustments. To facilitate our discussion, we later refer to CF interchangeably as cash flow revisions or cash flow news and to RP as risk pricing or risk premium revisions. Note that PV requires the discounting of cash flows at the term structure of riskfree interest rates, and that RA is solely the risk pricing adjustment. It is important to stress that CF partly reflects the (observable) change in interest rates, because future expected cash flows at time t enter the model estimation for their time-t present dollar value. A dollar expected in t years has a present value of a dollar discounted at the t-year riskfree rate. The change of interest rates is simply a revision in the dollar present value. R is therefore driven

[12] See, for e.g., Solnik (1974) and Stulz (1981).

[13] In the standard capital asset pricing model, the pricing kernel m can be represented as $m = a + bR_w$, where R_w is the return on the world market portfolio.

in part by revisions in cash flow expectations and in part by revisions in risk pricing. As SDF is observed to be volatile,[14] we expect RP to be volatile as well.

Our development of Eq. (2) differs from the traditional finance model, where expected cash flows are simply discounted at an implied cost of capital (identical for all maturities),[15] which is derived from the data at each point of time,[16] rather than at the term structure of interest rates. Both methodologies estimate CF and then assign the residual return as the market risk pricing adjustment RP. But our theoretical framework yields a cleaner return decomposition as CF is not affected by risk pricing, or by an estimation error associated with the implied cost of capital.[17]

Similar to Eq. (2), we also decompose the return on the world market portfolio and obtain the following expression,

$$R_w = CF_w + RP_w, \tag{3}$$

where CF_w is the global market-weighted cash flow component and RP_w is the global market-weighted risk pricing component.

B. R-square measures for global economic and financial integration

We employ a simple metric that allows us to study the evolution of integration over time. Our indicator of a country's financial integration with the world market is measured by the proportion of its risk pricing revisions (RP_c) that is influenced by global risk pricing revisions (RP_w). In other words, our measure of financial integration R^2_{Fin} is the R-square obtained from regressing country risk pricing revisions RP_c on global risk pricing revisions RP_w as follows.

$$RP_{c,t} \quad = \quad \alpha^{RP} + \beta^{RP} RP_{w,t} + \varepsilon_t^{RP}, \tag{4}$$

where β^{RP} represents a country's exposure of risk pricing adjustments to world risk pricing revisions, and ε_t^{RP} is the random error. Under the null hypothesis of full financial integration in a standard global CAPM, the R-Square should be one as mentioned above. If our benchmark does not apply and local risk pricing (i.e., country-level pricing kernel) is prevalent, then we would expect RP_c to be weakly correlated with RP_w. However, there is a possibility of other sources of global exposure, such as industry or other global factors. To address this issue, we perform additional multiple global-factor tests to evaluate the robustness of our measure in a subsequent section.

Measuring economic integration, however, is a formidable task. There is no widely-accepted

[14] The stock market volatility puzzle is commonly ascribed to the large volatility in the pricing kernel (stochastic discount factor). As Cochrane (2011) concludes in his Presidential address, "Discount rates vary a lot more than we thought" (p. 1091). Also, see a discussion and illustration for international markets in Campbell (1996).

[15] For estimations of the implied cost of capital, see, for e.g., Pástor, Sinha, and Swaminathan (2008), Hail and Leuz (2006), Chen and Zhao (2009), Lau, Ng, and Zhang (2012), and Chen, Da, and Zhao (2013).

[16] Chen, Da, and Zhao (2013) apply this decomposition to return data on US firms.

[17] The implied cost of capital is estimated from the data and can vary widely across firms and over time with some extreme values. However, it plays no role in our study.

measure of economic integration (see König and Ohr, 2013). Some researchers have tried to assess economic integration by looking at tariffs and barriers to trade, labor, and capital movements, or the extent to which the law of one price or purchasing power parity applies (e.g., Kalemli-Ozcan, Sørensen, and Yosha, 2001; Nowotny, Mooslechner, and Ritzberger-Grunwald, 2009). Others have looked at indicators of openness of economies, such as the ratio of imports or exports to national outputs (e.g., BHLS, 2011). More recent estimates of economic integration look at the measured commonality in country outputs (e.g., the correlation in GDP growth rates). Increasing integration of goods and factor markets would lead to increased similarities in the production structures and the pattern of foreign trade. Hence, countries are similarly affected by exogenous shocks. As König and Ohr (2013) state, "symmetry of business cycles, therefore, indicates that the economies are driven largely by common external shocks and that they are highly interdependent". Also, Dumas, Harvey, and Ruiz (2003) present an interesting theoretical model of the link between correlation in national output growth rates with global shocks and correlation in stock returns. Our metric of economic integration is inspired by this measure of national-output-growth correlation but uses data at the firm level rather than at the national output level. If countries become more integrated, then corporate cash flows should get more correlated across countries, suggesting that global shocks have a strong influence on firm cash flows.[18]

Similar to the measure of financial integration, the economic integration measure R^2_{Econ} is the R-square obtained from regressing a country's CF_c on global CF_w, as shown below.

$$CF_{c,t} \quad = \quad \alpha^{CF} + \beta^{CF} CF_{w,t} + \varepsilon_t^{CF}, \tag{5}$$

where β^{CF} represents the sensitivity of a country's cash flow news to world cash flow news. If countries are globally integrated, then they will be susceptible to the same global forces. Hence, their R^2_{Econ} as well as R^2_{Fin} measures are expected to be high as they reflect countries' common exposures to international macro economies and to changes in world risk pricing, respectively. If R^2_{Econ} and R^2_{Fin} are low, then the implication is that the country is primarily influenced by local or regional forces.[19] Results are reported in Section III.C.

Pukthuanthong and Roll (2009) and Eiling and Gerard (2015) employ the explanatory power of global factor models as a measure of global integration; their integration constructs are closest to our measures. PR (2009) use the R-square from the regression of a country's daily market index returns on the first 10 principal components extracted from a cross-section of daily returns on 17

[18] One could develop global equilibrium models of the real/financial sectors with home bias in the goods/financial markets that are somewhat limited and simplistic and not tractable for our purpose. While some home biases in consumption and production can be modeled in simple production and utility functions, financial autarchy is usually the only workable alternative to full financial integration. They could lead to various alternative conclusions on correlation. To be conservative, we therefore limit ourselves to the null hypothesis of perfect integration and deviations thereof.

[19] We are well aware that R^2_{Econ} would not be equal one even in a fully integrated world economy, given the diversity in firms and industries. To gain some perspective on the magnitude of our global economic integration measures, we use a benchmark of a large national economy that is regarded as integrated domestically, namely the U.S. We look at the domestic economic integration measures of US firms within the country (not globally).

most globally integrated countries as proxies for global risk factors. On the other hand, Eiling and Gerard measure market integration by the proportion of explained return variance of a single global factor model. Unlike our analysis, these two studies focus on measuring global financial integration as the R-square of total equity returns. However, equity returns tend to be more volatile than cash flow and risk pricing changes. Table 1 below shows that the country annual return variance is 3.63 (1.40) times larger than the annual variance of cash flow news (risk pricing changes). Such high equity return volatility, as BHLS (2011) point out, would reduce the power of a statistical test.

C. Comparison of R-squares and the earnings yield approach

An alternative approach to measuring market integration is BHLS's (2011) earnings yield methodology. We argue that this approach is not fitted well to derive measures of economic and financial integration within a unified framework. The approach employs a backward-looking measure and therefore suffers from a number of shortcomings. It is based on the premise that stock price valuation of past earnings should be identical (within an industry) across countries if the countries are financially integrated. Motivated by this argument, BHLS (2011) introduce a measure of financial segmentation, SEG, for a given country, as defined below.[20]

$$SEG = \sum_j IW_j |EY_j - EY_{w,j}|, \tag{6}$$

where IW_j is the weight of industry j in that country, and EY_j and $EY_{w,j}$ denote industry j's earnings yield determined in that country and the global capital market, respectively.[21] This ratio is computed using published (past) earnings divided by the current equity price.

In contrast, our measure of economic integration (cash flow effects) is unaffected by risk pricing effects and vice versa (see verification in Section IV.C). We employ the changes of PV normalized by the price (see CF in Eq. (2)) to estimate a country's economic integration, which is the R-square estimate from regressing a country's CF_c on the world CF_w. This results in a more sophisticated and forward-looking model to examine the correlation of *valuation changes* between countries, rather than their differences of *valuation levels*. Specifically, we focus on the interconnectedness (or "integration") of financial markets or economies worldwide. Thus, SEG and our measure reflect a somewhat different vision of integration.[22] As stressed in BHLS (2011, p. 3845-6), their justification assumes a special form of integration. Under the null of economic integration, all

[20]Their subsequent study (BHLS, 2013) measures economic and financial segmentation using predictive regressions for earnings and rates of return. That is, economic segmentation is linked to the dispersion in one-year-ahead earnings growth rates across countries/industries. The growth rate is predicted by past growth rates as well as a set of usual predictive variables. It is a special measure of segmentation. Even with a large set of predictive variables, their measures of economic and financial segmentation together explain only 17% of the variation in SEG in a simultaneous generalized method of moments system.

[21]The simple average of country SEG is their global segmentation measure.

[22]For short-term market dislocations resulting from limits to arbitrage and frictions such as funding illiquidity, see Pasquariello (2014) and Akbari, Carrieri, and Malkhozov (2017), among others.

firms in a worldwide country/industry are assumed to have the same growth rate, except for a white-noise, firm effect with no persistence. Under the null of financial integration, all firms are assumed to have the same risk pricing in a given industry worldwide (i.e., a firm's systematic risk is assumed to be simply equal to the world exposure, or world beta, of that industry). This is a narrow definition of integration.

National economies differ, even if they might be fully integrated. Economies, and industries within an economy, could have lower wages, flexible employment contracts, and varying prospects of rapid development in infrastructure, telecommunications, and education; all these lead to greater and more diverse growth opportunities. Differences in growth rates need not be a purely non-persistent white noise. Similarly, systematic risks (world betas) of different countries or industries could be persistently dissimilar for many reasons, even if the country is fully integrated with the world financial market. In the long run, the classical factor-equalization economic theory would suggest equalization of growth rates, but this is not suggested in the short or medium term. Thus, SEG can be explained not only by "valuation" segmentation but also by dispersion in national economic growth rates and risk characteristics. Our approach focuses on changes (shocks) in world cash flows. Even under the null of integration, we do not assume global equality of growth rates or of risk premiums. Instead, we assume long-term convergence to the global industry-level average earning yields in our computation of PVs (see Section III.A). Our approach assumes that global economic (or financial) shocks strongly and immediately affect a country if it is globally integrated, admittedly a concept of economic interconnectedness also opens to some criticism.

One striking feature of SEG is that it dramatically increases in periods of recessions or crises (see Figure 3 of BHLS (2011, p. 3878)). One can argue that the spikes observed in SEG are primarily caused by the empirical mix of *trailing* earnings and *current* stock price (impacted by expected future earnings) in the empirical estimation of the valuation model, not a fundamental change in valuation. On the other hand, our correlation-based measure of economic integration remains stable if a drop in expected future earnings is associated with the drop in prices. The comparison of dynamics between the two approaches is further detailed in Section IV, where we also provide an empirical verification that the industry composition has little impact on the dynamics of SEG.

In summary, both measures suffer from obvious shortcomings and the difficulty of benchmarking empirical results. Our empirical measure of expected cash flows could be tainted by analysts' biases and data quality, but our measure of economic integration is forward-looking. On the other hand, SEG is based on a simple valuation model that relies on a multiple of trailing earnings.

III. Measuring Economic and Financial Integration

In this section, we briefly describe how we compute cash flow revisions CF and risk pricing revisions RP and then employ these return components (CF and RP) to estimate measures of economic and financial integration of different markets worldwide. Finally, we analyze the robustness of our baseline evidence to alternative models, such as multifactor models, and to potential biases arising from analyst earnings forecasts.

A. *Cash flow and risk pricing revisions*

We employ a variant of Chen, Da, and Zhao's (2013) methodology in estimating CF and RP. Their approach employs the internal cost of capital as the discount factor, whereas ours follows the theoretical model by adopting the term structure of riskfree rates. We construct CF and RP by first estimating the firm-level PV (i.e., the first right-hand-side term in Eq. (1)) as follows:

$$\begin{aligned} PV_t &= \sum_{j=1}^{\infty} \frac{E_t d_{t+j}}{(1+r_{f,t+j})^j} \\ &= \sum_{j=1}^{15} \frac{EF_{t+j} \cdot (1-b_{t+j})}{(1+r_{f,t+j})^j} + \frac{TV_{t+15}}{(1+r_{f,t+15})^{15}}, \end{aligned} \tag{7}$$

where EF_{t+j} is the earnings forecast j years ahead, b_{t+j} is the plowback rate, TV_{t+15} is the terminal value, and $r_{f,t+j}$ is the term structure of riskfree rates. The expression of PV in Eq. (7) is quite similar to the empirical models used in the domestic context by Chen, Da, and Zhao (2013) and in the international context by Hail and Leuz (2006), Pástor, Sinha, and Swaminathan (2008), and Lau, Ng, and Zhang (2012). However, in discounting cash flows to value CF, these prior studies employ the implied cost of capital and not the riskfree rates as implied by the theoretical model shown in Eq. (1). As discussed above, the international asset pricing under perfect markets implies the existence of a unique SDF that prices all cash flows measured in one numeraire (currency), irrespective of their location. Consistent with extant international finance literature, we choose the US dollar as our base currency and express prices and earnings in dollars. Accordingly, we employ US Treasury bond yields as proxies for the term structure of riskfree rates.

Earnings forecasts, EF_{t+j}, are available from the I/B/E/S database. We use the median earnings per share (EPS) forecast of analysts for each company, as well as the forecast of EPS growth rates, from the Summary History Adjusted (consensus) dataset of I/B/E/S. We then convert these forecasts to their US Dollar equivalents using foreign exchange rates from Datastream. To compute each firm's PV_t, we require that the firm has non-missing earnings forecasts for the current year (EF_{t+1}), next two fiscal years ahead (EF_{t+2} and EF_{t+3}), or a long-term growth forecast (g_{t+3}).[23] For earnings forecasts beyond $t+3$, the long-term growth rate of each firm in country c is assumed to revert from g_{t+3} to the average long-term GDP growth rate of country c (lg_{t+3}) by $t+16$. lg_{t+3} is the expanding average of the country's GDP growth rates based on all available information to date, and all GDP growth rates are obtained from the World Development Indicators (WDI).

[23] If g_{t+3} is missing, then $g_{t+3} = EF_{t+3}/EF_{t+2} - 1$. If both EF_{t+3} and g_{t+3} are missing, then $g_{t+3} = EF_{t+2}/EF_{t+1} - 1$. If EF_{t+2} is missing, then $EF_{t+3} = EF_{t+2} \times (1 + g_{t+3})$. Following Pástor, Sinha, and Swaminathan (2008), firms with growth rates above 100% (below 2%) are assigned values of 100% (2%).

Hence, the earnings growth rate and earnings forecast are computed in the following manner.

$$\begin{aligned} g_{t+j} &= g_{t+j-1} \times \exp\left[\frac{log(lg_{t+3}/g_{t+3})}{13}\right] \\ EF_{t+j} &= EF_{t+j-1} \times (1 + g_{t+j}) \\ \forall j, &\quad 4 \leq j \leq 16. \end{aligned}$$

We obtain payout ratios (i.e., $1-b_{t+j}$) from Datastream to calculate b_{t+j} in Eq. (7). b_{t+j} is assumed to stay constant for three years and then linearly converge to the industry's average b_{t+j} for the rest of the investment horizon. Each firm's TV_{t+15} in industry k is estimated under the assumption that the price-earnings ratio of the firm converges to that of the industry k. To properly discount future cash flows in the above estimation, we use yields on US Treasury notes and bonds.

Based on Eq. (2), we can now compute a firm's cash flow (CF_t) and risk pricing (RP_t) revisions:

$$CF_t = \frac{PV_t - PV_{t-1}}{P_{t-1}}, \tag{8}$$

$$RP_t = R_t - CF_t, \tag{9}$$

where the variables in Eqs. (8)-(9) are as defined above. For every t, we construct value-weighted averages of CF_ts and RP_ts of all available firms within a country as proxies for the country's cash flow revisions ($CF_{c,t}$) and risk pricing changes ($RP_{c,t}$), respectively. Similarly, we use the value-weighted average of R_ts as a proxy for the country's stock market return ($R_{c,t}$).

To assess the relative contributions of a country's $CF_{c,t}$ and $RP_{c,t}$ to variations in the stock market return $R_{c,t}$, we decompose the variance of $R_{c,t}$ as follows:

$$\begin{aligned} Var(R_{c,t}) &= Cov(R_{c,t}, CF_{c,t} + RP_{c,t}), \\ 1 &= \frac{Cov(R_{c,t}, CF_{c,t})}{Var(R_{c,t})} + \frac{Cov(R_{c,t}, RP_{c,t})}{Var(R_{c,t})}. \end{aligned} \tag{10}$$

From Eq. (10), the proportionate contribution of $CF_{c,t}$ to $Var(R_{c,t})$ is the slope coefficient from regressing $CF_{c,t}$ on $R_{c,t}$, and the proportionate contribution of $RP_{c,t}$ to $Var(R_{c,t})$ is the slope coefficient from regressing $RP_{c,t}$ on $R_{c,t}$. We estimate these components on a total sample of 39,202 firms; 28,411 of them are from 21 DEV countries and 10,791 from 20 EMG markets. This sample of firms intersects the I/B/E/S and Datastream databases with non-missing earnings forecasts, payout ratios, and monthly returns information. Note that I/B/E/S typically excludes smaller firms with no analyst coverage, and such firms' stock returns available from Datastream are more prone to data errors, especially daily data (see Ince and Porter (2006)). To further mitigate possible returns data errors, we apply the filters suggested by Ince and Porter (2006) and employed by Karolyi, Lee, and van Dijk (2012). In addition, we winsorize firm-level CF and DR estimates before we aggregate them at the country level to reduce the effect of returns errors.

The start year on data availability and the number of unique firms employed in our sample are shown in the second and third columns of Table 1 by market type and by country, followed by summary statistics of return components (i.e., $R_{c,t}$, $CF_{c,t}$, and $RP_{c,t}$), as well as of individual variance components and variance decomposition. Panel A shows aggregate statistics of our sample of 41 countries, and Panels B and C report those of 21 DEV and 20 EMG markets, respectively.

Several noticeable results emerge from the table. Firm-level data from DEV countries are available starting in 1989, whereas those from EMG markets begin from 1989 to 1995. While there is limited information on firms from EMG markets at the start of our sample period, information becomes increasingly available by mid 1990s. Regardless of the types of markets, a larger fraction of the mean stock market return is due to risk pricing revisions rather than to cash flow revisions, and this result is more pronounced in DEV than in EMG countries. For example, in Panel A, on average, about 58% (=7.73%/13.26%) of annual country equity returns is due to $RP_{c,t}$, with the remaining 42% due to $CF_{c,t}$. For DEV countries, the return compositions are about 66% (=8.40%/12.70%) $RP_{c,t}$ and 34% $CF_{c,t}$, compared to 51% (=7.02%/13.84%) and 49% for EMG countries. In terms of volatility, the return variance is greater in EMG than in DEV countries, and the overall high variance is mainly attributed to a larger $RP_{c,t}$ variance than $CF_{c,t}$ variance. The last two columns of the table report the slope coefficients from regressing country cash flow revisions and risk pricing revisions separately on country stock returns. For both DEV and EMG countries, a substantial portion of their stock market return variation is driven by risk pricing revisions.

One may argue that PV, and therefore CF, are measured with noise, and that RP is simply a residual noise. If the estimate has a very low signal to noise ratio, CF would not be correlated to R and the variance of RP would be larger than that of R. CF is estimated independently of the market return R as it is estimated from earnings forecasts. Yet CF exhibits a significant explanatory power for R (unreported mean correlation of 0.54), but has a low positive correlation with RP (unreported mean 0.08). The variance of RP is significantly smaller than that of R (unreported mean 0.080 vs 0.112).

The finding that risk pricing effects explain a large fraction of stock market return variation is in line with prior evidence that stock market volatility is largely due to high volatility in stochastic discount rates (Campbell, 1996). For instance, using different methodologies and different samples, Ammer and Mei (1996) and Lau, Ng, and Zhang (2012) find that movements in equity risk premiums contribute significantly to variations in stock market returns for international markets, whereas others find consistent evidence based on US equity markets (Campbell, 1991; Chen, Da, and Zhao, 2013).

B. Estimating economic and financial integration

As discussed in Section II, our measures of a country's economic and financial integration are based on the explanatory powers of a single global-factor model, where we regress monthly country cash flow revisions (risk pricing adjustments) on monthly global cash flow revisions (risk pricing adjustments). The resulting estimated R-squares from the two regressions are our respective proxies for economic and financial integration. Results are reported in Table 2. Panel A shows cross-country averages of the economic integration measure (R^2_{Econ}), the slope coefficient β^{CF}, the financial integration metric (R^2_{Fin}), and the slope coefficient β^{RP}, by market type, and Panels B and C report those of individual DEV and EMG countries.

The table reveals a number of interesting findings. First, Panel A shows that countries tend to be more integrated through financial integration rather than through economic integration, and this finding is largely attributed to the greater degree of financial integration experienced by DEV than by EMG countries. The aggregate mean R^2_{Fin} is 45.2%, compared to 41.0% for the aggregate mean R^2_{Econ}. For DEV countries, their mean R^2_{Fin} is 55.2% and mean R^2_{Econ} is 48.2%, thereby underscoring the strength of financial integration in these countries. On the other hand, there is little difference in the degrees of financial and economic integration among EMG countries. Their average R^2_{Fin} and R^2_{Econ} are 34.8% and 33.4%, respectively. These results suggest that EMG countries lag behind their DEV counterparts in terms of economic and financial integration, consistent with the prior evidence (e.g., BHLS, 2011), but the gap between financial and economic integration seems much smaller for EMG than for DEV countries. However, it is necessary to stress that these findings are based on the assumption of time-invariant integration measures. In a subsequent section, we will allow integration to vary through time and then examine the dynamics of financial and economic integration across the two markets. In this analysis, we report that the dynamics of economic and financial integration are different.

One may argue that country CF_c or RP_c is possibly driven jointly by world RP_w and CF_w. To rule out the possibility of significant cross-effects between world cash flow revisions and risk pricing adjustments, we run regressions (4) and (5) by including both $RP_{w,t}$ and $CF_{w,t}$ as explanatory variables. The coefficient of the added variable is tiny and statistically insignificant, and the increase in R-square is quite small. For example, the average R^2_{Econ} (R^2_{Fin}) only increases from 41% (45.2%) to 42.5% (46.3%), which clearly suggests that the cross-effect of cash flow revisions and changes in risk pricing is negligible.

Second, the sensitivities of cash flow and risk pricing revisions, β^{CF} and β^{RP}, are greater in EMG than in DEV countries. The average β^{CF} and β^{RP} are 1.701 and 1.216 for EMG countries, compared to 1.163 and 1.036 for their DEV peers. If we use these sensitivity estimates as measures of global integration as in some existing studies,[24] we would have erroneously interpreted that EMG countries are more integrated with the world market than DEV countries. Such a concern is

[24] For example, Bekaert, Harvey, Kiguel, and Wang (2016) and Bekaert and Mehl (2017) advocate the sensitivity of a country's return to the world market return (i.e., the global beta) as a measure of financial integration. By definition, the market-cap weighted average beta must equal to one. This constraint is sometimes relaxed by taking the US market or a group of DEV markets (e.g., G7 countries) as a proxy for the world market index. But this ad hoc assumption changes the focus of the analysis. The stylized fact is that EMG markets typically have high betas and the U.S. has a low beta. This, however, does not necessarily imply that EMG markets are more integrated with the world market than US markets. Rather, it shows that EMG markets are more volatile (high betas) and a reduction of EMG market betas over time cannot be construed as a reduction in integration.

appropriately raised by Pukthuanthong and Roll (2009).

Lastly, individual country-level results, shown in Panels B and C, indicate that financial and economic integration vary widely across EMG and DEV countries. Specifically, 14 of the 21 DEV countries, while only half of the 20 EMG countries, exhibit a larger degree of financial than economic integration with the world market. Among DEV countries, the U.S. has the greatest degree of financial integration with the world market (82.4%), and Austria has the lowest (20.4%). Given the U.S.'s dominant financial role in world capital markets, it is not surprising that its markets are highly integrated with the world market. However, the U.K. displays the highest degree of economic integration (81.3%), followed by Germany (73.9%), whereas Spain is the lowest (16.2%). The U.S.'s economic integration of 49.5% places the U.S. way below the U.K. and Germany. Even though the US economy is the largest in the world, its economic interdependence with the rest of the world is small compared to its size. For example, its trade ratio (sum of exports and imports of goods and services measured as a share of GDP) is only 30%, compared to 84% for Germany and 60% for the U.K.[25] The strong economic integration of Germany and the U.K. (fourth and fifth world largest economies) with the global market lends support to their influential economic roles in Europe as well as in global markets. Japan is the world third largest economy and is globally more integrated through economic (64.6%) than through financial integration (45.7%).

Among EMG countries, Israel has the highest degree of financial integration with the world market (57.3%), whereas China has the lowest (10.9%). On the other hand, India displays the largest degree of economic integration (57.5%), and Egypt exhibits the weakest (11.1%). Of particular interest is China, the second-largest economy in the world. China has a larger degree of economic than financial integration; its R^2_{Econ} is 41.9%, compared to R^2_{Fin} of 10.9%. While China's government has recently improved capital mobility, there are still extensive capital controls in place, thereby inhibiting the extent of its financial integration with the world market. These measures of economic integration loom large for some EMG countries, but these countries have large trade ratios. For example, China has a trade ratio of 47%, compared to 30% for the U.S.

Overall, these findings underscore the importance of distinguishing each country's economic and financial integration with the world market.

C. US Integration Measures as Benchmarks

It is useful to gain some perspective on the significance of the estimated global economic and financial integration measures of our sample of 41 countries. To do so, we construct benchmark measures by looking at the level of integration within the U.S., a large country representative of a nationally integrated economy and financial market. The wide heterogeneity of US firms (i.e., differences in business diversification, locations, industries, size, leverage, earnings volatility, among others) makes the U.S. a reasonable benchmark. To illustrate the comparison with our global

[25]These are the average ratios given by the World Bank over the 2010-2015 period.

integration measures for 41 countries, we simulate US portfolios with similar numbers of firms as our typical countries; the average number of firms in our sample of countries is 956 firms and 680 if we exclude the U.S. We randomly draw 1,000 firms from a sample of 10,810 unique US firms and consider this random draw of firms as a pseudo-country. For this pseudo-country portfolio, we construct cash flow news and risk pricing adjustments and then regress them, separately, against their aggregate U.S. counterpart to estimate the pseudo country's R^2_{Econ} and R^2_{Fin}. We repeat this experiment 1,000 times. Based on the simulation, the average R^2_{Econ} is 69.9%, and its R^2_{Fin} counterpart is 90.2%. The 95% lower and upper bounds of R^2_{Econ} are 58.4% and 81.4%, respectively. Correspondingly, the bounds of R^2_{Fin} are 86.2% and 94.2%. Even within an integrated country such as the U.S., the measure of economic integration is much lower than that of financial integration (i.e., the difference of around 20%) and with greater dispersion. This result is perhaps expected. It is likely that the real economy of the U.S. with diverse firms does not adjust uniformly to countrywide shocks, and that there is a large variation in expected cash flow reactions. This could be explained, in part, by economic prices and real adjustments being sticky and by firms operating in different industries and at different levels of the value chain. In contrast, while US firms are diverse, their shares are predominantly listed in local markets. Expectedly, they are all affected by the same risk pricing effects, and their financial prices adjust immediately to market-wide shocks.

Comparing with the fully-integrated US benchmark, countries still seem far from attaining full global financial integration, on average, over our sample period. The closest to global financial integration are the U.S., France, the U.K., the Netherlands, and Germany. While many countries appear to have a relatively low measure of financial integration, their levels of economic integration are close to the within-US economic integration. What is remarkable is that the differences in our global financial and economic integration measures are small (i.e., on average, only 7.0% for DEV and 1.4% for EMG markets), while the difference for domestic (within) US financial and economic integration measures is large at 20.3%. In fact, many EMG and several DEV countries exhibit greater global economic integration than financial integration, but such observations are not evident in domestic US pseudo portfolios. Even though firms and economies are likely to be diverse across countries with different stages of development and with varying industry specializations, the global economic integration measures are surprisingly high relative to their financial integration measures, especially for EMG markets. The evidence reflects varying factors that influence risk pricing across different countries, such as differences in monetary and fiscal policies, differences in market sentiment or other behavioral biases, various institutional constraints, restrictions on capital flows, and other implicit and explicit financial barriers. On the other hand, nations and corporations face economic challenges from global competition and rapid international technological developments. As they trade and compete globally, their cash flows would be greatly affected by world economic conditions, even if their financial markets are partly segmented. These findings appear to suggest that economic realities of companies and nations may precede financial market openness in their path to global integration.

D. Robustness

In this section, we first check the robustness of our key conclusion based on a single global factor model and next verify whether our results are affected by the quality of analyst earnings forecasts.

D.1. *Multiple global-factor models*

We have shown that our single global factor explains a substantial variation of country cash flow news and risk pricing adjustments. One may, however, argue that in reality, there are several global factors and that using a single global factor might not capture the complete picture of a country's global integration (e.g., Pukthuanthong and Roll (2009); Hou, Karolyi, and Kho, 2011). To address this issue, we estimate our integration metrics, R^2_{Econ} and R^2_{Fin}, based on the explanatory power of multiple global-factor models, whose global market factors are estimated using a principal component approach.

We construct the global factors in the following manner. First, we compute the covariance matrix of cash flows news using 27 countries with non-missing information for the entire sample period of 1989-2015 and calculate the eigenvalues and corresponding eigenvectors of this covariance matrix. Next, the eigenvalues are sorted from the largest to smallest, and then principal components from the cash flow news are estimated. In 1990, data on Indonesia become available. The procedure is repeated using 28 countries for the period of 1990-2015, and accordingly, the principal components for 1990 onwards are updated based on the additional information. We do the same until information from the last country (i.e., Egypt in 1999) is added to the estimation process. By 1999, the information of all 41 country indexes is employed. The top five principal components, which account for 74% of the cumulative eigenvalues, are employed as proxies for global market factors. Our moving window approach exploits the full information of country cash flow news and is in the spirit of Pukthuanthong and Roll (2009), who estimate 10 principal components using index returns for 17 largest DEV countries with the longest period of available data. We repeat the same methodology to construct five principal components using 41 country-level risk pricing adjustments. Additionally, we conduct the same procedure using 39 value-weighted global industry portfolios of cash flow news and of risk pricing changes. Analyzing effects of global industry factors helps assess whether our main findings on the relative importance of economic and financial integration for DEV and EMG markets remain unaffected by national industry composition. Results are shown in Table 3, with cross-country averages of R^2_{Econ} and R^2_{Fin} using five global market factors in Panel A, and those using five global industry factors in Panel B.

We find that financial integration continues to be larger than its economic counterpart and that DEV countries are still more integrated than their EMG peers, consistent with the evidence from Table 2. Interestingly, the magnitudes of the multi-factor R^2_{Econ} and R^2_{Fin} are fairly similar across the two panels. For example, the degree of economic integration hovers between 48.1% (EMG) and 64.9% (DEV) based on five global market factors, and between 42.8% (EMG) and 60.0% (DEV) based on five global industry factors. Their financial integration measures are almost identical across market and industry factors. While increasing the number of global factors (i.e., principal components) will statistically improve the overall mean R-square, this increase is quite uniform across all integration measures. Importantly, the main findings on the relative size of economic and financial integration measures for DEV and EMG countries remain materially unchanged.

D.2. *Analyst earnings forecasts*

While international data on analyst earnings forecasts have been employed in extant studies (e.g., Hail and Leuz (2006) and Lau, Ng, and Zhang, 2012), earlier studies have raised concerns that earnings forecasts may be optimistic, inaccurate, or sluggish, and hence, variations in stock returns are likely driven by risk pricing adjustments rather than cash flow news in the short run. We adjust these biases, respectively, as follows: (i) by employing the minimum value of analyst forecasts (e.g., Li, Ng, and Swaminathan, 2013), (ii) by using the inverse of (1 + a firm's analyst forecast error) as the weight to compute weighted-averages of country and global portfolio cash flow news and risk-pricing adjustments, and (iii) by sorting firms in each country into five portfolios based on their past year's stock returns and then subtracting each firm's analyst forecast error from the average portfolio error (e.g., Guay, Kothari, and Shu, 2011).

Panel A of Table 4 shows, for ease of comparison, the mean R^2_{Econ} and R^2_{Fin} from our base model in Table 2, and Panels B-D highlight the cross-country mean R^2_{Econ} and R^2_{Fin} based on adjustments to the different analyst forecast biases. The results suggest that while the economic and financial integration measures remain materially unaltered, the bias associated with sluggish analyst forecasts has a slightly greater impact on the integration measures of DEV than on EMG markets. Comparing the results of Panels A and D, the average R^2_{Econ} drops by 6.3% in DEV countries, but by 1.3% in EMG markets.

In summary, our integration measures are robust to the inclusion of multiple global risk factors as well as to adjustments of analyst forecast biases.

IV. Dynamics of Economic and Financial Integration

A growing number of studies have shown that market integration is time-varying. Bekaert and Harvey (1995) are the first to study the time-series dynamics of market integration, and they characterize each market's integration process to switch between two regimes (i.e., full integration and complete segmentation).[26] In this section, we first conduct a simple sub-period analysis before developing our full-scale model of time-varying integration, followed by comparing our integration dynamics with that of BHLS's (2011) "point-in-time" *SEG* measure.

[26]Subsequent studies, such as Hardouvelis, Malliaropulos, and Priestley (2006), also employ the regime-switching method to study time-varying integration in European countries.

A. A sub-period analysis

We divide the entire sample period into four sub-periods (i.e., 1989-1995, 1996-2002, 2003-2009, and 2010-2015), and then re-estimate models (4) and (5) for each sub-period using country-level monthly observations to obtain measures of economic and financial integration. Average sub-period estimates of integration measures are depicted in Table 5 by market type.

A few interesting patterns emerge from the table. The results show that all countries have experienced increases in both economic and financial integration from the first (1989-1995) to third sub-period (2003-2009) but become less integrated following the global financial crisis (2010-2015). The process of economic integration seems slow during the first two sub-periods, but sharply increases in the third period and then reverses after the global financial crisis. Specifically, economic integration increases slowly from 23.4% in 1989-1995 to 25.3% in 1996-2002, and then peaks at 53.8% in 2003-2009 before trending downward to 45.1% after the global crisis. On the contrary, the pace of financial integration picks up earlier than that of economic integration. Financial integration surges from 21.0% in the first sub-period to 42.0% in the second sub-period, but its pace slows down thereafter. It is 55.8% during the third sub-period before declining to 51.7% in the last sub-period. Given that the analysis does not adjust for volatility bias, the sharp increase in the 2003-2009 period may be partly attributable to this bias. The next subsection addresses this issue.

B. Time-varying dynamics

A major problem with estimating the time-series dynamics of correlation is that changes in market volatility can bias correlation estimates. This bias can be large as illustrated in Boyer, Gibson, and Loretan (1997) and Forbes and Rigobon (2002). Boyer, Gibson, and Loretan provide a numerical simulation example where the true correlation is 0.5. When the sample correlation is estimated in periods of low volatility (50% of the observations), the estimated sample correlation is only 0.21, but it jumps to 0.62 in periods of high volatility (50% of the observations). In actuality, there is no correlation breakdown as the true correlation remains constant and equals 0.5 over the entire sample period. This issue is particularly acute in crisis periods when the upward bias on correlation can be large. Therefore, one needs to directly model volatility when estimating correlation.

In this section, we propose to model conditional volatility and conditional correlation using the smooth-transition dynamic conditional correlation (STDCC) model, developed by Ohashi and Okimoto (2016). The STDCC model expands Engle's (2002) dynamic conditional correlation (DCC) model to allow both the unconditional correlation, or the stationary level of correlation, and the conditional correlation to be time-varying.[27]

[27]The well-known DCC model assumes that the conditional correlation reverts back to an unconditional level fixed over the entire period, so it is poorly adapted to deal with time trends in correlation.

We assume that the country CF_c and world CF_w follow a bivariate AR(1)-GARCH(1,1) process,

$$\begin{aligned} CF_{c,t} &= c_0 + c_1 CF_{c,t-1} + u_{c,t}, &(11)\\ CF_{w,t} &= w_0 + w_1 CF_{w,t-1} + u_{w,t}, &(12)\end{aligned}$$

where $\mathbf{u_t} = (u_{c,t} \quad u_{w,t})' = \mathbf{H_t^{1/2}} \mathbf{v_t}$, with $\mathbf{H_t}$ being the 2×2 conditional covariance matrix at time t of CFs, and $\mathbf{v_t}$ is assumed to be independently, identically, and normally distributed with mean 0 and an identity covariance matrix $\mathbf{I_2}$. $\mathbf{H_t}$ can be expressed as $\mathbf{H_t} = \mathbf{D_t C_t D_t}$, where $\mathbf{D_t}$= diag$(h_{cc,t} \quad h_{ww,t})^{1/2}$. The conditional variance of each CF follows a GARCH(1,1) process,

$$\begin{aligned} h_{cc,t} &= \alpha_{0,c} + \alpha_{1,c} h_{cc,t-1} + \alpha_{2,c} u^2_{cc,t-1}, &(13)\\ h_{ww,t} &= \alpha_{0,w} + \alpha_{1,w} h_{ww,t-1} + \alpha_{2,w} u^2_{ww,t-1}, &(14)\end{aligned}$$

and $\mathbf{C_t}$ is the time-varying conditional correlation. $\mathbf{C_t}$ is modeled as follows.

$$\begin{aligned} \mathbf{C_t} &= \text{diag}(q_{cc,t} \quad q_{ww,t})^{-1/2}\, \mathbf{Q_t}\, \text{diag}(q_{cc,t} \quad q_{ww,t})^{-1/2}, &(15)\\ \mathbf{Q_t} &= (1-a-b)\, \mathbf{\bar{Q}_t} + b\, \mathbf{Q_{t-1}} + a\, \epsilon_{\mathbf{t-1}} \epsilon_{\mathbf{t-1}}{}', &(16)\\ \mathbf{\bar{Q}_t} &= (1 - G(s_t;\gamma,d))\, \mathbf{\bar{Q}^{(1)}} + G(s_t;\gamma,d)\, \mathbf{\bar{Q}^{(2)}}, &(17)\end{aligned}$$

where $q_{cc,t}$ and $q_{ww,t}$ are the diagonal elements of $\mathbf{Q_t}$, where $\mathbf{Q_t}$ is the 2×2 matrix driving the dynamics of $\mathbf{C_t}$, $\epsilon_\mathbf{t} = \mathbf{D_t}^{-1}\mathbf{u_t}$ is a standardized error vector, $\mathbf{\bar{Q}}_t$ is the unconditional correlation matrix of the standardized error $\epsilon_\mathbf{t}$, changing smoothly from $\mathbf{\bar{Q}^{(1)}}$ to $\mathbf{\bar{Q}^{(2)}}$ through time, and G is a logistic transition function given by

$$G(s_t;\gamma,d) = \frac{1}{1 + exp(-\gamma(s_t - d))}, \gamma > 0. \tag{18}$$

In expression (18), s_t (i.e., $s_t = t/T$) is a time trend, employed as a transition variable capturing long-run trends in unconditional correlation, d is a location parameter specifying the center of the transition, and γ is a smoothness parameter specifying the speed of transition. We repeat the same procedure when estimating the conditional correlation between the country RP_c and world RP_w.

Assuming $\mathbf{u_t}$ follows a multivariate normal distribution, we estimate the vector of parameters, $\mathbf{\Theta}$, in the bivariate AR(1)-GARCH(1,1) process using the maximum likelihood estimation.[28] The log likelihood function, $\mathcal{L}(\mathbf{\Theta})$, can be expressed as:

$$\mathcal{L}(\mathbf{\Theta}) = -T \times ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(ln|\mathbf{H_t}| \;+\; \mathbf{u_t'}\, \mathbf{H_t^{-1}}\, \mathbf{u_t}\right) \tag{19}$$

[28]If the normality assumption is violated, the estimators will have the quasi-maximum likelihood (QMLE) interpretation. Bollerslev and Wooldridge (1992) show that QMLE is consistent and asymptotically normal under fairly general regularity conditions.

Given $\mathbf{H_t} = \mathbf{D_t C_t D_t}$ and $\epsilon_\mathbf{t} = \mathbf{D_t^{-1} u_t}$, we can rewrite the likelihood function, $\mathcal{L}(\mathbf{\Theta})$ as

$$\mathcal{L}(\mathbf{\Theta}) = -T \times ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\Big(2\,ln|\mathbf{D_t}| \;+\; \mathbf{D_t^{-1}}\,\mathbf{u_t'}\,\mathbf{u_t}\,\mathbf{D_t^{-1}} + ln|\mathbf{C}_t| \;+\; \epsilon_\mathbf{t}'\,\mathbf{C_t^{-1}}\,\epsilon_\mathbf{t} -\; \epsilon_\mathbf{t}'\,\epsilon_\mathbf{t}\Big) \tag{20}$$

Notice that the first two terms of the above log-likelihood function are related to the conditional variance dynamics, whereas the last two terms are linked to the conditional correlation dynamics.

The log likelihood function can be written as the sum of two components, namely volatility and correlation. Let the variance parameters be denoted $\mathbf{\Theta_1} = (\alpha_0, \alpha_1, \alpha_2)$ for each country, and the additional correlation parameters be denoted $\mathbf{\Theta_2} = \big(a, b, \bar{\mathbf{Q}}^{(\mathbf{1})}, \bar{\mathbf{Q}}^{(\mathbf{2})}, d, \gamma\big)$. Then we have:

$$\mathcal{L}(\mathbf{\Theta}) = \mathcal{L}_1(\mathbf{\Theta_1}) + \mathcal{L}_2(\mathbf{\Theta_1}, \mathbf{\Theta_2}),$$

with

$$\mathcal{L}_1(\mathbf{\Theta_1}) = -T \times ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\Big(2\,ln|\mathbf{D_t}| \;+\; \mathbf{D_t^{-1}}\,\mathbf{u_t'}\,\mathbf{u_t}\,\mathbf{D_t^{-1}}\Big) \tag{21}$$

$$\mathcal{L}_2(\mathbf{\Theta_1}, \mathbf{\Theta_2}) = -\frac{1}{2}\sum_{t=1}^{T}\Big(ln|\mathbf{C}_t| \;+\; \epsilon_\mathbf{t}'\,\mathbf{C_t^{-1}}\,\epsilon_\mathbf{t} \;-\; \epsilon_\mathbf{t}'\,\epsilon_\mathbf{t}\Big) \tag{22}$$

In order to mitigate the dimensionality problems created by using 41 countries, we use the two-step approach initially proposed by Engle (2002) and widely used for these dynamic GARCH models. In the first step we maximize $\mathcal{L}_1(\mathbf{\Theta_1})$ to derive the value of the variance parameters for each country CF_c (and RP_c):

$$\widehat{\mathbf{\Theta}}_\mathbf{1} \in argmax \;\; \mathcal{L}_1(\mathbf{\Theta_1})$$

In the second step, we use these parameter values to maximize $\mathcal{L}_2(\mathbf{\Theta_1}, \mathbf{\Theta_2})$ to derive the correlation parameters for each country CF_c and CF_w (as well as RP_c and RP_w)

$$\widehat{\mathbf{\Theta}}_\mathbf{2} \in argmax \;\; \mathcal{L}_2(\widehat{\mathbf{\Theta}}_\mathbf{1}, \mathbf{\Theta_2}) \tag{23}$$

As stressed by Engle (2002), consistency in the first step will ensure consistency in the second step under reasonable regularity conditions.

Figures 1a and 1b plot the dynamics of economic and financial integration, as well as their 5% confidence intervals,[29] by market type. The integration dynamics of DEV (EMG) markets are

[29]The confidence intervals are computed using the empirical distribution of the average integration measures. Estimating the standard deviation of the integration measure is theoretically challenging. Therefore, we take a bootstrapping approach and from the estimated STDCC models, we randomly simulate the correlations between CF_c and CF_w pairs 1,000 times. From these series, we estimate, for each month, the standard errors of the measure of integration averaged separately over all developed and all emerging markets. These standard errors are used to compute the 5% confidence interval at each time period. We repeat this same procedure to simulate the correlations between RP_c and RP_w pairs 1,000 times.

measured by the squares of conditional correlations $\mathbf{C_t}$ averaged separately across all DEV (EMG) countries. Figure 1a shows that growth in economic integration has been slow but rather steady for both types of economies until 2005. The 2008-2009 global crisis has led to economies being much more interconnected and susceptible to the same economic shocks. As economic integration reflects the correlation of cash flow news across countries, a spike at the end of 2008 indicates worldwide revisions of future cash flow expectations. The interconnectedness continues to persist years after the initial shock. Interestingly, such shocks impact only revisions in cash flow expectations, but not revisions in risk pricing (see Figure 1b). Furthermore, the gap in economic integration between EMG and DEV countries has narrowed and subsequently converged by the end of our sample period. While economic integration has increased faster for DEV countries than EMG markets until 2005, the phenomenon has reversed in this recent decade, especially during the post-crisis period. The narowing gap is not due to the rising economic integration among EMG countries in the post-crisis period but is an outcome of a sharp reversal in DEV countries. This observed reversal may not be surprising because DEV economies seem less integrated following the wave of protectionism measures they employed in 2009. For example, according to a study by the World Trade Organization, G20 countries have imposed a total of 1,583 trade restrictive measures since 2008, but as of early 2016 only a quarter of these measures have been removed.[30] Similarly, the economic integration of EMG economies has also been trending downward, albeit at a much slower pace. This behavior can be explained by the continued growth of global businesses moving their manufacturing operations to EMG economies, and by the globalization of local companies as their exports thrive significantly in the recent two decades. For example, FDI inflows of EMG markets have soared from \$526 billion in 2007 to \$698 billion in 2014, whereas those of DEV countries have fallen from its 2007 peak of \$1,290 billion to a low of \$522 billion in 2014.[31]

Unlike Figure 1a, Figure 1b shows that while the gap in financial integration between EMG and DEV countries has slightly narrowed from 1989 to 2012, it still remains large. The reason is that financial integration in DEV countries has plateaued out as early as 2002, while that in EMG markets has kept slowly rising until 2012. Both markets, however, have experienced a drop in financial integration in recent years, probably due to the post-crisis wave of protectionism and financial regulation measures worldwide.[32] Many EMG markets have not really relaxed their restrictions on foreign ownership of their domestic capital, so it is not surprising that these markets are still financially segmented from the world market. Such capital restrictions do not prohibit these economies from enjoying the benefits of globalization. Combined, the evidence suggests that the driver of integration for EMG markets is economic rather than financial.

[30]WTO report: https://www.wto.org/english/news_e/news16_e/trdev_21jun16_e.htm.

[31]Source: UNCTAD.

[32]Note that STDCC accounts for changes in volatility (the GARCH type), so these results are not driven by volatility.

C. R^2_{Fin} *versus PR's R-Square and BHLS's SEG*

We now compare our financial integration measure R^2_{Fin} with two popularly referenced integration measures, namely PR's R-square and BHLS's SEG.

We first construct PR's R-square measures using the same daily data from Datastream following exactly their 10-factor methodology. Their measure of the annual global integration is defined as the R-square from regressing daily country returns on ten factors extracted from a principal component analysis of index returns of 17 DEV countries. The country universe of our study is different from theirs as they include many small countries classified as frontier markets whose firm-level cash flow data are not available. But we use the same 17 DEV countries to construct the global factors. To check the accuracy of our replication, we consider the case of DEV markets (pre-1974 cohort) as shown in Figure 4 of PR (2009, p. 225). The results of our own estimation are almost identical to theirs for the overlapping period (1989-2007) with a correlation of 0.99.[33]

Figure 2 depicts our R^2_{Fin} measures and PR's R-squares for DEV and EMG markets over the 1989-2015 period. There are some similarities in these measures. Regardless of market type, countries are becoming more integrated over the last couple of decades, and DEV countries are more integrated than their EMG counterparts. Integration trends upward until 2010 and then reverses downward. Furthermore, countries are distinctly more financially than economically integrated throughout the sample period. The order of magnitude between our measure and PR's R-square is roughly similar: PR'S use of daily data reduces correlation compared to monthly data, but the use of ten factors increases it. However, there are sharp differences between the two measures. PR R-squares are quite unstable and highly volatile, showing a clear volatility bias. In years of high volatility, the PR measure peaks dramatically: the 1990 oil shock, 1997 Asian crisis, 2001 dot-com bubble, and 2008-2009 global financial crisis. Actually, the correlation between VIX (US volatility) and PR measure for DEV countries is 0.38. Furthermore, PR estimate the correlation of total returns, whereas we remove the cash flow effect from total returns when examining the pure risk pricing effect. For example, we assign the increase in overall correlation of country returns during the 2008-2009 crisis (net of volatility bias) to the fact that national economies (i.e., firm cash flows) have become much more interconnected during the crisis, but not to a rise in the openness of financial markets. In contrast, PR do not differentiate the two effects, which partly explain the difference in financial integration measures during the recent financial crisis.

As discussed in Section II.C, BHLS (2011) construct a measure of segmentation (SEG) based on earnings yield (E/P) differentials across countries. In their empirical work, E is not forward-looking earnings but is past-year reported earnings. While P is the current stock price and reflects expectations about future cash flows, the numerator E is based on trailing realized cash flows published in the past twelve months.[34] With sticky trailing earnings, short-term changes in earnings

[33] A comparison graph is available upon request from the authors.

[34] When quarterly earnings are used, Datastream typically adds the last four published earnings. Hence, earnings are slowly revised when newly released recent quarterly earnings replace the oldest reported earnings in the database.

yields mostly come from P. For example, we have looked at the correlation of SEG for DEV markets used in Figure 3 of BHLS for 1973-2009, and the MSCI World index. It is -0.69 for levels and -0.57 for changes. The latter falls to -0.81 over the 2008-09 crisis period.[35] In the short-run, E/P behaves like $1/P$.

We now turn to BHLS's (2011) SEG as expressed in Eq. (6) and illustrate our comparison using an extreme example of a 50% global market crash (i.e., all stock prices move down by 50%). The market drop could be caused by a drastic worsening of the economic outlook (revision in expected cash flows), a drastic increase in risk aversion (increased risk pricing adjustments), or both. Trailing earnings will remain approximately the same in Eq. (6), but all prices drop by 50%, so earnings yields double and SEG will go up by 100%. Basically, there will be a peak in segmentation (doubling), but that is quite spurious based on the use of past and not forward-looking earnings, as opposed to P which immediately adjusts to changes in expectations. Those peaks are observed in all market crises (see, for e.g., Figure 3 of BHLS (2011, p. 3878)). This is markedly different from our approach based on expected future earnings: a drastic revision in future earnings caused by a crisis could "offset" the stock price drop. However, in the longer term, trailing earnings will catch up with future realized earnings, and the long-term trend of SEG would be unaffected. But it is poorly adapted for short-term movements, say within a year or two, especially around crisis periods.

To demonstrate, we consider the case of DEV markets as shown in Figure 3 of BHLS (2011, page 3878). BHLS report results for DEV markets up to 2009, therefore including the 2008-2009 crisis, while all other BHLS computations, including EMG market data, stop in 2005. Our own universe of DEV is identical to theirs. We recompute BHLS segmentation measure (using industries) for our data to check consistency. We replicate exactly their methodology using the same variables and data sources that they use; the methodology is described in Section II.C. The SEG estimates we have replicated match almost perfectly with the original BHLS estimates (correlation of 0.99).[36]

Recall that SEG is a segmentation measure, whereas ours are integration measures. For the purpose of comparison, we take 1 minus R^2_{Fin} ("Seg_{Fin}") as a proxy for financial segmentation. We plot the two measures in Figure 3 for the 1989-2009 period, where our sample period for DEV markets overlaps with BHLS's. SEG is primarily a financial segmentation measure as it is based on a financial valuation model (with trailing earnings). Its correlation with our financial integration measure is roughly -0.50 (or 0.50 between SEG and Seg_{Fin}), implying that both measures are related. While their scales are different, the dynamics can be compared.

Until a decade ago, companies in a large number of countries only reported annual earnings, so the lag was even more pronounced (e.g., earnings for November of year t are those for the previous full calendar year $t-1$). Therefore, unlike equity prices, earnings are backward looking.

[35]We thank Geert Bekaert for providing us with their time-series SEG results for developed markets from 1973 to 2009.

[36]A comparison graph between BHLS's original monthly results and our own SEG computation for the overlapping period 1989-2009 is available from the authors upon request. They are almost identical. We thank Geert Bekaert for providing us with their time-series SEG results for DEV markets from 1973 to 2009.

Both SEG and Seg_{Fin} show a downtrend in financial segmentation till 1997, but SEG exhibits wild peaks and bottoms lasting one or two years. Seg_{Fin} keeps showing a steady downtrend till 2002, while SEG tends to increase and exhibit a big bump in segmentation in the 2001-2002 Internet bubble. SEG experiences huge peaks during the 2008-2009 crisis; it triples between February 2007 and February 2009, while Seg_{Fin} remains stable.[37] Typically, the crisis affects both financial and economic aspects of countries; it results in an immediate downward revision in expected future earnings of all firms and that is accounted for in our forward-looking model. On the other hand, SEG is based on stable trailing earnings and gives the impression that earnings yield differentials jump dramatically (due to the $1/P$ effect), but unfortunately, this reflects an overly simplistic valuation model and not a fundamental change in valuation. Note that this spurious effect on SEG is not just a very short-term phenomenon as it spreads over two years. A similar effect shows during the 2002 Internet bubble burst and the untabulated 2011 Euro Sovereign crisis, even though stock price drops are less uniform across industries or countries.

Except in our robustness tests, we have not accounted for industry effects while SEG does to the extent that the industry mix is different across countries. If the reaction of industry factors to global shocks is disparate, it could affect segmentation measures. Past literature has shown that country factors tend to dominate industry factors, and this finding is further confirmed by BHLS (2011). We, therefore, check whether accounting for different national industry compositions that change over time makes a significant difference in the earnings yield approach and the dynamics of SEG. Computing the segmentation measure without taking into account the industry composition is straightforward. We simply look at the absolute earnings yield difference of each country with the world for each month. We then take the simple average over all DEV markets, as is done for SEG in Eq. (6). We call $SEG_{Country}$ the simple country segmentation measure and plot it in Figure 4 alongside SEG for the 1989-2009 period. The dynamics of $SEG_{Country}$ is similar to that of SEG. Accounting for different industry compositions and for changes thereof makes little difference in terms of trends or short-term dynamics of SEG.

Our financial integration measure is considerably smoother than estimates that do not adjust for the conditional volatility bias, especially during crises. That is intuitively appealing, as we would not expect financial markets to suddenly open up (as in PR) or be segmented (as in BHLS) during crisis periods. In their ground-breaking paper that examines the volatility bias, Forbes and Rigobon (2002, p. 2350) conclude, "When this unconditional correlation coefficient is used in tests for contagion, there is virtually no evidence of a significant increase in cross-market correlation coefficients during the 1997 east Asian crisis, 1994 Mexican peso devaluation, and 1987 U.S. stock market crash". We find a similar result, even for the 2007-2009 crisis. Hence, it might be useful to illustrate the importance of the volatility bias by using a simple exercise. We compute the RP correlations using a 36-month rolling window, averaged separately over DEV and EMG, as reported in Figure 5. We also plot the standard deviations of world RP returns (i.e., world RP volatility)

[37] This is another signal that our dynamic correlation methodology properly accounts for the drastic increase in volatility that could have led to "spurious" jumps in return correlation.

using a 36-month rolling window. The plots show dramatic changes in volatility over time and that peaks/troughs in correlation are associated with peaks/troughs in volatility. When volatility is not modeled, changes in volatility are spuriously picked up by time-varying correlation estimates which become quite volatile. After explicitly modeling time-varying volatility, as one should, we find that the underlying correlation estimate is much more stable.

V. Conclusion

Our study offers new insights on the cross-country variation of economic and financial integration. Over the full sample period, on average, DEV countries exhibit greater degrees of financial and economic integration than EMG markets but the gap between DEV and EMG markets is smaller for economic than for financial integration. The analysis of their time-series integration dynamics reveals several interesting phenomena. While the gap in financial integration between DEV and EMG markets is still large throughout the sample period, the EMG economies are catching up with their DEV counterparts in recent years – their level of economic integration has reached that of DEV countries. As opposed to some other studies, we do not find that financial integration exhibits wide swings or dramatically increases or drops in periods of crisis, a phenomenon that we assign to volatility bias. Financial integration increases gradually from 1989 to 2008 for both DEV and EMG markets, but slowly declines during the post 2008-2009 global crisis. However, economies have become more interconnected during the global crisis period and the ensuing recession. Such global shocks primarily affect cash flow expectations worldwide. Many countries have adopted various protectionist measures in the post-crisis period, which might explain why the level of financial integration has dropped subsequently. This drop is much more pronounced for DEV countries than for EMG markets, which have retained a high level of economic integration. Our results suggest that the path of market integration for EMG markets is through the economic realities of companies rather than through the local capital market openness.

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Figure 1. Dynamics of Economic (R^2_{Econ}) and Financial Integration (R^2_{Fin}) by Market Type

Figures 1a and 1b show the dynamics of economic (R^2_{Econ}) and financial integration (R^2_{Fin}) with their 5% confidence intervals. R^2_{Econ} (R^2_{Fin}) is proxied by the squares of conditional correlations of country cash flow news (risk pricing adjustments) and world cash flow news (risk pricing adjustments), as specified in Eqs. (11) to (18). The figure plots equal-weighted averages of R^2_{Econ} and R^2_{Fin} for DEV and EMG markets. Time-varying conditional correlations of country and world cash flow news and of risk pricing adjustments are derived using the smooth-transition dynamic conditional correlation specification. The 5% confidence intervals are constructed using a bootstrapping approach.

Figure 1a. Dynamics of R^2_{Econ}

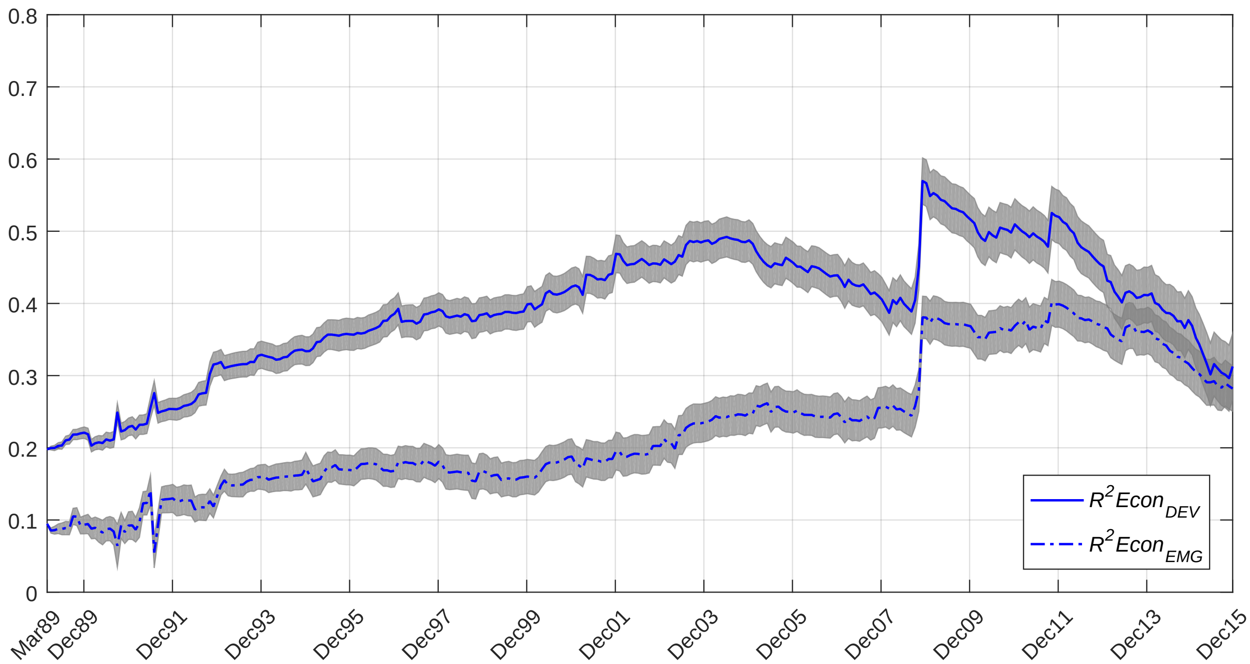

Figure 1b. Dynamics of R^2_{Fin}

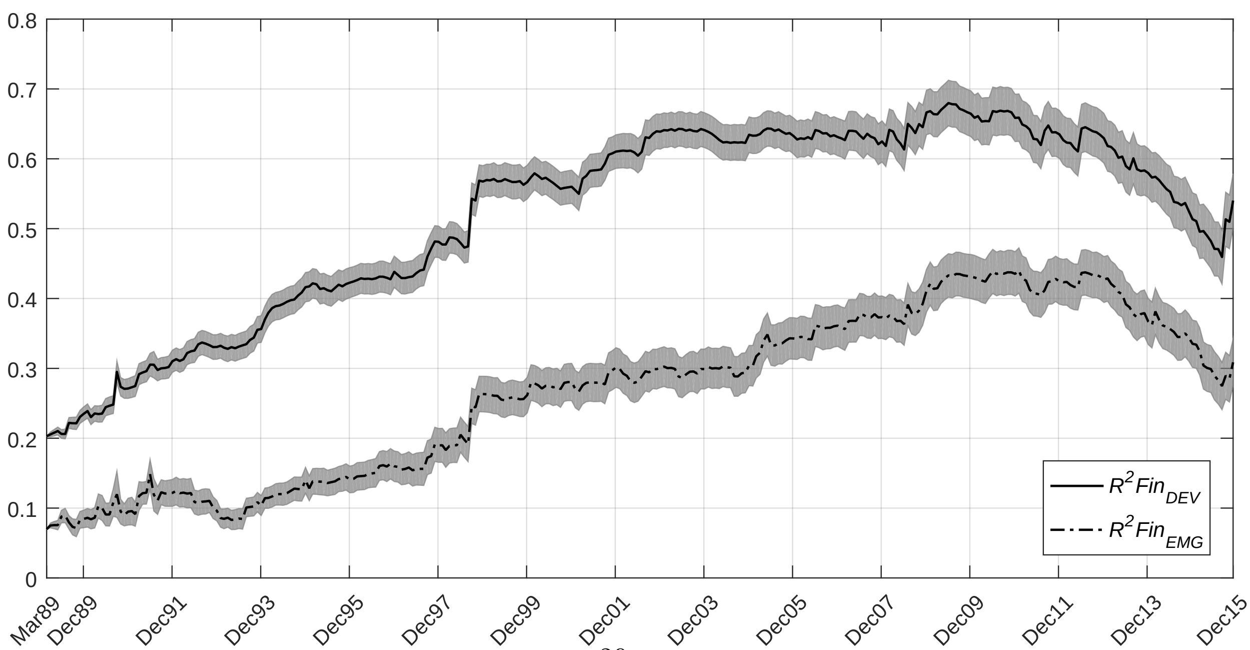

Figure 2. Comparison of Financial Integration Measures (PR's R-square vs. R^2_{Fin})

The graph shows Pukhuanthong and Roll's (PR's, 2009) R-square measure of market integration (black line marked with stars) and our proxy for financial integration R^2_{Fin} (red line). PR's R-square is obtained from a country-level analysis of a ten-factor international asset pricing model (the factors are extracted from a principal component analysis). The graph plots equal-weighted averages of the two measures for developed (DEV) and emerging (EMG) markets, shown with the solid and dashed lines respectively, during the 1989-2015 period.

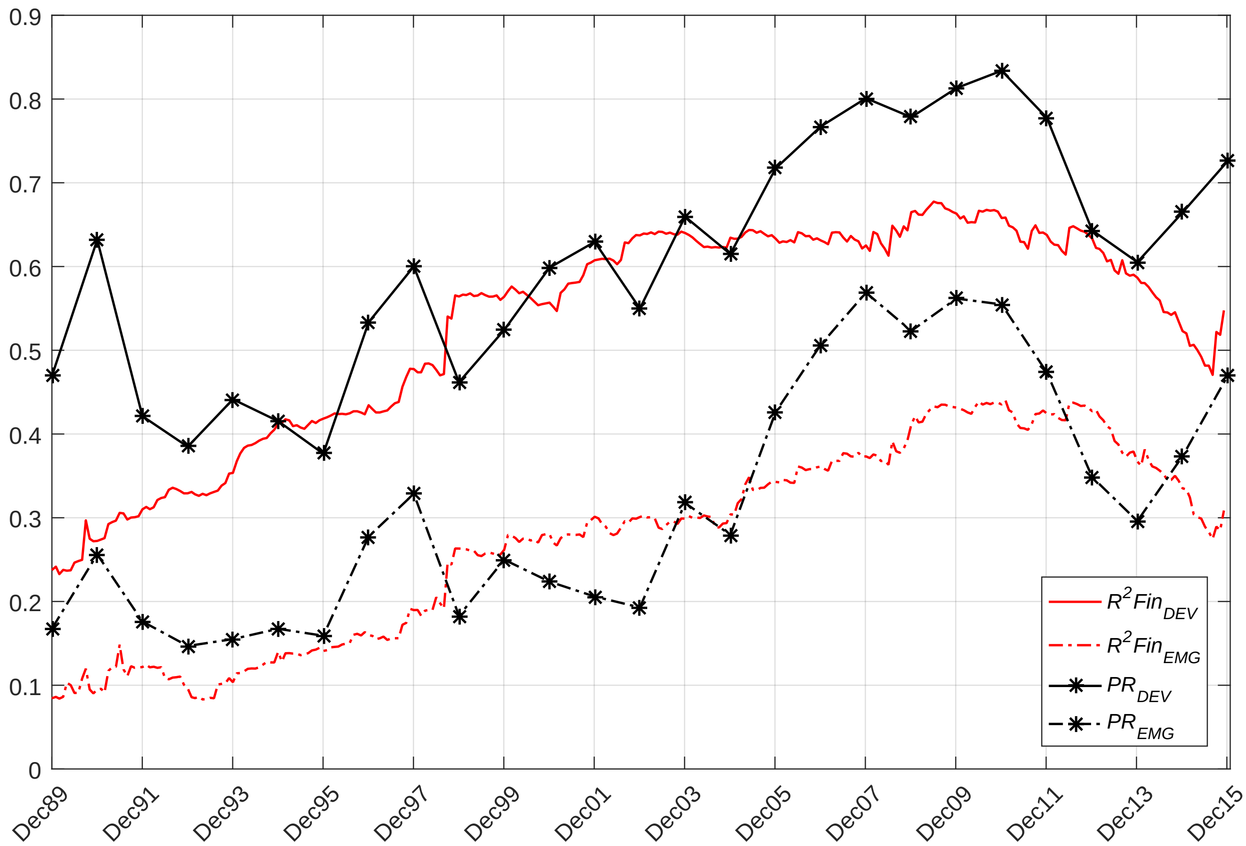

Figure 3. Comparison of Segmentation Measures for Developed Markets (BHLS's SEG vs. Seg_{Fin})

The graph shows BHLS's (2011) SEG Index, in black, (on the left Y-axis) and our proxy for financial segmentation ($Seg_{Fin} = 1 - R^2_{Fin}$), in blue, (on the right Y-axis). The SEG Index is calculated based on the sum of the weighted differences in earnings yields of industry portfolios between a country and the world market. The graph shows equal-weighted averages of the two measures for developed (DEV) markets during the 1989-2009 period. We thank Geert Bekaert for providing us with their time-series SEG results for developed markets from 1973 to 2009.

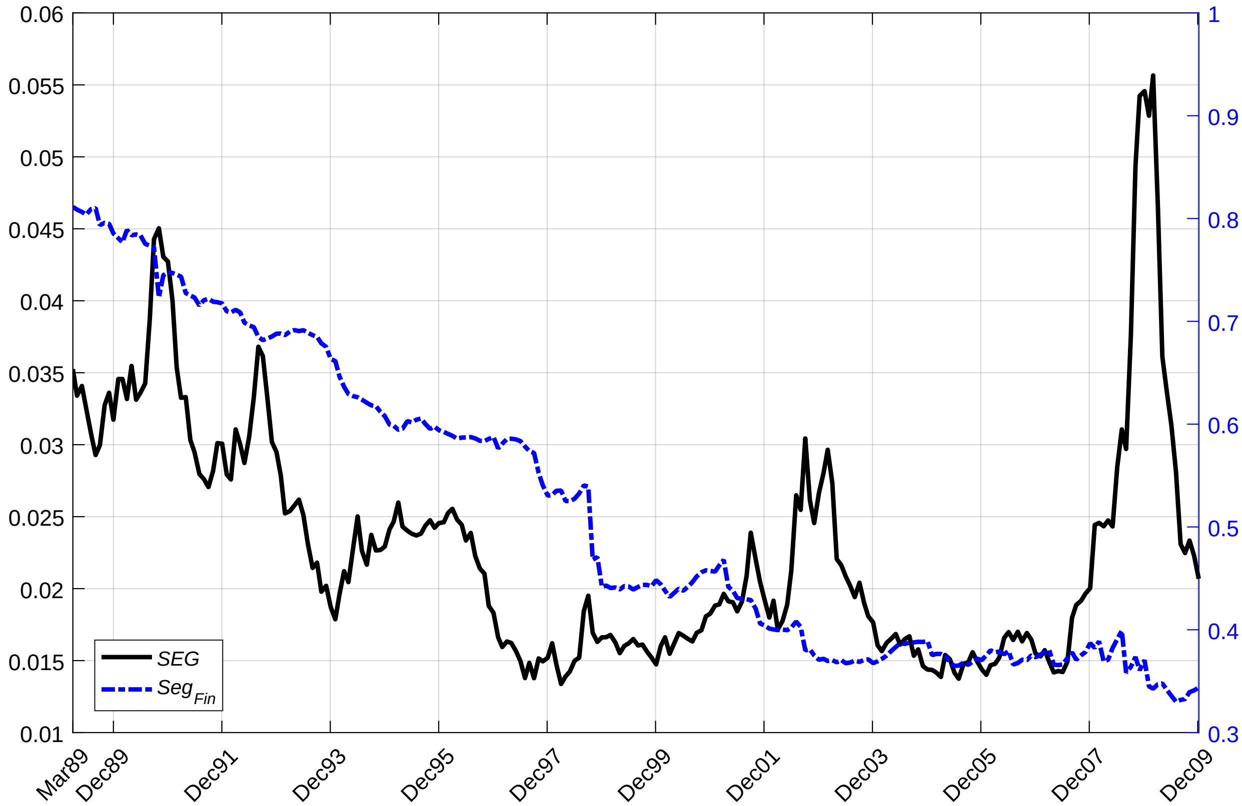

Figure 4. BHLS's Segmentation Measure (SEG) using Country/Industry-Level Earnings Yields

The graph shows BHLS's (2011) SEG Index, in black, (on the left Y-axis) and a $SEG_{Country}$ measure, in blue, (on the right Y-axis). The SEG Index is calculated based on the sum of the weighted differences in earnings yields of industry portfolios between a country and the world market. $SEG_{Country}$ is calculated similarly, but based solely on the absolute country-global earnings yield differentials and without taking industry composition into account. The graph shows equal-weighted averages of the two measures for developed (DEV) markets during the 1989-2009 period.

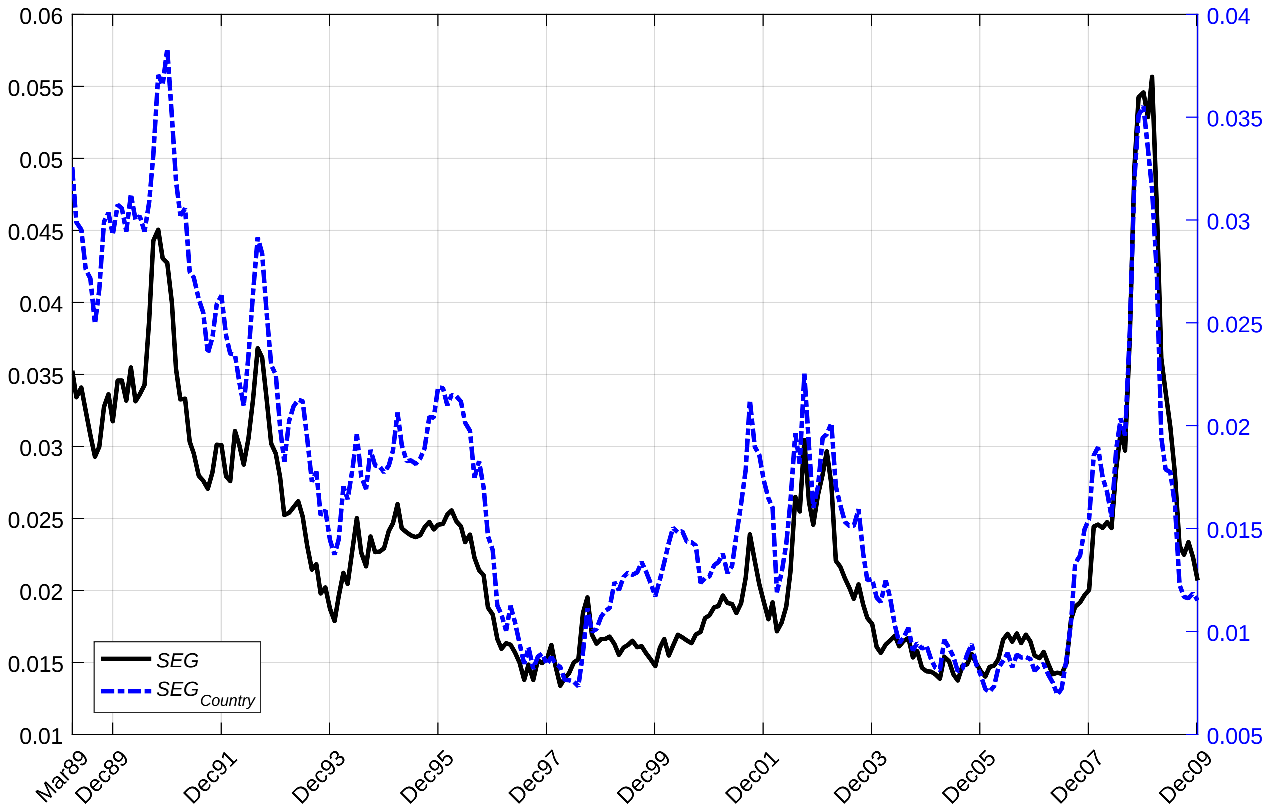

Figure 5. Conditional Risk-Pricing (RP) Correlations for Developed and Emerging Markets and World Market Volatility

The graph shows the dynamics of time-varying correlations of the risk pricing (RP) adjustment, in red, (scale on the left Y-axis) and the time-varying standard deviation of world RP returns, in black, (scale on the right Y-axis). For each country, we employ a 36-month rolling window to compute the RP correlation of that country and the world (RP_w). Similarly, we use a 36-month rolling window to compute the standard deviation of the world RP to estimate the world volatility (Stdev(RP_w)). The graph plots equal-weighted average of the correlations for developed (DEV) and emerging (EMG) markets, shown with the solid and dashed lines respectively, during the 1989-2015 period.

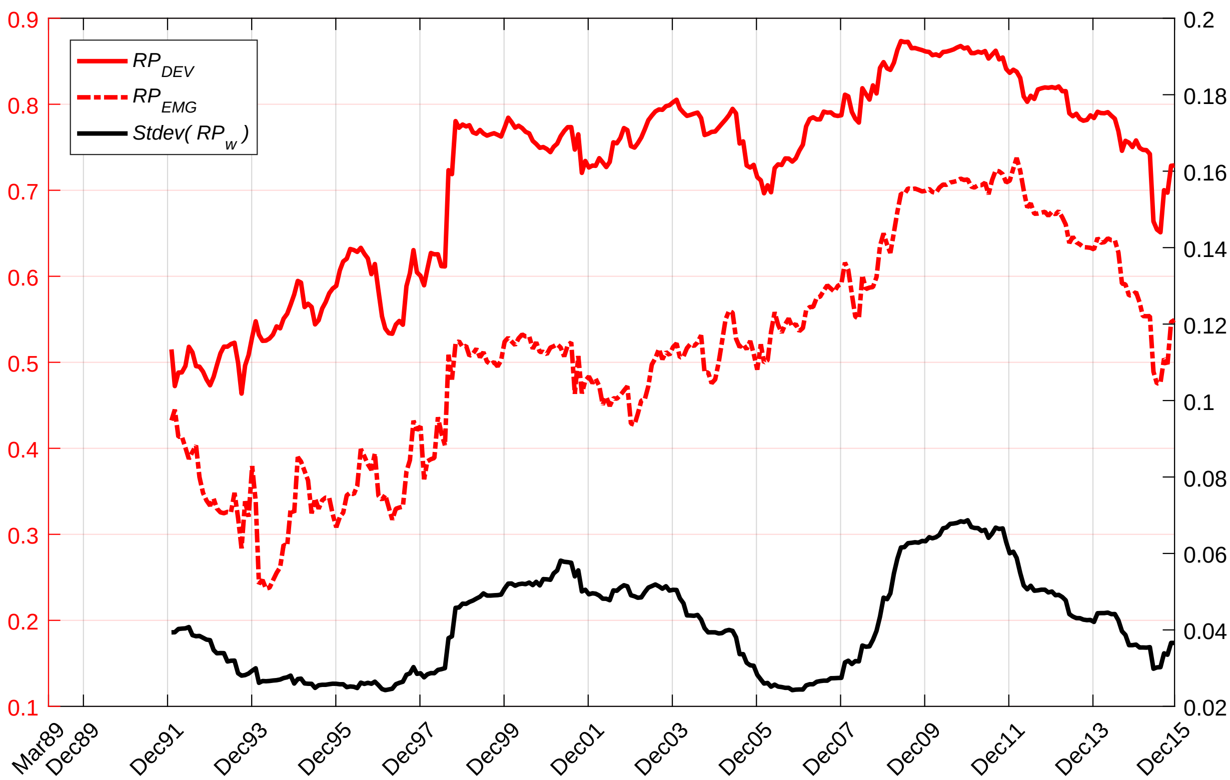

Table 1. Risk Pricing and Cash Flow Components derived from Return and Variance Decompositions by Country

This table reports the start-year of data availability, the total number of unique firms, mean return and variance, as well as the variance decomposition, by country. The average annual country return and variance are reported for returns (R_c), cash flow news (CF_c), and risk pricing adjustments (RP_c). For the variance decomposition, we report the slope coefficient from the regression of CF_c (RP_c) on R_c, and it is defined as the proportion of CF_c (RP_c) covariance with R_c in the variance of R_c. Panel A shows equal-weighted average values for the whole sample (ALL), developed (DEV), and emerging (EMG) countries; Panels B and C report those for 21 DEV and 20 EMG countries over the sample period of 1989-2015.

Country	Start Year	Total No. of Firms	Mean Return R_c	Mean Return CF_c	Mean Return RP_c	Variance R_c	Variance CF_c	Variance RP_c	Variance Decomposition $\frac{Cov(CF_c,R_c)}{Var(R_c)}$	Variance Decomposition $\frac{Cov(RP_c,R_c)}{Var(R_c)}$
Panel A: All, Developed (DEV), and Emerging Markets (EMG)										
Mean ALL	1989	39202	13.26%	5.53%	7.73%	0.112	0.031	0.080	0.252	0.748
Mean DEV	1989	28411	12.70%	4.30%	8.40%	0.066	0.013	0.048	0.226	0.774
Mean EMG	1989	10791	13.84%	6.82%	7.02%	0.161	0.050	0.114	0.279	0.721
Panel B: Developed Markets (DEV)										
Australia	1989	1515	13.25%	3.82%	9.43%	0.056	0.018	0.030	0.399	0.601
Austria	1989	139	11.06%	4.21%	6.86%	0.114	0.019	0.076	0.249	0.751
Belgium	1989	187	11.77%	4.38%	7.39%	0.055	0.010	0.047	0.168	0.832
Canada	1989	1959	12.23%	2.80%	9.43%	0.042	0.005	0.028	0.226	0.774
Denmark	1989	227	14.50%	5.01%	9.49%	0.047	0.006	0.036	0.171	0.829
Finland	1989	193	19.38%	3.53%	15.85%	0.168	0.032	0.118	0.245	0.755
France	1989	1124	11.58%	3.07%	8.51%	0.043	0.006	0.032	0.202	0.798
Germany	1989	1170	10.22%	3.33%	6.88%	0.060	0.007	0.046	0.172	0.828
Hong Kong	1989	831	15.98%	5.55%	10.43%	0.086	0.021	0.065	0.244	0.756
Ireland	1989	90	15.15%	7.48%	7.67%	0.065	0.015	0.049	0.241	0.759
Italy	1989	436	8.42%	3.26%	5.16%	0.063	0.010	0.048	0.203	0.797
Japan	1989	3890	4.24%	1.85%	2.40%	0.056	0.007	0.051	0.105	0.895
Netherlands	1989	265	12.36%	4.33%	8.03%	0.043	0.009	0.037	0.173	0.827
New Zealand	1989	149	14.03%	5.34%	8.68%	0.059	0.022	0.029	0.441	0.559
Norway	1989	356	15.33%	6.14%	9.19%	0.098	0.020	0.067	0.258	0.742
Singapore	1989	679	11.97%	5.04%	6.93%	0.086	0.014	0.056	0.253	0.747
Spain	1989	231	10.69%	4.03%	6.66%	0.059	0.019	0.047	0.254	0.746
Sweden	1989	519	16.23%	5.61%	10.62%	0.089	0.015	0.062	0.233	0.767
Switzerland	1989	295	13.87%	4.64%	9.23%	0.034	0.006	0.025	0.216	0.784
U.K.	1989	3346	10.25%	2.67%	7.58%	0.031	0.006	0.024	0.208	0.792
U.S.	1989	10810	14.20%	4.27%	9.93%	0.028	0.002	0.025	0.081	0.919
Panel C: Emerging Markets (EMG)										
Argentina	1993	73	14.39%	10.43%	3.95%	0.210	0.134	0.163	0.431	0.569
Brazil	1992	342	19.06%	10.43%	8.63%	0.226	0.072	0.142	0.345	0.655
Chile	1992	126	13.76%	5.18%	8.58%	0.107	0.019	0.071	0.260	0.740
China	1993	2375	15.25%	4.84%	10.41%	0.194	0.079	0.152	0.310	0.690
Egypt	1999	84	22.14%	14.66%	7.49%	0.358	0.168	0.132	0.549	0.451
Greece	1992	295	8.05%	2.93%	5.12%	0.196	0.051	0.160	0.220	0.780
India	1993	1313	17.85%	7.33%	10.52%	0.146	0.013	0.108	0.176	0.824
Indonesia	1990	325	15.02%	9.30%	5.72%	0.216	0.059	0.101	0.403	0.597
Israel	1995	110	11.65%	5.22%	6.43%	0.062	0.025	0.062	0.201	0.799
Malaysia	1989	934	14.06%	4.78%	9.28%	0.121	0.023	0.071	0.303	0.697
Mexico	1992	151	14.42%	5.66%	8.76%	0.117	0.015	0.088	0.187	0.813
Pakistan	1993	106	15.33%	8.78%	6.55%	0.180	0.098	0.208	0.194	0.806
Philippines	1989	146	15.44%	6.39%	9.05%	0.150	0.020	0.098	0.237	0.763
Poland	1995	307	10.44%	3.81%	6.63%	0.106	0.027	0.090	0.203	0.797
Portugal	1991	81	10.49%	3.56%	6.94%	0.079	0.018	0.060	0.230	0.770
South Africa	1989	477	12.34%	6.05%	6.29%	0.067	0.023	0.044	0.344	0.656
South Korea	1989	1446	8.91%	5.69%	3.23%	0.153	0.042	0.109	0.281	0.719
Taiwan	1989	1255	9.20%	4.62%	4.58%	0.106	0.022	0.082	0.213	0.787
Thailand	1989	559	10.97%	9.31%	1.66%	0.139	0.035	0.083	0.328	0.672
Turkey	1991	286	18.04%	7.42%	10.62%	0.298	0.059	0.262	0.159	0.841

Table 2. Measures of Economic and Financial Integration by Country

This table shows measures of economic and financial integration by market category. Economic integration is measured by the value of R-square (R^2_{Econ}) obtained from regressing a country's cash flow news (CF_c) on world cash flow news (CF_w). Financial integration is measured by the value of R-square (R^2_{Fin}) obtained from regressing a country's risk pricing adjustments (RP_c) on world risk pricing adjustments RP_w. Panel A reports equal-weighted averages of R^2_{Econ}, slope coefficient β_{CF}, R^2_{Fin}, and slope coefficient β_{RP} for the full sample (All), developed (DEV), and emerging (EMG) countries, as well as the difference of values between DEV and EMG countries, together with their $t-$statistic in parentheses. Panels B and C report those by DEV countries and by EMG countries. The sample consists of 21 DEV and 20 EMG countries for the 1989-2015 period.

	R^2_{Econ}	β^{CF}	R^2_{Fin}	β^{RP}
Panel A: All, Developed (DEV), and Emerging (EMG) Countries				
Mean ALL	0.410	1.425	0.452	1.124
Mean DEV	0.482	1.163	0.552	1.036
Mean EMG	0.334	1.701	0.348	1.216
DEV-EMG	**0.148**	**-0.538**	**0.203**	**-0.181**
	(3.16)	(-4.45)	(4.63)	(-2.11)
Panel B: Developed (DEV) Countries				
Australia	0.541	1.623	0.565	0.871
Austria	0.520	1.599	0.204	0.834
Belgium	0.438	1.094	0.509	1.039
Canada	0.649	0.925	0.592	0.862
Denmark	0.447	0.818	0.448	0.857
Finland	0.287	1.561	0.450	1.544
France	0.466	0.868	0.813	1.077
Germany	0.739	1.149	0.699	1.203
Hong Kong	0.329	1.362	0.427	1.122
Ireland	0.233	0.971	0.400	0.941
Italy	0.483	1.147	0.519	1.060
Japan	0.646	1.119	0.457	1.030
Netherlands	0.491	1.111	0.719	1.101
New Zealand	0.267	1.243	0.348	0.672
Norway	0.462	1.547	0.510	1.237
Singapore	0.588	1.454	0.519	1.147
Spain	0.162	0.893	0.587	1.121
Sweden	0.478	1.376	0.649	1.352
Switzerland	0.583	0.925	0.579	0.804
United Kingdom	0.813	1.136	0.765	0.908
United States	0.495	0.499	0.824	0.965
Panel C: Emerging (EMG) Countries				
Argentina	0.241	2.685	0.449	1.698
Brazil	0.255	2.026	0.393	1.484
Chile	0.483	1.478	0.333	0.979
China	0.419	2.694	0.109	0.796
Egypt	0.111	1.827	0.295	1.151
Greece	0.145	1.302	0.458	1.724
India	0.575	1.314	0.477	1.444
Indonesia	0.283	2.034	0.267	1.081
Israel	0.387	1.446	0.573	1.148
Malaysia	0.454	1.681	0.184	0.768
Mexico	0.479	1.301	0.467	1.301
Pakistan	0.165	1.914	0.346	1.690
Philippines	0.183	0.976	0.179	0.888
Poland	0.365	1.448	0.443	1.215
Portugal	0.255	1.055	0.521	1.162
South Africa	0.532	1.805	0.365	0.851
South Korea	0.237	1.628	0.295	1.204
Taiwan	0.469	1.623	0.244	0.941
Thailand	0.332	1.743	0.253	0.968
Turkey	0.303	2.037	0.315	1.833

Table 3. Measures of Economic and Financial Integration Using Multiple Global-factor Models

This table reports cross-country averages of economic and financial integration measures computed using the following multiple global-factor models.

$$CF_c = \alpha^{CF} + \sum_{j=1}^{5} \beta_j^{CF} CF_{w,j} + \varepsilon^{CF_c}$$
$$RP_c = \alpha^{RP} + \sum_{j=1}^{5} \beta_j^{RP} RP_{w,j} + \varepsilon^{RP}.$$

R^2_{Econ} is obtained from regressing a country's monthly cash flow news (CF_c) on five global market factors ($CF_{w,j}$, $j = 1, 2, ..., 5$), extracted from cash flow news of 41 DEV and EMG countries. Similarly, R^2_{Fin} is obtained from regressing a country's monthly risk pricing changes (RP_c) on five global market factors ($RP_{w,j}$, $j = 1, 2, ..., 5$), extracted from risk pricing changes of the 41 markets. The integration measures are reported in Panel A. Panel B reports similar measures of economic and financial integration but using five global industry factors, extracted from 39 global industry portfolios. The table also shows differential integration measures between EMG and DEV countries with $t-$statistic in parentheses.

	Economic Integration (R^2_{Econ})	Financial Integration (R^2_{Fin})
	Panel A: Using 5 World Market Factors	
Mean ALL	0.567	0.624
Mean DEV	0.649	0.701
Mean EMG	0.481	0.542
DEV-EMG	**0.168**	**0.159**
($t-$statistic)	(3.80)	(3.70)
	Panel B: Using 5 World Industry Factors	
Mean ALL	0.516	0.627
Mean DEV	0.600	0.704
Mean EMG	0.428	0.546
DEV-EMG	**0.172**	**0.158**
($t-$statistic)	(4.15)	(4.32)

Table 4. Robustness Tests of Baseline Models

This table reports equal-weighted averages of economic (R^2_{Econ}) and financial integration (R^2_{Fin}) measures. R^2_{Econ} is obtained from regressing country monthly cash flow news (CF_c) on world monthly cash flow news (CF_w). Similarly, R^2_{Fin} is measured by the R-square obtained from regressing country monthly risk pricing changes (RP_c) on world monthly risk pricing changes (RP_w). Panel A reports the results from Table 2, Panel A, as a benchmark for comparison purposes. Panels B-D report results that adjust for biases associated with (i) analyst optimism, (ii) analyst forecast errors, and (iii) sluggish analyst forecasts. To circumvent the bias in (i), we employ the consensus minimum value of analyst forecasts; to mitigate the error in (ii), we use the inverse of (1 + a firm's analyst forecast errors) as the weight to compute both the weighted-average country and weighted-average world cash flow and risk pricing changes; (iii) to address the problem of sluggish analyst forecasts, we take the difference between each firm's analyst forecast and its portfolio forecast error. The table also reports the differential integration measures between emerging and developed markets with $t-$statistics in parentheses.

	Economic Integration (R^2_{Econ})	Financial Integration (R^2_{Fin})
	Panel A: Baseline Model	
Mean ALL	0.410	0.452
Mean DEV	0.482	0.552
Mean EMG	0.334	0.348
DEV-EMG	**0.148**	**0.203**
($t-$statistic)	(3.16)	(4.63)
	Panel B: Analyst Optimism	
Mean ALL	0.402	0.446
Mean DEV	0.473	0.540
Mean EMG	0.327	0.347
DEV-EMG	**0.145**	**0.193**
($t-$statistic)	(3.30)	(4.48)
	Panel C: Analyst forecast Errors as Weights	
Mean ALL	0.409	0.451
Mean DEV	0.480	0.552
Mean EMG	0.335	0.345
DEV-EMG	**0.145**	**0.207**
($t-$statistic)	(3.10)	(4.63)
	Panel D: Sluggish Analyst Forecasts	
Mean ALL	0.372	0.417
Mean DEV	0.419	0.515
Mean EMG	0.321	0.315
DEV-EMG	**0.098**	**0.201**
($t-$statistic)	(2.06)	(4.32)

Table 5. Sub-period Analysis of Economic and Financial Integration by Market Type

This table replicates the regression analysis of Table 2 for each of the four sub-periods (i.e., 1989-1995, 1996-2002, 2003-2009, and 2010-2015) by market type. It reports equal-weighted averages of economic (R^2_{Econ}) and financial integration metrics (R^2_{Fin}), as well as the difference in integration levels between developed (DEV) and emerging markets (EMG), with $t-$statistics shown in parentheses. R^2_{Econ} is measured by the R-square obtained from regressing a country's monthly cash flow news (CF_c) on the world cash flow news (CF_w). R^2_{Fin} is measured by the R-square obtained from regressing a country's monthly risk pricing changes (RP_c) on the world risk pricing changes (RP_w). The sample consists of 41 countries (ALL), which are grouped into 21 DEV and 20 EMG countries.

	Economic Integration (R^2_{Econ})				Financial Integration (R^2_{Fin})			
Market	1989-1995	1996-2002	2003-2009	2010-2015	1989-1995	1996-2002	2003-2009	2010-2015
Mean ALL	0.234	0.253	0.538	0.451	0.210	0.420	0.558	0.517
Mean DEV	0.310	0.368	0.634	0.502	0.278	0.576	0.690	0.627
Mean EMG	0.115	0.131	0.436	0.397	0.122	0.257	0.420	0.401
DEV-EMG	**0.194**	**0.237**	**0.198**	**0.105**	**0.155**	**0.318**	**0.269**	**0.226**
($t-$statistic)	(3.61)	(6.72)	(4.82)	(3.27)	(2.86)	(6.89)	(5.51)	(5.10)