What Segments Equity Markets?

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We propose a new, valuation-based measure of world equity market segmentation. While we observe decreased levels of segmentation in many countries, the level of segmentation remains significant in emerging markets. We characterize the factors that account for variation in market segmentation both through time as well as across countries. Both a country's regulation with respect to foreign capital flows and certain nonregulatory factors are important. In particular, we identify a country's political risk profile and its stock market development as two additional local segmentation factors as well as the U.S. corporate credit spread as a global segmentation factor. (*JEL* F36, G15, G18)

The removal of capital controls in both developed countries (mostly during the 1980s) and emerging markets (mostly at the end of the 1980s and the early 1990s) has led to unparalleled financial openness across the world. The trade sector is also more open. These important structural changes should have had

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a profound effect on the valuation of stocks across the globe, and hence on important economic issues such as the cost of capital, international diversification benefits, and international risk-sharing. In particular, globalization may have narrowed valuation differentials between different equity markets.

Our research has three goals. First, we propose a new measure of the degree of effective or de facto equity market segmentation. The country-level measure is based on industry-level earnings yield differentials (relative to world levels), aggregated across all industries in a given country. Selecting industries as the anchor of our analysis has both empirical and economic appeal. Portfolio aggregation reduces noise, and firms within the same industry are most likely to have similar growth opportunities (as their input factors, production technology, and demand factors are similar) and similar systematic risk (the textbook finance assumption). We show that under the null hypothesis of full financial and economic integration, industry earnings yield differentials between a country and the world market should be (1) relatively small and fairly constant over time; and (2) explained entirely by differences in financial leverage and earnings volatility. Using data from within the United States, an effectively integrated economy, we confirm that segmentation within the United States is small (with a mean of 1.5%) and fairly constant (with a time-series standard deviation of 0.6%) relative to the level of measured segmentation for developed countries (with a mean of 3.0% and an average time-series standard deviation of 1.7%) and for emerging market economies (with a mean of 5.0% and an average time-series standard deviation of 3.1%). In contrast to most existing studies, our framework does not depend on a specific asset-pricing model.

Second, we apply our segmentation measure to sixty-nine countries over a sample period of more than twenty years. We document the extent to which market segmentation has decreased over time. While our segmentation measure is simple and imperfect, we observe convergence toward our null hypothesis of financial and economic integration. Using the U.S.-based empirical benchmark, we observe that the group of developed countries has been effectively integrated since 1993, while emerging markets continue to display levels of segmentation above the U.S. benchmark.

Third, we examine which country or global factors determine the cross-sectional and temporal variation in measured segmentation. Our factor regressions have two primary goals. Our first objective is to establish how much of the marked reduction in effective segmentation is accounted for by regulatory changes promoting financial and trade openness (de jure globalization). Previous research on this issue includes Nishiotis (2004) and Aizenman and Noy (2009), among others. Our second objective is to guide the literature on international pricing models in what concerns the factors affecting de facto segmentation. Early international asset-pricing models develop an endogenous relation between openness and market integration (see, for example, Stulz 1981; Errunza and Losq 1985). Recent efforts, while delivering subtle empirical predictions, tend to focus on only a few key determinants of international valuation differentials. For example, much of the recent literature (see, for example, Shleifer and Wolfenzon 2002; Hail and Leuz 2006; Albuquerque and Wang 2008) focuses on cross-country differences in corporate governance, setting aside other potentially important factors. However, other factors, such as political risk (Bekaert 1995; Erb, Harvey, and Viskanta 1996), liquidity risk (Lesmond 2005; Bekaert, Harvey, and Lundblad 2007), or inefficient markets (Morck, Yeung, and Yu 2000), may generate implicit barriers to important institutional investors and lead to de facto segmentation.[1] It is also possible that factors affecting investors in major markets (their preferences or the level of interest rates) affect price convergence across the world (e.g., Remolona, Scatigna, and Wu 2008; Baker, Wurgler, and Yuan 2010). Finally, note that under the alternative hypothesis (i.e., some degree of market segmentation), any country characteristic correlated with local growth opportunities or local discount rates may influence prices. We provide an empirical method to distinguish the relative importance of these factors, without imposing strong theoretical priors.

The remainder of the article is organized as follows. The second section introduces our measure of market segmentation. In Section 3, we characterize the degree of market segmentation across countries and industries. We apply our measure to the U.S. equity market in order to develop a benchmark for an effectively integrated market. In Section 4, we explore the link between de jure globalization and de facto segmentation. De jure openness significantly reduces de facto segmentation, but it cannot fully account for the downward trend we observe in segmentation levels. Section 5 examines what factors determine the variation in observed market segmentation across countries and time. In addition to financial and trade openness, a country's political risk profile, its stock market development, and the U.S. corporate credit spread (a measure of global risk aversion) are statistically and economically significant in explaining the variation in segmentation. Section 6 presents several robustness checks. In the final section, we offer some conclusions and discuss some related literature.

1. A New Measure of de Facto Market Segmentation

1.1 The measure

We view each country as a portfolio of N industries where an industry's portfolio weight corresponds to the relative (equity) market value of the industry in the country portfolio. Define the weight of industry j in country i by $IW_{i,j,t}$. Let $EY_{i,j,t}$ denote industry j's earnings yield, the inverse of the price-earnings (PE) ratio, as determined locally in country i and $EY_{w,j,t}$, the corresponding earnings yield as determined in global capital markets. Our main variable of

[1] In fact, using a quite different econometric framework, Carrieri, Chaieb, and Errunza (2010) demonstrate that local market risks are more likely to be significantly priced in emerging markets with poor institutional environments.

analysis is the absolute value of the difference between industry valuation ratios, $|EY_{i,j,t} - EY_{w,j,t}|$. We propose the weighted sum of these local-global industry valuation differentials as a measure of the degree of effective or de facto equity market segmentation for a country:

$$SEG_{i,t} = \sum_{j=1}^{N} IW_{i,j,t}|EY_{i,j,t} - EY_{w,j,t}|. \tag{1}$$

The use of industry-level aggregation is key for the market segmentation interpretation of our measure. Because we use absolute values in the computation, the measure is potentially sensitive to outliers and temporary volatility movements, therefore requiring some portfolio aggregation to reduce noise. The higher the number of firms in the portfolio, the more accurate the measure will be. The use of industry portfolios substantially increases the likelihood that firms within the same portfolio have similar growth opportunities (as they face similar production processes and market conditions) and similar systematic risk. In fact, the "finance textbook" assumption in corporate finance holds that systematic risk is industry-related.[2] Of course, the industry classification may be too coarse to prevent firms from being comparable across countries. We deal with this in two ways. We use an industry classification that is quite granular compared with that used in other work, involving thirty-eight different industries (see below). Selecting more industries than thirty-eight makes the measure too noisy, as in many countries we would have less than two firms in each of these more granular industry categories. We provide a robustness check by using a somewhat broader industry classification below (nineteen industries). In addition, in Section 3.2, we use this industry classification on a large integrated market (the United States) to verify that portfolios within industries have comparable multiples and to uncover biases that may arise in our measure.

Note that our measure requires only industry-level absolute valuation ratios that are observed at every point in time and are not estimated. From an implementation standpoint, the industry-based measure can be constructed in real time just by collecting the relevant components from widely available data sources. This contrasts with the standard international finance literature that employs econometrically *estimated* measures of segmentation based on, for example, the evolution of equity return correlations or systematic risk exposures (e.g., world market portfolio betas); see, for example, Baele (2005), Bekaert and Harvey (1995), Bekaert, Hodrick, and Zhang (2009), Eiling and Gerard (2011), Eun and Lee (2010), and Pukthuanthong and Roll (2009) for recent examples and Karolyi and Stulz (2003) for a survey of previous research.

[2] Edmans, Goldstein, and Jiang (2010) are a recent example of an article using industry valuations as a relevant benchmark for firm valuation. Nevertheless, we conduct two robustness checks on our main results. First, we use size-ranked portfolios as an alternative. Second, for our industry-based results, we consider an additional control variable that captures estimated industry-level global risk differences across countries. These are discussed in Section 6.

A recent example of the standard approach is Carrieri, Errunza, and Hogan (2009). They formulate a measure of integration based on a static asset-pricing model that links expected equity returns to local and global risk factors (variances and covariances) and prices of risks. In the empirical work, these prices of risk and risk factors are allowed to vary through time in a parametric fashion. Thus, the construction of these measures requires both historical data and a particular estimation methodology. Further, as their interpretation requires a formal international asset-pricing model (about which there is little consensus), estimation error is likely compounded by model misspecification.

Before proceeding, we should also acknowledge some shortcomings of our approach. Our framework relies on reported industry-level earnings yields as the building blocks for the construction of our segmentation measure. Reported earnings suffer from well-known errors and biases associated with accounting-based measures of earnings. That is, we never observe true (economic) earnings (see, for example, Black 1980). Further, there are well-known cross-country differences in accounting standards (see, for example, Joos and Lang 1994; Leuz, Nanda, and Wysocki 2003). Finally, efforts to harmonize international accounting standards (e.g., International Financial Reporting Standards [IFRS]; see Daske et al. 2008) may produce yield valuation ratio convergence through time, quite separate from a market integration trend.

1.2 Interpreting the measure: A simple pricing model

We now present a pricing model with stochastic growth opportunities and discount rates that links the measure to market integration. In sum, the model shows that under a strong notion of integration, encompassing both financial and economic integration, the time-varying components composing the industry PE ratios are identical across countries, being driven entirely by variation in the world discount rate and world growth opportunities.

We begin by defining real log earnings growth, $\Delta\ln(Earn_{i,j,t})$, with $Earn_{i,j,t}$, the earnings level in country i, industry j, as

$$\Delta\ln(Earn_{i,j,t}) = GO_{w,j,t-1} + \epsilon_{i,j,t}. \tag{2}$$

$GO_{w,j,t}$ represents the worldwide stochastic growth opportunity for each industry j that does not depend on the country to which the industry belongs; in contrast, $\epsilon_{i,j,t}$ is a country- and industry-specific earnings growth disturbance, which we assume to be $N(0,\sigma^2_{i,j})$. Because $\epsilon_{i,j,t}$ has no persistence, it will not lead to time variation in PE ratios.

The world growth opportunity follows a persistent stochastic process:

$$GO_{w,j,t} = \mu_j + \varphi_j GO_{w,j,t-1} + \epsilon_{w,j,t}. \tag{3}$$

We assume $\epsilon_{w,j,t} \sim N(0,\sigma^2_{w,j})$. The dichotomy between global "priced" growth opportunities and local "non-priced" earnings shocks imposes a form of *economic integration* across countries. If growth opportunities arise primarily through technological shocks, they may naturally lead to only world factors driving growth opportunities. In any case, the assumption is common in the literature; see, for example, Rajan and Zingales (1998) and Fisman and Love (2004). Bekaert et al. (2007) show that, in fact, global growth opportunities (measured using industry valuation ratios) predict real economic growth for both developed and emerging markets.

The real discount rate for each industry in each country, $\delta_{i,j,t}$, is affected only by the world discount rate, $\delta_{w,t}$, under the null of integration

$$\delta_{i,j,t} = r_f(1 - \beta_{i,j}) + \beta_{i,j}\delta_{w,t}, \tag{4}$$

where $\beta_{i,j}$ measures the exposure to the world market. The constant term, with r_f equal to the world risk-free rate, arises because the discount rates are *total*, not *excess*, discount rates. The assumption of a constant interest rate is inconsequential because real rates account for little of the variation in earnings yield ratios. The world market discount rate process follows

$$\delta_{w,t} = d_w + \phi_w\delta_{w,t-1} + \eta_{w,t}, \tag{5}$$

with $\eta_{w,t} \sim N(0, s_w^2)$. We assume the various shocks to be uncorrelated.

Assuming that each industry pays out all its economic earnings, $Earn_{i,j,t}$, each period, the valuation of the industry under (2)–(5) is

$$V_{i,j,t} = E_t\left[\sum_{k=1}^{\infty} exp\left(-\sum_{\ell=0}^{k-1}\delta_{i,j,t+\ell}\right)Earn_{i,j,t+k}\right]. \tag{6}$$

Given that we model earnings growth as in Equation (2), the earnings process is non-stationary. We must scale the current valuation by earnings and impose a transversality condition to obtain a solution:

$$PE_{i,j,t} = \frac{V_{i,j,t}}{Earn_{i,j,t}} = E_t\left[\sum_{k=1}^{\infty} exp\left(\sum_{\ell=0}^{k-1} -\delta_{i,j,t+\ell} + \Delta\ln(Earn_{i,j,t+1+\ell})\right)\right]. \tag{7}$$

Given the assumed dynamics for δ_w and $GO_{w,j}$ and normally distributed shocks, the PE ratio can be shown to be an infinite sum of exponentiated affine functions of the current realizations of the growth opportunity factor (with a positive sign) and the discount rate factor (with a negative sign) (a detailed derivation is available upon request):

$$PE_{i,j,t} = \sum_{k=1}^{\infty} exp(a_{i,j,k} + b_{i,j,k}\delta_{w,t} + c_{i,j,k}GO_{w,j,t}). \tag{8}$$

Because of log-normality, the constant in the expression for the PE ratio is affected positively by the volatility of the shocks to the discount rates, growth opportunities, and earnings growth rates.

The null of financial integration and the assumption that all firms in the same industry have the same systematic risk imply that industry systematic risk is the same across integrated countries; that is,

$$\beta_{i,j} = \beta_j. \tag{9}$$

This common assumption obviates the need to estimate betas and is the key assumption rendering the SEG measure independent of local discount rate variation under the null of integration.

This assumption also implies that financial risk through leverage is identical across countries. Because country-specific circumstances may induce different leverage ratios across countries, we include the average absolute difference between country-specific industry leverage and the corresponding global leverage ratio as an independent variable in the empirical work below. Note that other valuation measures, such as for example Tobin's q, would not require assumptions about financial risk. However, our pricing model is not necessarily applicable to such ratios and, most importantly, the time series of accounting data needed to calculate Tobin's q for a large set of countries is very limited and would not allow us to examine the long sample period in which we are interested.[3]

Under the above assumptions, we can rewrite (8) as

$$PE_{i,j,t} = \sum_{k=1}^{\infty} exp(a_{i,j,k} + b_{j,k}\delta_{w,t} + c_{j,k}GO_{w,j,t}). \tag{10}$$

An improvement in growth opportunities increases PE ratios for the industry everywhere in the world, and the change in the PE ratio is larger when $GO_{w,j,t}$ is more persistent. Similarly, a reduction in the world discount rate increases the PE ratio with the magnitude of the response depending upon the persistence of the discount rate process and the beta of the industry. Critically, the coefficients on $\delta_{w,t}$ and $GO_{w,j,t}$ are not country-specific. Note that valuation ratios for the same industry across countries do not need to be strictly identical, but this difference depends only on the constant $a_{i,j,k}$. In our empirical work, we are careful to add a measure of earnings growth volatility differentials to deal with this dependence.[4]

The equalization of industry valuations is consistent with factor price equalization as implied by classical trade models (see, for example, Samuelson 1948). But even under the more recent trade literature that explicitly allows for

3 For example, Chua, Eun, and Lai (2007) study market-level Tobin's q for forty-nine countries between 1999 and 2004. An, Bhojraj, and Ng (2010) study a variety of firm multiples across countries, and their sample starts in 1990.

4 Given the nonlinear transformation we employ, local variables may affect the dependence of the earnings yield on global variables, but this dependence is second-order, essentially because the $a_{i,j,k}$ terms depend on variances, whereas the other terms are persistence coefficients.

geography and differences in the level of productivity across countries (see, for example, Eaton and Kortum 2002), we expect industry valuations to be the same across countries unless entry or exit barriers exist, as factor prices for the immobile factors will adjust to the spatial variation in productivity such that capital is indifferent between different locations (see Venables 2006).

Note that above we describe the determinants of PE ratios; however, we use their inverse, earnings yields, in our empirical work. We do so for a number of reasons. First, the distribution of PE ratios is highly positively skewed, increasing the risk that outliers may affect the analysis. Second, and most important, price earnings ratios are not defined when earnings are zero. Third, earnings-yield differentials are easier to interpret given that they are expressed in percentage terms.

Of course, most countries will be segmented to some degree according to our definition of segmentation. Indeed, we do not view or require the null hypothesis of integration to hold in the data. Rather, we are interested in how close the data approach the implications of the null hypothesis. Given a reasonable intellectual benchmark, we can then explore whether there are variables that generate levels of valuation differentials inconsistent with the implications of financial and economic integration. Our philosophy is to take a simple model as a starting point and see if we can learn something about the departures from its implications.

With this in mind, our approach then tests the degree to which local and global factors matter for valuation once we have controlled for a country's global growth opportunities present in its industry mix. We conjecture that a main driver of such segmentation is de jure access: Some markets are simply legally closed for foreign investment. But even when a country is formally open to foreign capital, international investors may shun markets with weak corporate governance, keeping discount rates local and likely higher. There may also be interesting interaction effects between openness and weak corporate governance, which partially undo this effect. While one might want to associate segmentation with "low" valuations, high segmentation does not have to imply low valuations. For example, in markets with irrational agents, segmentation could cause overpricing (see Mei, Scheinkman, and Xiong 2009 for an argument as to how excessive speculation caused Chinese A-shares, traded by locals, to be overpriced relative to B-shares, traded by foreigners). Likewise, regulations may protect local industries against foreign competition and improve cash-flow prospects.

2. Characterizing Segmentation in Countries and Industries

In this section, we first describe the construction of the segmentation measure, SEG, and report summary statistics. We then measure the relative importance of country and industry effects in the SEG measures at the country-industry level. Finally, we establish an easily interpretable benchmark for the remainder of the analysis by examining the SEG measure within one large, integrated country, the United States.

2.1 Segmentation in countries and industries

We construct our measure of segmentation, SEG, for sixty-nine countries, using monthly equity industry portfolio data from Datastream as well as firm-level data from the Standard & Poor's Emerging Market Data Base (EMDB) between 1973 and 2005. Although monthly SEG measures are constructed (and are presented in some figures), we conduct most of our analysis at the annual frequency from 1980 to 2005 given the availability of other variables.

For twenty-three mostly developed countries, we collect market value data for industry portfolios constructed by Datastream.[5] In total, these portfolios typically cover about 85% of a country's equity market capitalization. We use the industry market value to determine a country's industry composition in the form of 38 portfolio weights, $IW_{i,j,t}$, that reflect the Industry Classification Benchmark (ICB) framework employed by Datastream.[6] For the same set of countries and industries, we also obtain industry earnings yields from Datastream. Datastream calculates these earnings yields by adding (generally trailing) twelve-month non-negative firm-level earnings across firms in a given industry and country and then dividing aggregated earnings by the aggregated market value of the firms in the industries.

For the remaining forty-six countries, we use EMDB to obtain market values and trailing twelve-month earnings data at the firm level. We construct earnings yields using the same method as Datastream. We then aggregate the firm-level data according to the industry classification employed by Datastream.[7] For each industry and country, we calculate local earnings yields and portfolio weights. Appendix Table 1 lists all sixty-nine countries and the data source used for each country.

For the construction of our segmentation measure as defined in Equation (1), we also require global industry earnings yields. We obtain these from Datastream's global industry portfolios that represent a weighted average of local industry portfolios. Across all industries, the United States and Japan have the largest share of the global market portfolio. Between 1980 and 2005, the U.S. average relative market share is 41%, while Japan's average share is 25%. In the robustness section, we consider constructing our segmentation measure relative to the United States alone. Previous research (see, for example, French

[5] Note that three countries in this set—namely Greece, Portugal, and South Africa—are for purposes of this study classified as Emerging Market countries.

[6] Note that in addition to the thirty-eight industries used in our study (see Table 2 for a list of these industries), Datastream also employs a "Nonequity Investment Instruments" category, which we exclude.

[7] EMDB classifies firms according to the Global Industry Classification Standard (GICS). We construct a concordant table between the 150 GICS categories used by EMDB and the thirty-eight ICB categories used in this study and assign each firm an ICB industry code. The concordant table between both classification systems is available upon request.

and Poterba 1991) has shown that Japanese accounting standards lead to an artificial depression of Japanese earnings yields. Of course, as we mentioned before, (changing) differences in accounting standards across countries could generally influence our results. Therefore, we have verified that dropping Japan from the global industry portfolios as well as the dataset does not alter our findings.[8] It is also possible that perceived risks associated with lax accounting standards or the opacity of corporate records affect the cost of capital across countries (see Hail and Leuz 2006). While data on earnings quality or alternative earnings data are not available over the wide cross-section and long time series that are necessary for this study, it is likely that our proxies for economic and institutional development are correlated with accounting quality measures.

Table 1 first reports the time-series average and standard deviation of our country segmentation measure, SEG, for all countries in our sample. Our sample is unbalanced: We have twenty-six years of data for most developed countries, but the average number of years with data for emerging market countries is only about twelve.[9] At the bottom of the table, we report the cross-sectional averages and standard deviations of these statistics for the set of developed, emerging, and all countries. We observe that emerging markets on average exhibit larger earnings yields differentials as well as larger fluctuations of SEG over time than do developed countries. The "Rank" column shows that between 2001 and 2005, the United States, Australia, Switzerland, Denmark, and the United Kingdom are the least segmented countries, whereas Ghana, Bulgaria, Venezuela, Lithuania, and Ivory Coast are the most segmented ones in our sample.

The columns in the middle produce some preliminary information about how our measure of segmentation evolves over time. Segmentation for developed markets has fallen considerably. The absolute earnings yield differential is 4.8%, on average, during 1980–1984, but only 2.0%, on average, during the 2001–05 period. For emerging markets, the average market segmentation measure falls from 6.4% in the first five years to 4.3% during 2001–05. Although both developed and emerging markets exhibit yield convergence over time, industrialized countries experience the largest drop in percentage terms. It should be pointed out that segmentation also increases for a few emerging markets, such as Venezuela, a country that experienced a significantly deteriorating political risk profile. Figure 1 presents, separately for developed and emerging markets, a cross-country average for SEG along with a time trend. Consistent with the results in Table 1, emerging markets appear more segmented relative to developed ones, but SEG exhibits a strong downward trend through 2005 for both sets of countries. It is this variation of segmentation over time as well as across countries that we seek to explain in this article.

[8] Results that exclude Japan are available upon request.

[9] Coverage for most developed countries starts in 1973, but our empirical analysis focuses on 1980 to 2005. See Appendix Table 1 for details.

Table 1
Summary Statistics by Country
Annual Segmentation 1980–2005

		Segmentation		Segmentation over Time				Rank	Fixed Effect	
Country	Sample	Average	St. Dev.	Year of first observation	Average segmentation over first five years	Average segmentation 2001–2005	Change in segmentation	Rank based on average segmentation 2001–2005	Country fixed effect – accounting for year effects	Number of firms (*as of 2006)
ARG	EM	5.3%	6.0%	1988	9.9%	4.9%	−50.6%	16	7.8%	26
AUS	DEV	2.4%	1.5%	1980	4.4%	1.1%	−75.2%	**68**	4.2%	160*
AUT	DEV	2.2%	0.8%	1980	2.2%	2.6%	21.7%	38	4.0%	50*
BEL	DEV	3.1%	1.7%	1980	4.1%	2.1%	−48.1%	56	4.9%	90*
BGD	EM	6.5%	2.5%	1998	7.8%	6.0%	−23.2%	11	9.4%	50
BGR	EM	12.7%	9.6%	1999	17.0%	10.4%	−38.8%	**2**	15.8%	12
BHR	EM	2.2%	1.0%	2001	2.2%	2.2%	0.0%	54	5.6%	11
BRA	EM	6.7%	4.7%	1988	11.3%	5.0%	−55.5%	15	9.2%	77
BWA	EM	2.5%	1.4%	1998	3.2%	2.1%	−36.2%	57	5.5%	7
CAN	DEV	2.7%	1.2%	1980	4.0%	1.6%	−60.7%	63	4.5%	250*
CHE	DEV	2.4%	1.6%	1980	4.2%	1.2%	−70.6%	**67**	4.2%	150*
CHL	EM	2.9%	2.6%	1989	4.6%	2.4%	−48.2%	47	5.6%	41
CHN	EM	2.0%	0.7%	1995	2.0%	2.0%	2.9%	58	5.0%	224
CIV	EM	7.3%	2.0%	1998	8.0%	6.9%	−13.8%	**5**	10.2%	13
COL	EM	5.0%	3.5%	1986	9.1%	3.0%	−66.7%	31	7.3%	20
CZE	EM	3.9%	2.6%	1996	3.3%	4.5%	34.6%	18	6.9%	24
DEU	DEV	2.5%	1.1%	1980	3.4%	2.8%	−16.5%	34	4.3%	250*
DNK	DEV	3.4%	2.9%	1980	6.3%	1.3%	−80.1%	**66**	5.2%	50*
ECU	EM	6.4%	5.2%	1998	9.0%	3.7%	−59.4%	24	9.3%	6
EGY	EM	6.2%	3.2%	1998	8.0%	6.1%	−23.4%	9	9.2%	51
ESP	DEV	2.5%	1.9%	1989	4.9%	1.3%	−73.6%	64	5.2%	120*
EST	EM	2.8%	2.2%	1999	3.4%	2.6%	−24.6%	39	5.9%	8
FIN	DEV	4.5%	3.3%	1990	7.9%	2.3%	−70.9%	49	7.3%	50*
FRA	DEV	2.9%	1.4%	1980	4.1%	2.1%	−47.8%	55	4.7%	250*
GBR	DEV	2.3%	1.3%	1980	4.2%	1.3%	−69.4%	**65**	4.1%	550*
GHA	EM	10.8%	6.6%	1998	13.5%	11.8%	−12.3%	**1**	13.8%	10
GRC	EM	3.8%	2.7%	1991	6.5%	2.7%	−58.5%	37	6.7%	50*
HRV	EM	6.0%	2.2%	1999	6.5%	6.4%	−1.1%	8	9.1%	6

(continued)

Table 1
Continued

		Segmentation		Segmentation over Time				Rank	Fixed Effect	
Country	Sample	Average	St. Dev.	Year of first observation	Average segmentation over first five years	Average segmentation 2001–2005	Change in segmentation	Rank based on average segmentation 2001–2005	Country fixed effect – accounting for year effects	Number of firms (*as of 2006)
HUN	EM	2.7%	1.2%	1994	2.8%	2.6%	−7.5%	40	5.7%	15
IDN	EM	3.6%	1.4%	1991	2.7%	4.4%	62.1%	19	6.5%	56
IND	EM	2.7%	1.5%	1988	1.7%	2.5%	49.3%	42	5.2%	103
IRL	DEV	4.2%	3.1%	1980	8.7%	1.9%	−78.6%	60	6.0%	50*
ISR	EM	2.3%	0.5%	1999	2.4%	2.2%	−10.1%	53	5.4%	50
ITA	DEV	2.2%	0.8%	1988	3.2%	1.8%	−44.3%	61	4.7%	160*
JAM	EM	9.0%	5.9%	1998	12.0%	5.3%	−55.8%	14	11.9%	19
JOR	EM	2.8%	1.6%	1988	4.4%	2.7%	−38.5%	35	5.3%	32
JPN	DEV	2.8%	0.6%	1980	3.6%	2.4%	−34.2%	46	4.6%	1000*
KEN	EM	5.3%	3.1%	1998	7.0%	3.9%	−44.5%	20	8.2%	18
KOR	EM	2.9%	1.6%	1988	1.8%	3.8%	114.4%	22	5.4%	129
LKA	EM	6.4%	4.4%	1995	7.6%	3.5%	−54.2%	25	9.5%	41
LTU	EM	8.6%	5.0%	1998	12.0%	7.1%	−40.5%	**4**	11.6%	18
LVA	EM	6.9%	3.4%	1999	7.5%	5.6%	−25.3%	13	9.9%	11
MAR	EM	2.5%	1.2%	1998	2.8%	2.8%	2.0%	33	5.5%	19
MEX	EM	4.1%	4.2%	1988	7.4%	2.4%	−66.9%	45	6.6%	60
MYS	EM	2.5%	0.9%	1986	2.5%	2.4%	−3.4%	48	4.8%	94
NGA	EM	6.8%	4.4%	1986	12.6%	2.0%	−84.1%	59	9.0%	25
NLD	DEV	3.1%	1.5%	1980	4.7%	2.7%	−42.4%	36	5.0%	130*
NOR	DEV	6.0%	4.5%	1982	11.7%	3.5%	−70.4%	26	8.0%	50*
NZL	DEV	3.2%	1.6%	1990	3.6%	2.5%	−31.3%	43	6.1%	50*
OMN	EM	3.1%	1.7%	2001	3.1%	3.1%	0.0%	28	6.5%	31
PAK	EM	5.8%	5.4%	1988	5.4%	6.8%	25.4%	6	8.3%	51
PER	EM	2.7%	0.8%	1994	2.1%	3.0%	46.1%	30	5.7%	32
PHL	EM	3.0%	1.2%	1990	3.7%	2.6%	−30.9%	41	5.8%	44
POL	EM	3.5%	1.9%	1994	4.5%	3.3%	−26.2%	27	6.5%	28
PRT	EM	2.3%	1.1%	1990	3.1%	2.3%	−26.5%	51	5.1%	50*
ROM	EM	8.8%	4.1%	1999	10.0%	6.8%	−32.1%	7	11.8%	24
RUS	EM	7.7%	7.1%	1998	10.8%	4.6%	−57.8%	17	10.6%	24

(*continued*)

Table 1
Continued

		Segmentation		Segmentation over Time				Rank	Fixed Effect	
Country	Sample	Average	St. Dev.	Year of first observation	Average segmentation over first five years	Average segmentation 2001–2005	Change in segmentation	Rank based on average segmentation 2001–2005	Country fixed effect – accounting for year effects	Number of firms (*as of 2006)
SGP	DEV	2.9%	1.7%	1980	5.6%	2.4%	−56.5%	44	4.7%	100*
SVN	EM	2.5%	1.0%	1998	3.0%	2.3%	−25.2%	52	5.5%	14
SWE	DEV	3.1%	1.7%	1984	3.2%	2.3%	−29.2%	50	5.2%	70*
THA	EM	4.0%	1.9%	1988	3.7%	3.9%	3.4%	21	6.5%	59
TTO	EM	1.8%	0.7%	1998	1.8%	1.7%	−3.8%	62	4.7%	12
TUN	EM	4.0%	1.5%	1998	4.9%	3.8%	−23.3%	23	7.0%	17
TUR	EM	3.8%	2.5%	1989	4.3%	3.0%	−31.5%	32	6.5%	43
UKR	EM	8.7%	6.5%	1999	11.1%	5.9%	−46.7%	12	11.8%	11
USA	DEV	1.2%	0.7%	1980	1.5%	0.7%	−53.6%	**69**	3.0%	1000*
VEN	EM	6.9%	5.4%	1988	6.2%	10.1%	63.4%	**3**	9.4%	15
ZAF	EM	2.6%	1.2%	1980	3.6%	3.1%	−13.9%	29	4.5%	70*
ZWE	EM	10.5%	10.1%	1988	19.8%	6.1%	−69.3%	10	13.0%	23
Averages of country-level data										
DEV	20	3.0%	1.7%	1982	4.8%	2.0%	−51.6%	54	5.0%	229
EM	49	5.0%	3.1%	1994	6.4%	4.3%	−18.9%	29	7.8%	38
ALL	69	4.4%	2.7%	1990	5.9%	3.6%	−28.4%		7.0%	37
Dispersion of country-level data										
DEV	20	1.0%	1.0%	3.79	2.4%	0.7%	25.2%		1.1%	289
EM	49	2.7%	2.3%	5.30	4.2%	2.3%	39.2%		2.7%	38
ALL	69	2.5%	2.1%	7.20	3.8%	2.2%	38.5%		2.7%	39

The sample includes 20 developed (DEV) and 49 emerging market (EM) countries detailed in Appendix Table 1. For each country, we report the time-series average and standard deviation of the annual (end of December) segmentation measure *SEG*. We also compare the average segmentation between 1980 and 1984 (or over the first five years for which segmentation data are available) with the average segmentation between 2001 and 2005, indicating the relative change in segmentation over time for each country as well as a country's segmentation rank based on the measured segmentation between 2001 and 2005. A rank of one indicates the highest degree of segmentation. Ranks one through five and 65 through 69 appear in bold. We regress the annual segmentation measure onto a set of country and year dummies and report the estimated fixed effect for each country. The last column reports for each country the number of firms used in the construction of *SEG*. For countries with data from Standard & Poor's Emerging Market Data Base (EMDB), we report the average number of firms over the sample period; for countries with data from Datastream, we only have the approximate number of firms Datastream used in 2006 to calculate country-specific indices. At the bottom of Table 1, we report the cross-sectional average and standard deviation of the country-level statistics reported in the upper part of the table.

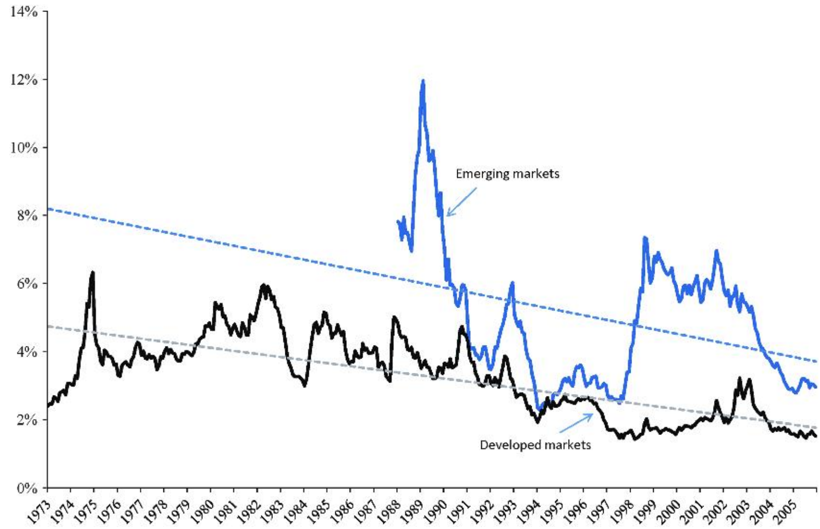

Figure 1
Average segmentation measure: Developed markets and emerging markets, 1973–2005
Emerging Markets: Segmentation (solid, blue line), Linear Trend (dashed, blue line); Developed Markets: Segmentation (solid, black line), Linear Trend (dashed, gray line).

While most of our focus is on country segmentation, Table 2 also reports the main statistics from Table 1 for industry-specific segmentation.[10] We observe that the absolute value of the yield differential has decreased for twenty-one, but increased for seventeen industries over the past two decades. The most integrated industry in recent years is the Software and Computer Services industry. Four out of the five industries that appeared to be the most segmented in 1980–84, namely, Banks, Life Insurance, General Retailers, and Non-Life Insurance, exhibit a significant reduction in their degree of measured segmentation. Interestingly, several of these industries have experienced substantial deregulation and privatization in many countries over the past two decades. Our measure thus captures the globalization of the financial sector, occurring over the past twenty years. This raises the question of whether some of the country effects we document later may be influenced by the industry mix of the country. For example, imagine that most countries protect their banking sectors, even after official liberalization, until worldwide technological (i.e., in telecommunication and Web services) and regulatory changes (i.e., changing Bank for International Settlements standards) force global deregulation. In this case, countries will appear more or less segmented depending on the relative importance of the banking sector in the industry mix. Using a well-known

[10] Carrieri, Errunza, and Sarkissian (2004) also explore country-and industry-level segmentation using a different econometric approach and document different degrees of integration across different industries.

Table 2
Summary statistics by industry
Annual segmentation 1980–2005

		Segmentation		**Segmentation over Time**			**Rank**		**Fixed Effect**
Industry	Code	Average	St. Dev.	Average segmentation 1980–1984	Average segmentation 2001–2005	Change in segmentation	Rank based on average segmentation 1980–1984	Rank based on average segmentation 2001–2005	Industry fixed effect – accounting for year effects
Aerospace & Defense	AERSP	3.3%	2.1%	3.4%	3.1%	−8.8%	27	33	4.0%
Automobiles & Parts	AUTMB	5.2%	1.6%	5.5%	5.3%	−4.8%	7	**5**	5.9%
Banks	BANKS	6.1%	2.9%	10.0%	3.5%	−64.9%	**1**	30	6.8%
Beverages	BEVES	3.9%	1.7%	4.4%	4.2%	−3.1%	19	14	4.6%
Chemicals	CHMCL	4.6%	1.8%	5.5%	4.5%	−17.3%	9	9	5.3%
Construction & Materials	CNSTM	4.0%	1.3%	5.0%	3.7%	−25.0%	15	25	4.7%
Electricity	ELECT	3.9%	1.4%	5.2%	3.7%	−28.6%	12	26	4.6%
Electronic & Electrical Equipment	ELTNC	3.6%	1.5%	2.5%	4.4%	76.9%	**37**	10	4.3%
Equity Investment Instruments	EQINV	4.5%	1.7%	4.4%	5.1%	14.4%	18	6	5.2%
Food & Drug Retailers	FDRGR	3.2%	1.3%	5.0%	2.9%	−42.3%	14	**36**	3.9%
Food Producers	FOODS	3.7%	1.4%	3.5%	4.6%	29.8%	25	8	4.4%
Forestry & Paper	FSTPA	5.7%	2.2%	4.3%	5.9%	36.4%	20	**2**	6.4%
General Financial	GENFI	5.0%	1.9%	3.5%	4.2%	20.1%	26	16	5.7%
General Industrials	GNIND	4.1%	1.4%	4.3%	3.9%	−8.5%	21	21	4.8%
General Retailers	GNRET	4.6%	2.5%	8.0%	4.2%	−48.0%	**3**	17	5.3%
Gas, Water & Multiutilities	GWMUT	2.7%	1.0%	2.9%	3.6%	23.0%	**34**	28	3.4%
Healthcare Equipment & Services	HCEQS	3.1%	1.5%	3.2%	3.5%	10.8%	31	29	3.8%
Household Goods	HHOLD	4.3%	1.8%	4.0%	4.1%	1.8%	22	20	5.0%
Industrial Engineering	INDEN	4.5%	1.6%	6.0%	4.1%	−31.7%	6	19	5.2%
Industrial Metals	INDMT	6.5%	2.0%	6.4%	7.0%	9.2%	**5**	**1**	7.2%
Industrial Transportation	INDTR	4.6%	1.4%	5.3%	4.3%	−18.9%	11	12	5.3%
Leisure Goods	LEISG	4.7%	2.1%	5.1%	4.1%	−19.4%	13	18	5.4%
Life Insurance	LFINS	5.1%	3.2%	8.5%	3.0%	−65.0%	**2**	**35**	5.8%
Media	MEDIA	2.9%	1.5%	4.6%	3.1%	−33.2%	16	**34**	3.6%
Mining	MNING	5.2%	2.2%	3.9%	5.7%	46.3%	23	**3**	5.9%
Nonlife Insurance	NLINS	4.8%	2.0%	7.3%	4.2%	−42.1%	**4**	15	5.5%

(*continued*)

Table 2
Continued

Industry	Code	Segmentation: Average	Segmentation: St. Dev.	Segmentation over Time: Average segmentation 1980–1984	Segmentation over Time: Average segmentation 2001–2005	Segmentation over Time: Change in segmentation	Rank: Rank based on average segmentation 1980–1984	Rank: Rank based on average segmentation 2001–2005	Fixed Effect: Industry fixed effect – accounting for year effects
Oil Equipment & Services	OILES	3.3%	1.7%	3.8%	3.7%	−3.6%	24	27	4.0%
Oil & Gas Producers	OILGP	4.5%	1.5%	5.5%	4.3%	−22.5%	8	11	5.2%
Personal Goods	PERSG	4.9%	2.6%	2.7%	4.8%	80.9%	**36**	7	5.6%
Pharmaceuticals & Biotechnology	PHARM	3.6%	1.8%	3.2%	4.3%	31.7%	29	13	4.3%
Real Estate	RLEST	3.3%	1.2%	3.4%	3.8%	11.5%	28	24	4.0%
Software & Computer Services	SFTCS	2.8%	1.4%	3.2%	2.0%	−38.2%	30	**38**	3.5%
Support Services	SUPSV	3.1%	1.6%	2.9%	3.2%	9.3%	33	32	3.8%
Technology Hardware & Equipment	TECHD	3.5%	1.2%	2.4%	3.3%	35.9%	**38**	31	4.2%
Fixed Line Telecommunications	TELFL	3.8%	1.6%	5.3%	3.9%	−27.1%	10	22	4.5%
Mobile Telecommunications	TELMB	2.8%	1.2%	4.5%	2.8%	−38.5%	17	**37**	3.5%
Tobacco	TOBAC	3.9%	1.6%	3.0%	3.9%	28.6%	32	23	4.6%
Travel & Leisure	TRLES	4.0%	1.9%	2.9%	5.4%	90.0%	**35**	**4**	4.7%
Average of industry-level data	38	4.1%	1.7%	4.6%	4.1%	−0.9%			4.8%
Dispersion of industry-level data	38	0.9%	0.5%	1.7%	1.0%	37.8%			0.9%

For each of the 38 industries in our sample, we report the time-series average and standard deviation of the annual (end of December) industry segmentation. Industry segmentation is measured as the equally weighted cross-sectional average of the absolute difference between a country-specific industry valuation and the corresponding global industry valuation. We also compare the average industry segmentation between 1980 and 1984 with the average segmentation between 2001 and 2005, indicating the relative change in segmentation over time for each industry as well as an industry's segmentation rank 1980 and 1984 and between 2001 and 2005. A rank of one indicates the highest degree of segmentation. Ranks one through five and 34 through 38 appear in bold. We regress the annual segmentation measure onto a set of industry and year dummies and report the estimated fixed effect for each industry. At the bottom of Table 2, we report the cross-sectional average and standard deviation of the industry-level statistics reported in the upper part of the table.

technique introduced by Heston and Rouwenhorst (1994), we have verified that country effects dominate industry effects when regressing industry-country segmentation levels onto country and industry fixed effects. Finally, notice that the four most segmented industries during the more recent period (2001–05), Forestry & Paper, Industrial Metals, Travel & Leisure, and Mining, are largely endowment-based industries, the value of which depends to some extent on the price of the immobile factor, land.

2.2 Developing a benchmark: Segmentation in the United States

Over the past five years, the average segmentation measure in the industrialized countries was 2.0%. Given differences in leverage, earnings volatility across countries, imperfect homogeneity within industry classes, and/or just plain measurement error, is this a large number, a small number, or what we would expect in relatively integrated countries? In this section, we benchmark our measure of segmentation by examining its value within one country, the United States. Given that we sample firms within one country, any measured segmentation cannot be ascribed to international market segmentation.

We obtain earnings and equity market value data from Datastream and annual leverage data from Compustat between 1973 and 2005 for the 4,594 firms that are covered by both data vendors. We classify each firm into one of the thirty-eight Datastream ICB industries.

We use the U.S. sample of firms to construct one hundred random samples, each of which resembles our actual dataset of sixty-nine countries, with the aggregate U.S. market playing the role of the world market. As Appendix A describes in detail, the random datasets approximately replicate both the cross-sectional and temporal variation in the number of firms in our sample. For each random dataset and each "pseudo-country" within such a set, we then compute the segmentation measure exactly as we do for the actual countries. Clearly, such an exercise can be implemented only for a developed country that has thousands of firms, such as the United States. Figure 2 shows the average, as well as the 5th and 95th percentiles, of the degree of measured segmentation across the one hundred random replications over time. The U.S. segmentation measure does not exhibit an obvious trend. The degree of segmentation for developed countries has declined through time to the average segmentation level in our U.S. benchmark case, which is about 1.5%. Since about 1993, segmentation in developed markets has moved within the 90th percentile confidence bound of the U.S. random measure, but the measured segmentation for emerging markets is still well above it.[11]

To understand better what may cause the apparent segmentation found in the U.S. data, we relate the annual segmentation measures for U.S. "pseudo-countries" to four factors: a time trend, the log of the number of firms in a

[11] We also conduct the more precise exercise of randomizing twice to be consistent with the separate groups of developed and emerging countries, respectively. This exercise yields very similar results.

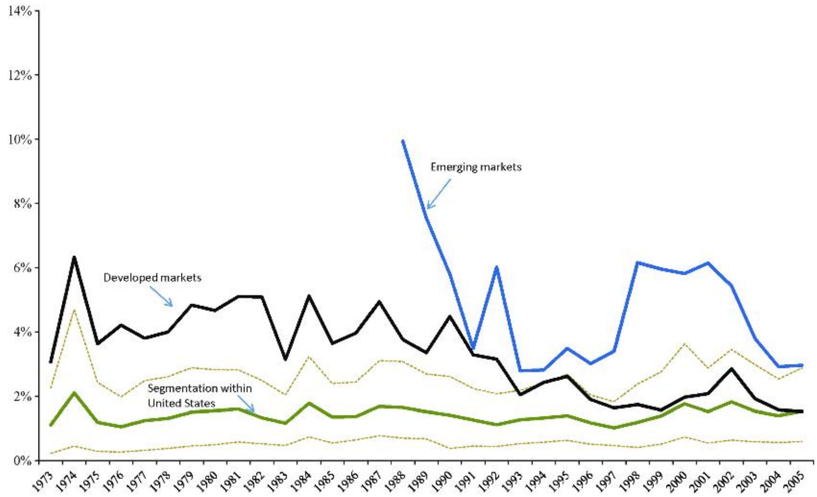

Figure 2
Benchmarking the segmentation measure: Segmentation within the United States, 1973–2005
100 Random Samples of 69 "Pseudo-Countries." Segmentation within the United States: Average (solid, green line) and 5th and 95th percentile (dashed, green lines); Segmentation in Emerging Markets (solid, blue line) and Developed Markets (solid, black line).

given "pseudo-country" and year, the weighted average of the absolute difference between industry leverage in a given "pseudo-country" and in the United States as a whole, and the weighted average of the absolute difference between industry log earnings growth volatility in a given "pseudo-country" and the United States.[12]

The earnings volatility and leverage variables have obvious implications for valuation detailed earlier in Section 2, even if markets are fully integrated. Importantly, their temporal variation may induce a downward trend in our segmentation measure. For example, the decline in macroeconomic volatility in the 1985–2005 period may have narrowed earnings volatility differentials between firms. Likewise, general financial development may make it easier for firms to hit their target debt levels, narrowing leverage differentials among firms. Finally, as in our international dataset, a larger number of firms should improve the accuracy of the measure as it decreases the possibility of outliers and idiosyncratic variability, which would bias the measure upward as we use absolute values. Not controlling for the number of firms could therefore induce a downward trend in segmentation as the number of public firms increase. Cross-sectionally, "pseudo-countries" with more firms would on average show lower segmentation levels than those with fewer public firms.

Table 3 reports the results from running the regression on the one hundred replications of our dataset. We report the distribution of coefficient estimates

12 The data sources and computations are described in Appendix Table 2. We clarify how we compute standard errors in Section 4.

Table 3
Segmentation for the U.S. benchmark
100 random samples of 69 "Pseudo-Countries" 1973–2005

	Percentile				
Distribution of coefficient estimates	5th	10th	50th	90th	95th
Trend (x 100)	−0.0207	−0.0189	−0.0125	−0.0077	−0.0059
Number of Public Firms (log)	−0.0033	−0.0032	−0.0027	−0.0022	−0.0022
Abs. Difference in Financial Leverage (|Local - US|)	0.0058	0.0111	0.0267	0.0415	0.0457
Abs. Difference in Log Earnings Growth Volatility (|Local - US|)	0.0024	0.0032	0.0066	0.0100	0.0110
Distribution of t- stats	5th	10th	50th	90th	95th
Trend	−3.303	−2.990	−2.053	−1.241	−0.948
Number of Public Firms (log)	−10.346	−9.682	−7.148	−5.444	−5.161
Abs. Difference in Financial Leverage (|Local - US|)	0.430	0.844	2.219	3.546	4.269
Abs. Difference in Log Earnings Growth Volatility (|Local-US|)	1.018	1.388	2.457	3.821	4.369

Using annual data for U.S. firms between 1973 and 2005, we construct 100 random samples, each of which resembles our actual dataset of 50 countries with respect to the cross-sectional and temporal variation in the number of firms used. For each random sample and each "country" within such a set, we compute the segmentation measure as we do for the actual data, with the U.S. market playing the role of the world market. For each sample, we regress the annual "country"-level segmentation measure on the following control variables: (1) a time trend; (2) the natural logarithm of the number of firms that are used in the construction of the segmentation measure for a given "country" in a given year; (3) the absolute difference between the industry leverage in a given "country" and the U.S. market as a whole, averaged across all industries in a given "country" and year; and (4) the absolute difference between the industry log earnings growth rate volatility in a given "country" and the U.S. market as a whole, averaged across all industries in a given "country" and year. We report the distribution of coefficient estimates and t-statistics from the 100 pooled OLS regressions. The reported t-statistics account for serial correlation by "country" and contemporaneous correlation across "countries."

and t-statistics. The signs of the coefficients are as expected, with the trend and number of firms coefficients being negative and the earnings growth volatility and leverage differential coefficients being positive. Focusing on the 95th (5th) percentile of the t-statistic distribution for the negative (positive) coefficients, only the number of firms coefficient is significantly different from zero.

3. Market Segmentation Dynamics

Using an unbalanced dataset of annual data from 1980 to 2005 for sixty-nine countries, we perform panel regressions of the form

$$SEG_{i,t} = \alpha + \beta' x_{i,t} + \eta_{i,t}, \tag{11}$$

where $SEG_{i,t}$ is the year t measure of segmentation for country i, and $x_{i,t}$ represents the various candidate explanatory variables. We use pooled ordinary least squares (OLS) to estimate the model. However, the standard errors are corrected for unspecified serial correlation within a given country and for cross-sectional correlation across countries in a given year, as proposed by Thompson (2006) and Petersen (2009). These corrections have the effect of generally increasing the standard errors relative to simple OLS. Throughout the remainder of the article, bold coefficients denote statistical significance at the 5% level.[13]

Globalization, particularly de jure financial and goods trade openness, has increased at a rapid pace over the past thirty years. Accordingly, the de jure globalization process is the most obvious candidate determinant for the downward trend in SEG that we observe. In Table 4, we investigate the role of de jure financial and trade openness on market segmentation.

We use two different measures of financial openness, one focusing on the entire capital account and the other based exclusively on equity markets. Given that the two measures are alternative proxies for financial openness, we use them separately (Panel A and Panel B in Table 4) in our regressions.[14] The capital account openness measure compiled in Quinn (1997) and Quinn and Toyoda (2008) is based on information from the International Monetary Fund. A value of one indicates full capital account openness, a value of zero a closed capital account, and larger intermediate values indicate increasingly fewer regulations on international capital flows. The equity market openness measure is based upon the ratio of the market capitalization of the Standard & Poor's (S&P) investable to the S&P global indices in each country, following Bekaert (1995) and Edison and Warnock (2003). The S&P global stock index seeks to represent the local stock market, whereas the investable index corrects the market capitalization for foreign ownership restrictions. Hence, a ratio of one means that all of the stocks in the local market are available to foreigners.

To measure regulatory trade openness, we use the 0/1 trade liberalization dates developed in Wacziarg and Welch (2008) (based on the earlier work of Sachs et al. 1995). Wacziarg and Welch look at five criteria: high tariff rates, extensive non-tariff barriers, large black-market exchange rate premia, state monopolies on major exports, and socialist economic systems. If a country meets any of these five criteria, it is classified with an indicator variable equal to zero and deemed closed.

In columns I, II, and III across two panels, Table 4 reports the effect of capital account, equity market, and trade openness on market segmentation. Although all coefficients are negative, as expected, only the two financial openness effects are consistently significant. Note also that capital account openness as well as equity market openness each have higher explanatory power

13 We have also explored an alternative approach: In a first step, we eliminate the serial correlation in the error term by applying the Prais and Winsten 1954) transformation to Equation (11). In a second step, we apply OLS to the transformed data. To address heteroscedasticity across countries as well as contemporaneous correlation of the error term between countries, we calculate panel-corrected standard errors as proposed by Beck and Katz (1995). Our findings based on this alternative estimation procedure are very similar to those reported here.

14 We have also considered a specification that includes both proxies at the same time. We find that the coefficient estimates for both proxies are statistically significant with a coefficient estimate of −0.0194 for capital market openness and of −0.0173 for equity market openness. These results are available upon request.

Table 4
Market segmentation determinants 1980–2005

Panel A: Equity Market Openness

	I	II	III	IV	V
Equity Market Openness	**−0.0293**		**−0.0257**	**−0.0295**	**−0.0258**
	(0.0072)		(0.0075)	(0.0074)	(0.0075)
Trade Openness		**−0.0262**	−0.0121	−0.0096	−0.0043
		(0.0106)	(0.0109)	(0.0110)	(0.0101)
Trend (x 100)				**−0.0951**	**−0.1180**
				(0.0346)	(0.0317)
Number of Public Firms (log)					−0.0026
					(0.0019)
Abs. Difference in Financial Leverage (|Local – Global|)					0.0479
					(0.0641)
Abs. Difference in Log Earnings Growth Volatility (|Local – Global|)					**0.1068**
					(0.0238)
Intercept	**0.0596**	**0.0628**	**0.0679**	**1.9670**	**2.4153**
	(0.0072)	(0.0109)	(0.0113)	(0.6925)	(0.6350)
N	1,078	1,078	1,078	1,078	1,078
Adj. - R^2	0.11	0.05	0.12	0.14	0.21

Panel B: Capital Account Openness

	I	II	III	IV	V
Capital Account Openness	**−0.0415**		**−0.0387**	**−0.0381**	**−0.0318**
	(0.0095)		(0.0094)	(0.0098)	(0.0085)
Trade Openness		**−0.0189**	−0.0055	−0.0049	−0.0034
		(0.0096)	(0.0097)	(0.0097)	(0.0081)
Trend (x 100)				−0.0599	**−0.0853**
				(0.0321)	(0.0312)
Number of Public Firms (log)					**−0.0050**
					(0.0012)
Abs. Difference in Financial Leverage (|Local – Global|)					0.0296
					(0.0588)
Abs. Difference in Log Earnings Growth Volatility (|Local – Global|)					**0.0791**
					(0.0227)
Intercept	**0.0684**	**0.0541**	**0.0713**	**1.2662**	**1.7825**
	(0.0093)	(0.0100)	(0.0117)	(0.6421)	(0.6217)
N	1,002	1,002	1,002	1,002	1,002
Adj. - R^2	0.08	0.02	0.08	0.10	0.18

The sample includes 20 developed and 49 (40 in Panel B) emerging market countries detailed in Table 1. We regress the annual country-level segmentation measure *SEG* onto the following variables: (1) the degree of equity market openness (investability) (Panel A) or a continuous measure of the degree of capital account openness from Quinn (only 60 countries are available) (Panel B); (2) a 0/1 indicator of trade openness based on trade liberalization dates from Wacziarg and Welch (2003); (3) a time trend; (4) the natural logarithm of the number of publicly traded firms in a given country and year; (5) the absolute difference between the industry leverage in a given country and the world market as a whole, averaged across all industries in a given country and year; and (6) the absolute difference between the industry log earnings growth rate volatility in a given country and the world market as a whole, averaged across all industries in a given country and year. We report coefficient estimates from pooled OLS regressions. Reported standard errors in parentheses account for serial correlation by country and contemporaneous correlation across countries. Bold coefficient estimates denote statistical significance at the 5% level under the panel OLS specification. N denotes the number of country-years, and *Adj. -* R^2 denotes the adjusted coefficient of determination.

(in terms of R^2) than trade openness. Countries with completely open capital accounts or equity markets feature yield differentials that are about three hundred to four hundred basis points smaller than those with completely closed financial systems. Given that trade and financial openness are positively correlated, these coefficients decrease in joint regressions, but they remain statistically and economically significant.

In column IV, we add a trend term to the regression to explore the extent to which de jure openness subsumes a pure time trend. In both sets of regressions, the time trend is significantly different from zero, at least at the 10% level, but its inclusion adds only 2% to the R^2 of the regression. The point estimates suggest a downward trend in segmentation of between six and ten basis points per year. Both openness variables are essentially unaffected and clearly also explain cross-sectional differences in segmentation.

Finally, in column V, we also include the three control variables examined in the U.S. benchmark regression in Section 3.2. The R^2s increase significantly in both cases, reflecting the importance of the additional regression controls. Earnings growth volatility differentials are significantly associated with larger earnings yield spreads across both samples. This is consistent with the theoretical prediction in the valuation model. While the leverage differential has the expected sign in both cases, it is not statistically significant. Finally, we find a significant role for the number of firms in Panel B, but not in Panel A. The inclusion of these control variables does slightly reduce the estimated financial openness effects, but they remain statistically and economically significant. A closed-to-open difference still implies a 260- to 320-basis-point differential in earnings yields. While retaining the expected sign, the trade openness effect remains statistically insignificant.

4. Determinants of Market Segmentation

De jure globalization measures together with controls for earnings volatility, leverage differentials, and the number of firms explain about 20% of the total panel variation in SEG. Here we consider a number of other factors, listed in Appendix Table 3, potentially associated with segmentation. Section 5.1 provides the economic rationale for why they are considered. We relegate a detailed description of the sources and variable construction to Appendix Table 2. Our goal is to find a parsimonious set of factors that maximizes the explanatory power for the segmentation variable. To this end, we employ statistical model reduction techniques, detailed in Section 5.2. We investigate the economic significance of the results, using a variance decomposition analysis on the selected models.

4.1 Other segmentation factors.

We consider six categories of variables.

4.1.1 Measures of de facto openness. In addition to the de jure measures of financial and trade openness provided above, we also employ a traditional de facto measure of trade openness, computed as the sum of exports and imports as a share of gross domestic product. In a robustness exercise, we also consider real interest rate differentials as an alternative de facto measure of money market segmentation (see, e.g., Frankel 1992).

4.1.2 Political risk and institutions. There are many additional country characteristics that may effectively segment markets other than formal capital or trade restrictions. La Porta et al. (1997) emphasize the importance of investor protection and, more generally, the quality of institutions and the legal environment. Poor institutions and political instability may affect risk assessments of foreign investors, effectively segmenting capital markets (see Bekaert 1995), and financial openness might not suffice to attract foreign capital if the country is viewed as excessively risky.

To explore these effects, we consider several variables that measure different aspects of the institutional environment. First, we consider several subindexes of the International Country Risk Guide (ICRG) political risk index: (1) the quality of institutions, reflecting corruption, the strength and impartiality of the legal system (law and order), and bureaucratic quality; and (2) the investment profile, reflecting the risk of expropriation, contract viability, payment delays, and the ability to repatriate profits. The latter measure is closely associated with the attractiveness of a country for foreign direct investment (FDI). We also separately consider the subindex for law and order, which measures both the quality of the legal system and whether laws are actually enforced. It is likely closely associated with investor protection. Note that high ratings are associated with less risk. Finally, we consider the country's legal origin (Anglo-Saxon, French, and other), an often-used instrument for corporate governance and a "good" legal system.

4.1.3 Financial development. Poorly developed financial systems may also be an important factor driving market segmentation. For example, in a survey by Chuhan (1992), equity market illiquidity was mentioned as one of the main reasons that prevented foreign institutional investors from investing in emerging markets. Moreover, poor liquidity as a priced local factor may lead to valuation differentials. When markets are closed, efficient capital allocation should depend on financial development (see Wurgler 2000; Fisman and Love 2004). Because banks are still the dominant financing source in many countries, poor banking sector development may severely hamper growth prospects and lower valuations. We employ several measures to quantify stock and banking sector development.

Our first equity market liquidity measure relies on the incidence of observed zero daily returns, following the work of Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), and Bekaert, Harvey, and Lundblad (2007). Our other measures of equity market trading and efficiency include (1) turnover as the value traded relative to gross domestic product (GDP), a standard measure of stock market development (see Atje and Jovanovic 1993); (2) the size of the equity market as measured by total market capitalization relative to GDP; and (3) equity market synchronicity (see Morck, Yeung, and Yu [henceforth MYY] 2000), computed as an annual value-weighted local market model R^2 obtained from each firm's returns regressed on the local market portfolio return for that year. Finally, we proxy for the development of the banking system by the amount of private credit divided by GDP (see King and Levine 1993).

4.1.4 Risk appetite and business cycles. We also consider a number of variables that capture potential push factors driving capital flows. Given that all these variables are based on U.S. or global data, they exhibit only time-series variation. An established literature argues that market conditions in developed countries, such as the level of interest rates, may drive capital flows and thus affect international valuation differentials (see, e.g., Fernandez-Arias 1996). In particular, low real rates in developed markets would cause capital to flow into emerging markets, bringing their valuations closer to developed market levels. Although the evidence on this effect is mixed (see Bekaert, Harvey, and Lumsdaine 2002), we nonetheless try to capture it using the level of the real interest rate across G7 countries.[15]

The real rate effect may reflect a behavioral search for yield, but real rates may affect capital flows and valuations as they proxy for risk aversion (Sharpe 1990) or "global liquidity." We include the growth rate of the U.S. money supply (M2) as a more direct measure of global liquidity. We use the U.S. corporate bond spread and the Chicago Board Options Exchange Market Volatility (VIX) Index as proxies for risk aversion or sentiments of world investors.[16] Keim and Stambaugh (1986) show that the Baa-Aaa spread has some explanatory power for variation in equity risk premia. The VIX index is generally viewed as an indicator of market uncertainty and sudden increases in its level with a flight to safety. Indeed, Bollerslev and Zhou (2006) employ the VIX index to construct a measure of aggregate market risk aversion. Accordingly, increases in these measures may lead to a retreat of U.S. capital from foreign markets, leading to divergence in valuations.[17] We also include a more "fundamental" measure of U.S. risk aversion computed from consumption data using the habit model in Campbell and Cochrane (1999) (see Bekaert and Engstrom 2010). This measure tends to behave countercyclically.

[15] Alternatively, one could use data on actual capital flows as captured for the United States by the Treasury International Capital System (TIC). See Warnock and Warnock (2009) for a recent study of TIC data.

[16] See Coudert and Gex (2008) for a survey of risk aversion indicators.

[17] Alternatively, the VIX index is simply a measure of the U.S. stock market's volatility, which may proxy for U.S. earnings growth and discount rate volatility.

We also include world GDP growth, which may act as an indicator of the world business cycle. To the extent the world business cycle affects global discount rates and growth opportunities, it should not affect segmentation levels under the null of integration, but it can cause variation in segmentation levels for markets that are segmented. For the same reason, we include a measure of world equity market volatility.

Finally, we also investigate one country-specific factor, the level of the lagged country portfolio return over the past year to potentially proxy for return chasing effects by international investors (see, for example, Bohn and Tesar 1996).

4.1.5 Information variables. A rather extensive literature on home bias (see especially Portes and Rey 2005) shows that informational frictions play a large role in determining international transactions in financial assets and the level of home bias. To the extent that there is a link between home bias and valuation, such measures may help determine segmentation levels. We therefore also include several proxies for the degree to which countries are connected with the world through telecommunication. In particular, we include the number of telephone line subscribers per one hundred people and the number of Internet users per one hundred people.

4.1.6 Growth determinants. Under the null of integration, a country's growth opportunities should be reflected in the global valuation measure of its industry basket. However, it is conceivable, especially for developing countries, that growth prospects are more local in nature. Following the extensive work on growth determinants (see, e.g., Barro 1997), we therefore include several measures related to cross-country expected growth differentials: the initial level of per-capita GDP, the percentage of secondary school enrollment as a measure of human capital, the log of life expectancy, and population growth.

4.2 Multivariate analysis: Model selection and results

Our goal is to find a parsimonious set of factors that best explain the variation in SEG. With a large number of highly correlated explanatory variables (there are twenty-nine independent variables), this is no easy task. We employ two procedures. The first procedure is the general-to-specific search algorithm of Hendry (1995) and Hendry and Krolzig (2001), implemented, for example, in PcGets. The algorithm constitutes a "testing-down" process that in multiple steps eliminates variables with coefficient estimates that are not statistically significant, leading to a parsimonious model with mostly significant regressors. Appendix B provides a more detailed discussion of the test procedure.

Eliminating insignificant regressors may sound worrisome to finance researchers, as it may lead to false rejections of the null of a zero coefficient, especially when many regressors are involved. It is instructive to elaborate why such concerns are largely unfounded in this application. Suppose there are forty useless regressors and we conduct forty t-tests, eliminating insignificant regressors using a test with significance level α. The probability of rejecting the null of a zero coefficient when true is thus α. The probability of falsely accepting the significance of at least one regressor after forty tests is $1-(1-\alpha)^{40}$, which is 87.15% for a 5% test. The probability that one of the factors in the regression will be spurious is indeed quite large. While this is a serious problem in regressions that test, say, market efficiency, such an outcome is not as big of a problem for our purposes. Our main interest is in eliminating as many useless factors as possible. It is straightforward to compute the expected number of useless factors that would remain after forty t-tests; It is 40α, which is two for a 5% test (see Campos, Ericsson, and Hendry 2005). In other words, a simple t-test procedure would eliminate thirty-eight useless factors, which is a good outcome from our perspective. Economic priors can be used to suggest which useless factors remain. Of course, the general-to-specific search algorithm as implemented in PcGets is much more sophisticated than simply using forty individual t-tests, using many joint tests on coefficients both to increase the chance of eliminating useless factors and to avoid the trap of eliminating useful ones.[18]

Our second methodology is a simple jackknife procedure. For each candidate variable separately, we randomly sample from the twenty-eight other possible variables for which we have full sample data. The number of additional variables and their identities are completely random, but we force the selection to have between eight and twenty-eight additional variables. For each set of randomly selected explanatory variables, we perform a regression with SEG as the dependent variable, eliminate variables with t-statistics below one, and perform a second regression on the remaining set. This regression always contains the candidate variable. We then retain the regression coefficient of the candidate variable and the overall contribution that the particular variable makes for predicted segmentation. We iterate this procedure one thousand times for each candidate variable to construct confidence intervals on these quantities. Those variables whose 90% confidence interval excludes zero are included in our second specification.

We initially consider the various candidate variables mentioned above for which we have data for almost the entire sample of sixty-nine countries.[19] For each set of selection procedures, we employ two versions differentiated by the inclusion of either the equity market or capital account openness variables as above. In addition, we add to the segmentation factors the three control variables, leverage, earnings volatility, and the number of listed firms (suggested

[18] Hoover and Perez (2002, 2004) examine the efficacy of the general-to-specific modeling approach using Monte Carlo simulations as well as a replication of Sala-i-Martin (1997), who ran two million regressions. Their findings are supportive of the search algorithm we use in this study.

[19] The capital account openness measure is missing for nine, mostly Eastern European countries.

by our U.S. case study), plus a time trend. In the robustness section, we consider three additional variables, liquidity, synchronicity, and real interest rate differentials, for which coverage is available for only a subset of our data.

4.2.1 Statistical significance. Table 5 provides the regression specifications selected using either the general-to-specific search algorithm as implemented in PcGets (columns 1 and 3) or the alternative jackknife procedure (columns 2 and 4). In addition to the point estimates and the regular standard errors, we also report the 90% confidence intervals from the jackknife approach (columns 2 and 4). Focusing on equity market openness (columns 1 and 2), we observe substantial overlap between the sets of variables selected by both approaches,

Table 5
Determinants of market segmentation 1980–2005

	Equity Market Openness		Capital Account Openness	
	PcGets	Jackknife	PcGets	Jackknife
Capital Account Openness			**–0.0237**	**–0.0179**
			(0.0063)	(0.0073)
				[–0.0277, –0.0156]
Equity Market Openness	**–0.0145**	–0.0114		
	(0.0055)	(0.0062)		
		[–0.0210, –0.0109]		
Trade Openness		–0.0025		
		(0.0094)		
		[–0.0119, –0.0012]		
Investment Profile	**–0.0302**	**–0.0281**	**–0.0253**	**–0.0216**
	(0.0083)	(0.0071)	(0.0076)	(0.0076)
		[–0.0378, –0.0136]		[–0.0350, –0.0109]
Law and Order				–0.0087
				(0.0087)
				[–0.0267, –0.0010]
Legal Origin (French)	–0.0063	–0.0073		–0.0059
	(0.0036)	(0.0040)		(0.0040)
		[–0.0120, –0.0045]		[–0.0086, –0.0027]
Local Equity Market Turnover		–0.0036		–0.0025
		(0.0022)		(0.0024)
		[–0.0074, –0.0025]		[–0.0061, –0.0014]
Private Credit/GDP	–0.0069	–0.0060		–0.0043
	(0.0047)	(0.0048)		(0.0047)
		[–0.0179, –0.0043]		[–0.0167, –0.0037]
MCAP/GDP	**–0.0095**	**–0.0103**	**–0.0103**	**–0.0100**
	(0.0031)	(0.0032)	(0.0033)	(0.0031)
		[–0.0190, –0.0106]		[–0.0174, –0.0101]
U.S. Risk Aversion	**–0.0107**		–0.0093	
	(0.0052)		(0.0049)	
World GDP Growth	**0.3160**		**0.3631**	
	(0.0989)		(0.0981)	
U.S. Corporate Bond Spread	**2.6461**	**1.7156**	**2.6344**	**1.7074**
	(0.6051)	(0.3785)	(0.5590)	(0.3732)
		[0.8317, 2.7301]		[1.0016, 2.7401]

(*continued*)

Table 5
Continued

	Equity Market Openness		Capital Account Openness	
	PcGets	Jackknife	PcGets	Jackknife
VIX Option Volatility Index	**0.0533**	**0.0660**	**0.0589**	**0.0652**
	(0.0179)	(0.0181)	(0.0143)	(0.0147)
		[0.0129, 0.0819]		[0.0110, 0.0816]
Past Local Equity Market Return	**–0.0112**	–0.0090	**–0.0106**	**–0.0085**
	(0.0046)	(0.0047)	(0.0042)	(0.0041)
		[–0.0142, –0.0092]		[–0.0139, –0.0084]
Abs. Difference in Log Earnings Growth Volatility	**0.0738**	**0.0728**	**0.0562**	**0.0529**
(|Local - Global|)	(0.0226)	(0.0205)	(0.0243)	(0.0253)
		[0.0600, 0.0990]		[0.0471, 0.0803]
Number of Public Firms (log)	–0.0020	–0.0015	**–0.0039**	–0.0029
	(0.0019)	(0.0020)	(0.0012)	(0.0016)
		[–0.0046, –0.0013]		[–0.0051, –0.0023]
Intercept	**0.0825**	**0.0581**	**0.1074**	**0.0643**
	(0.0216)	(0.0191)	(0.0189)	(0.0133)
N	1,078	1,078	1,002	1,002
Adj. - R^2	0.30	0.29	0.29	0.28

The sample includes 20 developed and 49 (40 in the case of the last two columns) emerging market countries detailed in Table 1. We regress the annual country-level segmentation measure SEG onto the independent variables that have survived either the model reduction algorithm (PcGets), detailed in Appendix Table 3, or the jackknife experiment (Jackknife) described below. For a detailed description of all variables, see Appendix Table 2. In all cases, we report coefficient estimates from pooled OLS regressions. Reported standard errors in parentheses account for serial correlation by country and contemporaneous correlation across countries. Bold coefficient estimates denote statistical significance at the 5% level under the panel OLS specification. Finally, for the two specifications based on the jackknife experiment, we provide a confidence interval for each entry, in brackets beneath the standard errors. The jackknife experiment is designed as follows. Separately for each of the 29 variables listed in Appendix Table 3, we randomly sample between 8 and 28 additional variables from the 28 *other* possible variables. For this set of explanatory variables, we perform a regression with SEG as the dependent variable, eliminate variables with t-statistics below 1, and perform a regression on the remaining set. For each case, we retain the regression coefficient. We iterate this procedure 1,000 times for each variable separately. Those variables whose 90% confidence interval excludes zero are included in the above Jackknife specifications. We report the 5th and 95th percentiles in brackets. N denotes the number of country-years, and *Adj. -* R^2 denotes the adjusted coefficient of determination.

which gives us confidence that the relevant variables are being selected. While equity market openness survives using both methodologies, only trade openness survives the jackknife procedure, but it is statistically insignificant. The PcGets procedure selects five variables in the "Risk appetite and business cycles" category. Of those, U.S. risk aversion and world GDP growth, which have surprising signs, do not survive the jackknife procedure.

The second set of specifications using capital account openness, presented in columns 3 and 4 for the PcGets and jackknife methodologies, respectively, confirms this general picture. The selected variables overlap almost entirely with those selected when equity market openness is used as the de jure capital liberalization measure. The only "new" variable is "Law and Order," which is retained by the jackknife procedure.

Overall, when we search for factors that are (nearly) significant across both methodologies and both the equity and capital market specifications, it appears that segmentation is primarily driven by three types of factors: de jure globalization (financial openness and Investment Profile being correlated with a regulatory climate conducive to FDI), local financial market development (equity market capitalization to GDP in particular), and measures correlated with global risk premia and appetites (the corporate bond spread and the VIX). In addition, we document a robust return chasing effect and show that earnings volatility matters greatly.

4.2.2 Economic significance. The signs and significance of the preferred multivariate specifications are fairly straightforward to interpret, but the results do not provide clear guidance on which factors are relatively more important in explaining market segmentation. For the two main multivariate regressions selected under PcGets and reported in Table 5, we conduct two experiments to reveal the economic importance of the factors, both reported in Table 6. For both panels (equity market and capital account openness), we report the change in

Table 6
Contribution of market segmentation determinants 1980–2005

Panel A: Equity Market		Variance Decomposition				
	Effect on Segmentation	Overall Contribution	y_{it}-y_i (TS)	remainder (CS)	y_{it}-y_i (CS)	remainder (TS)
Equity Market Openness	−0.0079	0.1784 [0.1557, 0.3465]	0.0268	0.1516	0.1719	0.0065
Investment Profile	−0.0031	0.1358 [0.0688, 0.2231]	0.0419	0.0939	0.1483	−0.0125
Legal Origin (French)	0.0013	0.0046 [0.0035, 0.0114]	0.0000	0.0046	0.0046	0.0000
Private Credit/GDP	−0.0034	0.0989 [0.0693, 0.3588]	0.0153	0.0836	0.0904	0.0085
MCAP/GDP	−0.0024	0.1498 [0.1358, 0.3886]	0.0664	0.0834	0.1363	0.0135
U.S. Risk Aversion	−0.0056	0.0110 [−0.0045, 0.0166]	0.0110	0.0000	0.0000	0.0110
World GDP Growth	0.0042	−0.0140 [−0.0159, 0.0095]	−0.0140	0.0000	0.0000	−0.0140
U.S. Corporate Bond Spread	0.0126	0.1295 [0.0517, 0.1681]	0.1295	0.0000	0.0000	0.1295
VIX Option Volatility Index	0.0039	0.0510 [0.0164, 0.0987]	0.0510	0.0000	0.0000	0.0510
Past Local Equity Market Return	−0.0002	0.0606 [0.0557, 0.1045]	0.0545	0.0061	0.0346	0.0260
Abs. Diff. in Log Earnings Growth Volatility (|Local - Global|)	−0.0047	0.1450 [0.1360, 0.2624]	−0.0215	0.1665	0.1525	−0.0075
Number of Public Firms (log)	−0.0015	0.0486 [0.0336, 0.1444]	0.0049	0.0437	0.0522	−0.0036
Total Variance Contribution		1.00	0.37	0.63	0.79	0.21
N	1,078					
R^2	0.30					

(*continued*)

Table 6
Continued

Panel B: Capital Account		Variance Decomposition				
	Effect on Segmentation	Overall Contribution	y_{it}-y_i (TS)	remainder (CS)	y_{it}-y_i (CS)	remainder (TS)
Capital Account Openness	−0.0066	0.1596 [0.1169, 0.2533]	0.0609	0.0987	0.1337	0.0259
Investment Profile	−0.0026	0.1204 [0.0581, 0.2206]	0.0622	0.0582	0.1210	−0.0006
MCAP/GDP	−0.0023	0.1910 [0.1812, 0.4265]	0.0853	0.1057	0.1603	0.0307
U.S. Risk Aversion	−0.0049	0.0058 [−0.0035, 0.0094]	0.0058	0.0000	0.0000	0.0058
World GDP Growth	0.0048	−0.0145 [−0.0164, 0.0069]	−0.0145	0.0000	0.0000	−0.0145
U.S. Corporate Bond Spread	0.0125	0.1886 [0.0841, 0.2527]	0.1886	0.0000	0.0000	0.1886
VIX Option Volatility Index	0.0043	0.0658 [0.0156, 0.1184]	0.0658	0.0000	0.0000	0.0658
Past Local Equity Market Return	−0.0001	0.0606 [0.0537, 0.1123]	0.0596	0.0010	0.0501	0.0105
Abs. Difference in Log Earnings Growth Volatility (|Local - Global|)	−0.0034	0.1114 [0.1034, 0.2269]	−0.0344	0.1458	0.1402	−0.0288
Number of Public Firms (log)	−0.0026	0.1101 [0.0782, 0.2018]	0.0082	0.1019	0.0913	0.0188
Total Variance Contribution		1.00	0.49	0.51	0.70	0.30
N	1,002					
R^2	0.30					

We further analyze the PcGets specifications from Table 5. Panel A reports results for Equity Market Openness and Panel B for Capital Account Openness. In each panel and for each segmentation determinant, we first report the product of the coefficient estimate and either the difference between the average value for developed countries and the average value for emerging market countries or, in the case of variables that vary only over time, one standard deviation of that variable. We then report results from a variance decomposition. In particular, we report the contribution of each variable to the variation of the predicted degree of segmentation, defined as the ratio of the covariance between the given variable and the predicted degree of segmentation relative to the variance of the predicted degree of segmentation. We further distinguish between the time-series (TS) and cross-sectional (CS) component of this overall contribution in two different ways. For details on this distinction, see the corresponding section of the article. Finally, beneath the estimated overall contribution in brackets, we provide a confidence interval for each entry. These are derived from a jackknife experiment where, for each variable separately, we randomly sample between 8 and 28 additional variables from the 28 *other* possible variables (noted in Appendix Table 3). For this set of explanatory variables, we perform a regression with SEG as the dependent variable, throw out variables with t-statistics below 1, and perform a regression on the remaining set. For each case, we retain the overall contribution that the particular variable makes for predicted segmentation. We iterate this procedure 1,000 times for each variable separately. The 5th and 95th percentiles are presented in the brackets. Finally, N denotes the number of country-years and R^2 denotes the coefficient of determination.

the segmentation level when the independent variable moves from the average value of an emerging to the average value of a developed market. For the time-series variables, we simply consider the response to a one-standard-deviation change in the independent variable. The most important determinants for the equity openness regression, with induced changes of seventy-nine basis points or more, are equity openness and the U.S. credit spread. Past equity market returns, legal origin, and the number of firms are least important. For the capital account regression, the story is very similar.

In a second experiment, we examine how much of the variation in the segmentation variable is explained by the right-hand-side explanatory variables and what is the relative contribution of each. We use a simple R^2 concept computed as $\frac{Var(S\hat{E}G_{i,t})}{Var(SEG_{i,t})}$, where $S\hat{E}G_{i,t} = \hat{\alpha} + \hat{\beta}' X_{i,t}$, and $X_{i,t}$ is the vector of explanatory variables. The denominator is defined as

$$Var(SEG_{i,t}) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T_i} \sum_{t=1}^{T_i} (SEG_{i,t} - S\bar{E}G)^{2,} \tag{12}$$

where $S\bar{E}G = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T_i} \sum_{t=1}^{T_i} SEG_{i,t}$. The numerator is defined analogously as

$$Var(S\hat{E}G_{i,t}) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T_i} \sum_{t=1}^{T_i} (S\hat{E}G_{i,t} - S\bar{\hat{E}}G)^{2,} \tag{13}$$

where $S\bar{\hat{E}}G = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T_i} \sum_{t=1}^{T_i} S\hat{E}G_{i,t}$. Across the regression specifications provided, the predicted market segmentation explains about 30% of the variation of the observed market segmentation in the data.

To examine the contributions of each of the independent variables to the overall variation of the predicted market segmentation, we compute the following covariance for each explanatory variable j:

$$Cov(S\hat{E}G_{i,t}, \hat{\beta}_j x_{i,j,t}) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T_i} \sum_{t=1}^{T_i} \hat{\beta}_j (S\hat{E}G_{i,t} - S\bar{\hat{E}}G)(x_{i,j,t} - \bar{x}_j), \tag{14}$$

where $\bar{x}_j$ is the mean of variable $x_{i,j}$ across countries and time. Summed across all individual explanatory variables, these covariance terms must exactly equal the variance of the predicted market segmentation. In Table 6, we report the ratio of each covariance term to the overall predicted market segmentation variance, $\frac{Cov(S\hat{E}G_{i,t}, \hat{\beta}_j x_{i,j,t})}{Var(S\hat{E}G_{i,t})}$, where each column must necessarily sum to one. We report this variance decomposition for the two main regression specifications. In addition, we report a 90% confidence interval for this statistic, computed from the jackknife experiment.

In the main equity market openness specification (see Panel A), the largest contributors to the overall variation in the predicted market segmentation are equity market openness (around 18%), the investment profile (around 14%), private credit to GDP and market capitalization (MCAP)/GDP (together about 25%), the two control variables (collectively around 20%), and the U.S. credit spread (13%). Panel B provides comparable evidence for the main capital account openness specification. The general magnitudes are comparable. The confidence intervals (in both panels) provided by the jackknife analysis yield useful additional information. First, they confirm that U.S. risk aversion and world GDP growth may be spurious. The confidence intervals straddle zero. Second, for six variables, the contribution based on the selected specification is near the lower bound of the jackknife confidence interval, indicating that these variables are more important than the final regression point estimates indicate. These variables include the de jure financial openness, the past market return, earnings growth volatility and, most strikingly, the financial development variables (private credit to GDP and MCAP/GDP, but also the number of public firms, which may be correlated with stock market development).

Our measure of predicted segmentation variation captures both time-series and cross-sectional effects. We further perform two decompositions of these covariance terms into separate effects that capture each of these features. The first decomposition splits the total covariation for each explanatory variable into a within-country component (similar to taking out country fixed effects) and a pure cross-sectional between-country component (that is, the variation of fixed effects relative to the unconditional means):

$$Cov(S\hat{E}G_{i,t}, \hat{\beta}_j x_{i,j,t}) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_{t=1}^{T_i}\hat{\beta}_j(S\hat{E}G_{i,t} - S\bar{\hat{E}}G_i)(x_{i,j,t} - \bar{x}_{i,j}) + \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_j(S\bar{\hat{E}}G_i - S\bar{\hat{E}}G)(\bar{x}_{i,j} - \bar{x}_j), \quad (15)$$

where $S\bar{\hat{E}}G_i = \frac{1}{T_i}\sum_{t=1}^{T_i} S\hat{E}G_{i,t}$ and $\bar{x}_{i,j} = \frac{1}{T_i}\sum_{t=1}^{T_i} x_{i,j,t}$ denote the within-country means of the relevant variables. The second decomposition splits the total covariation into a within-year component (similar to investigating cross-sectional dispersion) and a pure time-series between-year component (the year effects relative to unconditional means):

$$Cov(S\hat{E}G_{i,t}, \hat{\beta}_j x_{i,j,t}) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_{t=1}^{T_i}\hat{\beta}_j(S\hat{E}G_{i,t} - S\bar{\hat{E}}G_t)(x_{i,j,t} - \bar{x}_{j,t}) + \frac{1}{T_i}\sum_{t=1}^{T_i}\hat{\beta}_j(S\bar{\hat{E}}G_t - S\bar{\hat{E}}G)(\bar{x}_{j,t} - \bar{x}_j), \quad (16)$$

where $S\bar{\hat{E}}G_t = \frac{1}{N}\sum_{i=1}^{N} S\hat{E}G_{i,t}$ and $\bar{x}_{j,t} = \frac{1}{N}\sum_{i=1}^{N} x_{i,j,t}$ denote the within-year cross-country means of the relevant variables.

Table 6 reports both decompositions. All covariance terms are again scaled by the variance of the predicted degree of segmentation, $Var(S\hat{E}G_{i,t})$. Both decompositions suggest that the largest contribution to the variation in predicted market segmentation is the cross-sectional component, the between-country component in the case of the first decomposition (accounting for around 63% of the explained variation), and the within-year component in the case of the second decomposition (accounting for 79%). The temporal variation is mostly accounted for by the global factors, but temporal variation in the openness, investment profile, MCAP/GDP, and past local equity market returns also contribute.

Overall, regulatory globalization, including the rules applying to foreign direct investments, is clearly a very important determinant of observed market segmentation. However, beyond regulatory openness, financial market development (especially stock market development) and global risk factors are also important determinants of de facto market segmentation.

5. Robustness Checks

We discuss several robustness checks.

5.1 Additional possible determinants of market segmentation

We have also applied the general-to-specific search algorithm to a smaller dataset with a larger set of possible segmentation factors that includes a measure of local market illiquidity, synchronicity, and the absolute differences between the local real interest rates and the global real interest rates, measured as the average across G7 countries.[20]

When financial openness is measured by equity market openness, thirteen variables survive the selection, including all three of the additional variables as well as equity market openness. Illiquidity and the real interest rate differential are also statistically significant. The effect of equity market openness is of the right sign, but its statistical significance is reduced. This may not be too surprising, though, given that Bekaert, Harvey, and Lundblad (2007) document that the process toward equity market openness itself directly affects the local trading environment, so we may in fact be capturing a channel through which financial openness operates. The remaining variables are similar to those presented in Table 5.

When financial openness is instead measured by capital account openness, twelve variables survive the selection. While the real rate differential and our measure of illiquidity are among those retained, only the real interest rate differential is statistically significant. The effect of capital account openness is smaller than that reported in Table 5, but remains highly significant. The other results are similar to those presented in Table 5.

5.2 United States as a benchmark

Using the world market as a benchmark to compare valuation levels has the disadvantage that the number of countries in the benchmark and their relative

20 See Appendix Table 3 for a list of all thirty-two variables considered. The results are available upon request.

weights change over time. Therefore, we repeat all of our empirical exercises using the U.S. stock market, the world's largest, as the benchmark. To do this, we drop the United States from the list of countries to investigate. Our results, available upon request, are robust to this change in benchmark, with slightly stronger effects associated with financial openness.

5.3 Differential risk exposure

A maintained assumption in the benchmark against which we evaluate our segmentation measure is that systematic industry risk is identical across countries. However, our measure could also reflect differences in global risk exposure for a particular industry across countries. In particular, variation in exposures to a "value factor" may be important given the role of valuation ratios in the construction of our segmentation measure. To address this issue, we run rolling time-series regressions (with sixty monthly observations), separately for each country-industry portfolio, of the portfolio returns onto three global return factors; the world market, the world size factor, and the world value factor.[21] We run the same regressions using global industry portfolio returns. Every month, we then calculate the absolute difference between the local industry value factor loading and its global counterpart and form the weighted average of these absolute value factor-loading differences across all industries in a country. The absolute difference captures the degree to which the constituent firms of a particular country-industry portfolio have different value exposures than the global benchmarks against which they are evaluated in our construction of SEG.

With the absolute differences in hand, we then repeat the main regressions presented in Table 4 (results are available upon request). While there is indeed a positive and significant relationship between our segmentation measure and differences in the value factor exposure in a univariate regression, the inclusion of our standard set of controls renders the coefficient of the value factor exposure insignificant. Importantly, the effects associated with financial openness are unchanged.

5.4 Equally weighted industry differentials

As we indicated before, the industry mix of a country may affect its segmentation level. To more cleanly focus on country regulations, we investigate an alternative SEG measure for which we employ *equal* weights for the various industries within each country. Table 7 reports these results, again, for the baseline specifications in Table 4 as well as the PcGets specifications in Table 5. Our results are also largely unchanged under this alternative weighting scheme.

21 These factor portfolios are constructed as in Zhang (2006).

Table 7
Market segmentation measured as equally weighted absolute industry differences 1980–2005

	Base Specification		PcGets Selection	
	Equity Market Openness	Capital Account Openness	Equity Market Openness	Capital Account Openness
Equity Market / Capital Account Openness	**–0.0271**	**–0.0337**	**–0.0198**	**–0.0289**
	(0.0080)	(0.0097)	(0.0061)	(0.0079)
Trade Openness	–0.0105	–0.0065		
	(0.0121)	(0.0088)		
Trend (x 100)	–0.0521	–0.0169		
	(0.0448)	(0.0468)		
Investment Profile			**–0.0226**	–0.0124
			(0.0108)	(0.0079)
Legal Origin (French)			–0.0056	
			(0.0049)	
Private Credit/GDP			–0.0085	
			(0.0054)	
MCAP/GDP			**–0.0082**	**–0.0112**
			(0.0028)	(0.0037)
U.S. Risk Aversion			–0.0032	–0.0021
			(0.0055)	(0.0052)
World GDP Growth			0.2530	**0.2991**
			(0.1409)	(0.1238)
U.S. Corporate Bond Spread			**2.0391**	**1.9665**
			(0.6492)	(0.6189)
VIX Option Volatility Index			**0.1142**	**0.1181**
			(0.0257)	(0.0231)
Past Local Equity Market Return			**–0.0155**	**–0.0140**
			(0.0048)	(0.0042)
Abs. Difference in Financial Leverage (| Local- Global|)	–0.0690	–0.1011		
	(0.0721)	(0.0714)		
Abs. Difference in Log Earnings Growth Volatility (|Local - Global|)	**0.1220**	**0.0865**	**0.0867**	**0.0619**
	(0.0279)	(0.0225)	(0.0249)	(0.0281)
Number of Public Firms (log)	–0.0035	**–0.0056**	–0.0030	**–0.0052**
	(0.0020)	(0.0016)	(0.0020)	(0.0015)
Intercept	1.1246	0.4419	**0.0617**	**0.0656**
	(0.8909)	(0.9305)	(0.0238)	(0.0200)
N	1,078	1,002	1,078	1,002
Adj. - R^2	0.21	0.17	0.32	0.30

Table 7 reports the analyses reported in Tables 4 and 5 when segmentation is measured as an equally weighted average industry valuation difference (as opposed to a value-weighted average). For a detailed description of all variables, see Appendix Table 2. We report coefficient estimates from pooled OLS regressions. Reported standard errors in parentheses account for serial correlation by country and contemporaneous correlation across countries. Bold coefficient estimates denote statistical significance at the 5% level under the panel OLS specification. N denotes the number of country-years, and *Adj.*- R^2 denotes the adjusted coefficient of determination.

5.5 Alternative portfolio formation criteria

Our results so far are based on an industry classification that allows for up to thirty-eight different industries per country. To better understand how sensitive our findings are to the granularity of the industry classification, we construct a segmentation measure that is based on only nineteen different industries. Our main findings as presented in Table 4 are largely unaltered.

Finally, we also examine whether our results are robust to forming portfolios by firm size. Size may be related to risk but unrelated to industry. Alternatively, small stocks may be more prevalent in emerging markets and such stocks may have higher betas, leading to lower valuations and higher segmentation levels. We construct a segmentation measure that is based on ten size portfolios, where size is measured as the annual sales revenue of a firm. Specifically, using firm-level data from Datastream for as many countries as possible, we form ten annual global size portfolios by ranking all firms based on their sales revenue in U.S. dollars (USD). We choose this characteristic because it is related to firm size, but not contingent on market capitalization, which could contaminate our subsequent measures that are also based on valuation information. We then measure segmentation for each country and year as the value-weighted absolute valuation differential between these global size portfolios and their country-specific counterparts. To make portfolios comparable across countries, we apply the same global cutoff points to all countries.

We find that segmentation levels were similar across different size portfolios in the early 1980s, but between 2001 and 2005 larger firms (in terms of annual revenue) are more integrated now than smaller firms. We reproduce Table 4 using this alternative grouping criterion. The results are surprisingly similar. This result also implies that the link between de jure openness and effective openness does not reflect an emerging market size bias.

5.6 Yield-level effect

It is conceivable that the segmentation level is biased upward in times of high earnings yields. To evaluate the importance of this effect, we add the world earnings yield to the baseline specifications in Table 4 as well as the PcGets specifications from Table 5. The coefficient on the new variable is negative, but statistically insignificant.

5.7 Interaction effects

Finally, the effects of a number of our explanatory variables may themselves be a function of the de jure openness of the country. For example, it is conceivable that financial development contributes to valuation convergence only in financially closed markets. Therefore, we investigate the role for interaction effects with equity market openness for all the variables in the main specification from column 1 in Table 5. We examine these effects one by one to prevent the proliferation of the independent variables. Only three of the variables, private credit to GDP, MCAP/GDP, and past local equity market returns, exhibit a significant interaction effect. For the most part, interaction effects are not statistically significant.

6. Conclusions

We propose a new, model-free measure of market segmentation, SEG, the absolute differential between local and global valuation ratios. It will shrink as discount rates and growth opportunities become global in nature.

While it is well accepted that the forces of globalization have reduced effective market segmentation over the past few decades, it is difficult to quantify the magnitude, the timing, and the sources of this reduction. Indeed, globalization (regulatory openness) is not a proxy for market integration, and it is important to note that past literature, for example, Bekaert and Harvey (1995) and Carrieri, Errunza, and Hogan (2009), has reported reversals in the degree of market integration despite increasing globalization. Our measure allows us to characterize both the time-series and cross-country variation in observed segmentation. De jure globalization, such as the openness of equity markets to foreign investors, plays a pivotal role in explaining cross-country differences in valuation differentials, but so does the institutional environment and local financial market development. Variables reflecting global risk conditions, such as the U.S. credit spread, also account for a significant proportion of SEG's variation. These variables alongside de jure openness explain about 30% of the variation in our measure of market segmentation. We find equity market openness to be the single most important economic explanatory variable, accounting for the largest share of the explained segmentation variance, but stock market development is almost as important.

Finally, since our segmentation measure employs a country's industrial structure as a key building block, we also explore market segmentation at the industry level. We find that historically heavily regulated industries, such as the banking and insurance sectors, were among the least integrated early in our sample and are now among the most integrated.

Much of the literature has focused on equity returns—for example, examining return correlations (see Bekaert, Hodrick, and Zhang 2009 and the references therein), or the evolution of betas with respect to a global benchmark (see Bekaert and Harvey 2000 and Baele 2005, among others). Often such tests fail to find strong evidence in favor of increased integration. Our method offers an alternative and perhaps more powerful perspective. A recent article by Pukthuanthong and Roll (2009) also finds a significant increase in the degree of integration using the R^2 produced by global factors for country equity returns. However, their measure also requires time-series estimation. With our "point-in-time" measure, it is more straightforward to answer the important questions of why one country is more segmented than another and why the degree of segmentation changes over time. For example, we can easily construct our segmentation measure for the recent crisis period (see Figure 3).

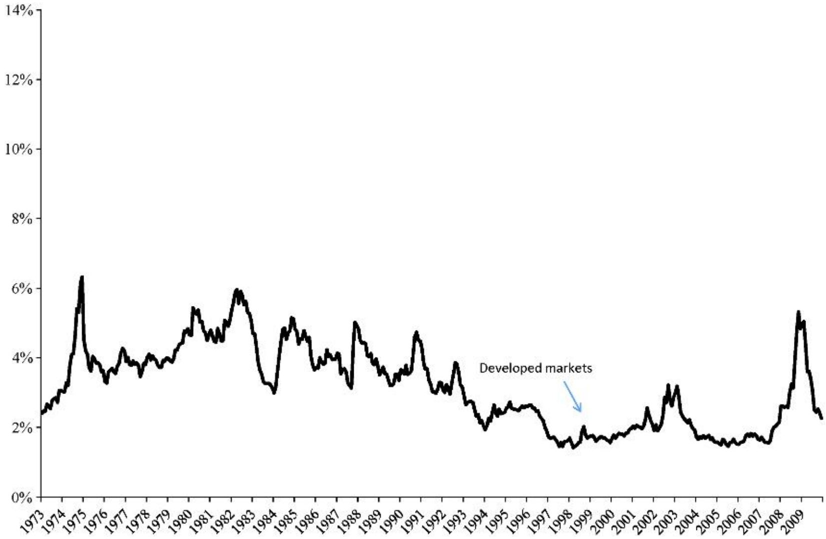

Figure 3
Average segmentation measure: Developed markets, 1973–2009

As expected, given the historical correlation between our segmentation measure and the VIX and the U.S. corporate credit spread, the average measured segmentation increases toward the end of 2008, but then falls back to near pre-crisis levels in 2009.

7. Appendix

A: Constructing 100 random samples of 69 "pseudo-countries" from U.S. data

We use the sample of 4,594 U.S. firms to construct 100 random samples, each of which resembles our actual dataset of 69 countries with respect to the approximate number of firms used.[22] In particular, we allow for cases where a "pseudo-country" contains 10, 20, 30, 40, 50, 60, 100, 150, 200, 250, 350, 500, or 1,000 firms. We start by defining country $i = 1$ and randomly selecting 10 U.S. firms. We then add another 10 firms randomly selected from the remaining set of firms, then another 10 firms, and so on until we have randomly selected 1,000 U.S. firms. We repeat this process 100 times, obtaining 100 "pseudo-countries" $i = 1, 2, 3, ..., 100$ each with 10, 20, 30, ..., 1,000 randomly selected firms. We then randomly select, without replacement, 69 out of the 100 "pseudo-countries" and associate them with the 69 countries present

[22] We know the exact number of firms used in a given year for countries for which we use EMDB data; we only know the approximate number of firms used by Datastream in 2006. For countries for which we obtain industry data from Datastream, we assume that the number of firms used until 1989 is about half (but not less than fifty) of the 2006 number of firms and is at the 2006 levels from 1990 onward.

in our actual international dataset. For example, Argentina could be associated with $i = 5$, Australia with $i = 43$, and so on. We then choose the number of randomly selected firms that is approximately equal to the number of firms present in the actual data. Assume, for example, that if we have 13 firms for Argentina in 1994 and 24 in 1995, we would work with the 10 randomly selected U.S. firms for $i = 5$ in 1994 and with the 20 randomly selected U.S. firms for $i = 5$ in 1995 and so on. Finally, we repeat this random selection process 100 times, obtaining 100 datasets that approximate our actual datasets with respect to the number of firms used in a given year and country. In each case, we proceed exactly as described in Section 3 to calculate a "pseudo-country's" degree of segmentation—that is, we first aggregate earnings yields across firms in the same industry and take absolute differences with respect to the corresponding U.S. earnings yield for the given industry and then aggregate this absolute difference across industries in a given country using industry market values as weights.

B: General-to-specific search algorithm (PcGets)

We employ the general-to-specific search algorithm of Hendry (1995) and Hendry and Krolzig (2001), as implemented in PcGets. The algorithm constitutes a "testing-down" process that starts with a general unrestricted model that in our case includes up to thirty-two possible explanatory variables. In multiple steps, the algorithm eliminates variables with coefficient estimates that are not statistically significant, leading to a parsimonious model. In particular, we first estimate the general unrestricted model that contains all available variables by OLS. We then eliminate variables that are statistically insignificant. The new model is then reestimated, and a multiple reduction path search is used to find all terminal models—that is, models in which all variables have statistically significant coefficient estimates. Finally, if more than one terminal model exists, the different terminal models are compared with each other and one is chosen as the unique final model. Appendix Table 4 presents the entire search process step by step as well as the chosen significance levels.

Hendry and Krolzig (2004) compare the model selection algorithm implemented in PcGets with alternative approaches used in the empirical growth literature, including the approach by Sala-i-Martin (1997), who ran two million regressions. They find strong support for the efficiency and accuracy of PcGets. Hoover and Perez (2004) examine the efficacy of the general-to-specific modeling approach using Monte Carlo simulations. Their findings are also supportive of the search algorithm we use in this study.

Table Appendix 1
Data availability

Developed				Emerging			
Source	**Code**	**Name**	***SEG data start***	**Source**	**Code**	**Name**	***SEG data start***
DS	AUS	Australia	1973	EMDB	ARG	Argentina	1986
DS	AUT	Austria	1973	EMDB	BHR	Bahrain	1999
DS	BEL	Belgium	1973	EMDB	BGD	Bangladesh	1996
DS	CAN	Canada	1973	EMDB	BWA	Botswana	1996
DS	DNK	Denmark	1973	EMDB	BRA	Brazil	1986
DS	FIN	Finland	1988	EMDB	BGR	Bulgaria	1996
DS	FRA	France	1973	EMDB	CHL	Chile	1986
DS	DEU	Germany	1973	EMDB	CHN	China	1993
DS	IRL	Ireland	1973	EMDB	COL	Colombia	1984
DS	ITA	Italy	1986	EMDB	CIV	Cote d'Ivoire	1996
DS	JPN	Japan	1973	EMDB	HRV	Croatia	1997
DS	NLD	Netherlands	1973	EMDB	CZE	Czech Republic	1994
DS	NZL	New Zealand	1988	EMDB	ECU	Ecuador	1996
DS	NOR	Norway	1980	EMDB	EGY	Egypt	1996
DS	SGP	Singapore	1973	EMDB	EST	Estonia	1997
DS	ESP	Spain	1987	EMDB	GHA	Ghana	1996
DS	SWE	Sweden	1982	DS	GRC	Greece	1989
DS	CHE	Switzerland	1973	EMDB	HUN	Hungary	1992
DS	GBR	United Kingdom	1973	EMDB	IND	India	1986
DS	USA	United States	1973	EMDB	IDN	Indonesia	1989
				EMDB	ISR	Israel	1997
				EMDB	JAM	Jamaica	1996
				EMDB	JOR	Jordan	1986
				EMDB	KEN	Kenya	1996
				EMDB	KOR	Korea	1986
				EMDB	LVA	Latvia	1997
				EMDB	LTU	Lithuania	1996
				EMDB	MYS	Malaysia	1984
				EMDB	MEX	Mexico	1986
				EMDB	MAR	Morocco	1996
				EMDB	NGA	Nigeria	1984
				EMDB	OMN	Oman	1999
				EMDB	PAK	Pakistan	1986
				EMDB	PER	Peru	1992
				EMDB	PHL	Philippines	1984
				EMDB	POL	Poland	1992
				DS	PRT	Portugal	1990
				EMDB	ROM	Romania	1997
				EMDB	RUS	Russia	1996
				EMDB	SVN	Slovenia	1996
				DS	ZAF	South Africa	1973
				EMDB	LKA	Sri Lanka	1993
				EMDB	THA	Thailand	1986
				EMDB	TTO	Trin. & Tobago	1996
				EMDB	TUN	Tunisia	1996
				EMDB	TUR	Turkey	1986
				EMDB	UKR	Ukraine	1997
				EMDB	VEN	Venezuela	1986
				EMDB	ZWE	Zimbabwe	1986

Appendix Table 1 lists the source of the data used in the construction of the measure of segmentation SEG: Datastream (DS) or Standard & Poor's Emerging Market Data Base (EMDB). The table also lists the country code and the corresponding country name as well as the first year for which the segmentation measure is available. In our analysis, we generally only include observations after 1979 for which our main independent variables are available. Due to the calculations of the volatility of log earnings growth, a country with data availability starting after January 1978 (1979) is included in our analysis with a delay of one (two) year(s). For Figures 1 and 2, we report observations prior to 1980. For those early years, we include all data points available.

Table Appendix 2
Description of all variables

Variable	Description
SEG	*SEG* measures the value-weighted average of the absolute difference between a country's local industry earnings yields and the corresponding global industry earnings yields. Available for all countries. For details, see Sections 2 and 3. Frequency: Monthly and Annual. Sources: Datastream and Standard & Poor's Emerging Market Data Base.
Openness	
Capital account openness	Quinn's capital account openness measure is created from the text of the annual volume published by the International Monetary Fund (IMF), *Exchange Arrangements and Exchange Restrictions.* Quinn's openness measure is scored 0–4, in half-integer units, with 4 representing a fully open economy. The measure hence facilitates a more nuanced view of capital account openness than the usual 0/1 indicator, and is available for 48 countries in our study. We transform the measure into a 0 to 1 scale. Frequency: Annual.
Equity market openness	Following Bekaert (1995) and Edison and Warnock (2003), the equity market openness measure is based on the ratio of the market capitalization of the constituent firms composing the International Finance Corporation (IFC) Investable index to those that compose the IFC Global index for each country. The IFC Global index, subject to some exclusion restrictions, is designed to represent the overall market portfolio for each country, whereas the IFC Investable index is designed to represent a portfolio of domestic equities that are available to foreign investors. A ratio of one means that all of the stocks are available to foreign investors. Fully segmented countries have an intensity measure of zero, and fully liberalized countries have an intensity measure of one. Frequency: Annual.
Trade openness	We obtain the trade liberalization dates developed in Wacziarg and Welch (2008). Wacziarg and Welch look at five factors: average tariff rates of 40% or more; non-tariff barriers covering 40% or more of trade; a black market exchange rate that is depreciated by 20% or more relative to the official exchange rate, on average, during the 1970s or 1980s; a state monopoly on major exports; and a socialist economic system. If a country meets any of these five criteria, it is classified with indicator variable equal to zero and deemed closed. Frequency: Annual.
Trade/GDP	The sum of exports and imports of goods and services measured as a share of gross domestic product. Frequency: Annual. Source: World Bank Development Indicators.
Political Risk and Institutions	
Quality of institutions	The sum of ICRG subcomponents: Corruption, Law and Order, and Bureaucratic Quality. Available for all countries. Frequency: Annual.
Corruption	ICRG political risk subcomponent. This is a measure of corruption within the political system. Such corruption distorts the economic and financial environment, reduces the efficiency of government and business by enabling people to assume positions of power through patronage rather than ability, and introduces an inherent instability into the political process. The most common form of corruption met directly by business is financial corruption in the form of demands for special payments and bribes connected with import and export licenses, exchange controls, tax assessments, police protection, or loans. Although the Political Risk Service (PRS) measure takes such corruption into account, it is more concerned with actual or potential corruption in the form of excessive patronage, nepotism, job reservations, "favor-for-favors," secret party funding, and suspiciously close ties between politics and business. In PRS's view these sorts of corruption pose risk to foreign business, potentially leading to popular discontent, unrealistic and inefficient controls on the state economy, and encourage the development of the black market. Frequency: Annual.

(*continued)*

Table Appendix 2
Continued

Variable	Description
Law and order	ICRG political risk subcomponent. PRS assesses Law and Order separately, with each subcomponent comprising zero to three points. The Law subcomponent is an assessment of the strength and impartiality of the legal system, while the Order subcomponent is an assessment of popular observance of the law. Thus, a country can enjoy a high rating (3.0) in terms of its judicial system, but a low rating (1.0) if the law is ignored for a political aim. Frequency: Annual.
Bureaucratic quality	ICRG political risk subcomponent. The institutional strength and quality of the bureaucracy can act as a shock absorber that tends to minimize revisions of policy when governments change. Therefore, high points are given to countries where the bureaucracy has the strength and expertise to govern without drastic changes in policy or interruptions in government services. In these low-risk countries, the bureaucracy tends to be somewhat autonomous from political pressure and to have an established mechanism for recruitment and training. Countries that lack the cushioning effect of a strong bureaucracy receive low points because a change in government tends to be traumatic in terms of policy formulation and day-to-day administrative functions. Frequency: Annual.
Investment profile	ICRG political risk subcomponent. Investment Profile reflects the risk of expropriation, contract viability, payment delays, and the ability to repatriate profits. This measure is closely associated with the attractiveness of a country for FDI. Available for all countries. Frequency: Annual.
Legal origin	Identifies the legal origin of the company law or commercial code of each country (English, French, Socialist, German, Scandinavian). We construct three indicators that take the value of one when the legal origin is Anglo-Saxon (English law), French (French law), or other (law other), and zero otherwise. This variable is purely cross-sectional and available for all countries. Available for all countries. Source: La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997).
Financial Development	
Illiquidity	Following Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), and Bekaert, Harvey, and Lundblad (2007), we construct the illiquidity measure as the proportion of zero daily returns observed over the relevant year for each equity market. We obtain daily returns data in local currency at the firm level from the Datastream research files. For each country, we observe daily returns (using closing prices) for a large collection of firms. The total number of firms available from the Datastream research files accounts for about 90%, on average, of the number of domestically listed firms reported by the World Bank's World Development Indicators. For each country, we calculate the capitalization-weighted proportion of zero daily returns across all firms, and average this proportion over the year. Available for forty-six countries. Frequency: Annual.
Equity market turnover	The ratio of equity market value traded to the market capitalization. The data are available for all countries. Frequency: Annual. Source: Standard and Poor's/International Finance Corporation's *Emerging Stock Markets Factbook* and World Bank Development Indicators.
MYY R^2 synchronicity	Equity market synchronicity as developed in Morck, Yeung, and Yu (2000). The measure is an annual value-weighted local market model R^2 obtained from each firm's daily returns regressed on the local market portfolio return for that year. Available for forty-seven countries. Frequency: Annual.

(*continued*)

Table Appendix 2
Continued

Variable	Description
Private credit/GDP	Private credit divided by gross domestic product. Credit to private sector refers to financial resources provided to the private sector, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable that establish a claim for repayment. Available for all countries. Frequency: Annual. Source: World Bank Development Indicators.
MCAP/GDP	Equity market capitalization divided by gross domestic product. Available for all countries. Frequency: Annual. Source: World Bank Development Indicators.
Risk Appetite and Business Cycle	
G7 real rate	Weighted average real short term interest rate in G7 countries: the prime lending interest rate adjusted for inflation as measured by the GDP deflator. Frequency: Annual.
U.S. money supply growth	Annual growth in money supply (M2) for the United States. Frequency: Annual. Source: World Bank Development Indicators.
U.S. risk aversion	We measure U.S. risk aversion based on the parameter estimates of the habit-persistence model from Campbell and Cochrane (1999). Frequency: Annual. Source: Bekaert and Engstrom (2010).
World GDP growth	Growth of real world per capita gross domestic product. Frequency: Annual. Source: World Bank Development Indicators.
U.S. corporate bond spread	The yield spread between U.S. Baa and Aaa rated bonds obtained from the Federal Reserve Board. Frequency: Annual.
VIX option volatility index	The VIX option volatility index available from the CBOE (www.cboe.com). The December value of the volatility index is used for each year. The volatility index covers 1986 to the present, before which we take the square root of the average daily squared Center for Research in Securities Prices (CRSP) U.S. total market return over the year to extend the index back to 1980. Frequency: Annual.
Past local equity market return	The lagged annual return, from December to December, on the country-level market portfolio. Available for all countries. Frequency: Annual. Sources: Datastream and Standard & Poor's Emerging Market Data Base.
World equity market volatility	The variance of the world market portfolio return, measured as the five-year rolling variance of the monthly return on the world market portfolio. Frequency: Annual. Source: Datastream.
Information Variables	
Phone lines per 100 people	Number of fixed lines and mobile phone subscribers per 100 people. Available for all countries and years. Frequency: Annual. Source: World Bank Development Indicators.
Internet users per 100 people	Number of internet users per 100 people. Available for all countries and years. Frequency: Annual. Source: World Bank Development Indicators.
International voice traffic	The number of minutes of international phone calls per person. Available for a subset of countries and years. Frequency: Annual. Source: World Bank Development Indicators.
Growth Determinants	
Initial log GDP	Logarithm of real per capita gross domestic product reset every five years in 1980, 1985, 1990, 1995, and 2000. Source: World Bank Development Indicators.
Secondary school enrollment	Secondary school enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the secondary level of education. Accordingly, the reported value can exceed (or average) more than 100%. Available for all countries. Frequency: Annual. Source: World Bank Development Indicators.

(*continued*)

Table Appendix 2
Continued

Variable	Description
Log life expectancy	Growth rate of total population that counts all residents regardless of legal status or citizenship. Available for all countries. Frequency: Annual. Source: World Bank Development Indicators.
Population growth	Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life. Available for all countries. Frequency: Annual. Source: World Bank Development Indicators.
Controls	
Number of public firms (log)	The log of the number of publicly traded firms in a given country. Frequency: Annual. Source: World Bank Development Indicators.
Number of public firms (log) (U.S. benchmark)	The natural logarithm of the number of U.S. public firms used in the construction of the segmentation measure for a given state or "country" in a given year. Frequency: Annual.
Abs. difference in financial leverage (|Local - Global|)	We obtain annual accounting data for all public firms contained in Bureau van Dijk's OSIRIS data base. For industrial firms, we define financial leverage as the ratio of long-term interest-bearing debt to total assets. For financial firms, we define financial leverage as the ratio of total liabilities to total assets. Weighting each observation by total assets, we aggregate this ratio across all firms per industry, country and year. Since coverage is limited in time and across industries and countries, we use linear regressions based on country dummies, industry dummies, private credit over GDP, as well as industry return volatility to predict industry leverage when leverage data are not available. We then take the absolute difference between local industry leverage and the corresponding global industry leverage, which we calculate as the weighted average across all firms around the world in a given industry. Finally, for each country and year we average this absolute leverage difference across all industries in a country using an industry's market value as its weight. Available for all countries. Frequency: Annual.
Abs. difference in financial leverage (|Local - US|)	Used in the U.S.Benchmark Analysis Industry leverage is the ratio of long term debt, data item 9 in Compustat, summed over all firms in a given industry and state/"country," to total assets, data item 6 in Compustat, summed over all firms in a given industry and state/"country." We use an industry's equity market value to average the absolute differences between state/"country" and U.S. market leverage across all industries in a given state/"country." Frequency: Annual.
Abs. difference in log earnings growth volatility (|Local - Global|)	We measure log earnings growth volatility by calculating the five-year standard deviation of quarterly log growth rates of twelve-month earnings for all industries at the country and global level. We require at least eight quarters of data for the calculation. We then form the weighted average of the absolute difference between local and global industry log earnings growth volatility for each country and year, where we use industry market values as weights. Available for all countries. Frequency: Annual.

(*continued*)

Table Appendix 2
Continued

Variable	Description
Abs. difference in log earnings growth volatility (|Local - US|)	Used in the U.S. Benchmark Analysis We calculate the volatility of log industry earnings growth each December by aggregating quarterly firm-level earnings across firms with consecutive earnings data in a given industry and state/"country," taking the log of the growth rate in industry earnings and calculating the standard deviation of the log growth rate over the past twenty quarters, as long as we have non-missing data for at least eight quarters. We use an industry's equity market value to average the absolute differences between state/"country" and U.S. market log earnings growth volatility across all industries in a given state/"country." Frequency: Annual.
Abs. Difference in Real Interest Rate (|Local - Global|)	The absolute difference between the local real interest rate (i.e., prime rate less inflation as measured by the GDP deflator, obtained from World Bank World Development Indicators) and the weighted average real short term interest rate in G7 countries. Frequency: Annual.

We considered several other potentially useful measures, such as earnings expectations, measures of regulatory conditions and labor market frictions, accounting standards and earnings management, etc., but had to drop them because of data limitations.

Table Appendix 3
Variables considered for segmentation model 1980–2005

Candidate Variables	Candidate Variables (continued)
Trend	**Information Variables**
	Phone Lines per 100 people
Openness	Internet Users per 100 people
Equity Market Openness	
Capital Account Openness	**Growth Determinants**
Trade Openness	Initial Log GDP
Trade/GDP	Secondary School Enrollment
	Log Life Expectancy
Political Risk and Institutions	Population Growth
Quality of Institutions	
Investment Profile	**Controls**
Law and Order	Abs. Difference in Financial Leverage (|Local - Global|)
Legal Origin (English)*	Abs. Difference in Log Earnings Growth Volatility (|Local - Global|)
Legal Origin (French)*	Number of Public Firms (log)
Financial Development	**Additional Candidate Variables**
Local Equity Market Turnover	Local Equity Market Illiquidity
Private Credit/GDP	MYY R^2 Synchronicity
MCAP/GDP	Abs. Difference in Real Interest Rate (|Local - Global|)
Risk Appetite and Business Cycles	
G7 Real Rate	
U.S. Money Supply Growth	
U.S. Risk Aversion	
World GDP Growth	
U.S. Corporate Bond Spread	
VIX Option Volatility Index	
Past Local Equity Market Return	
World Equity Market Volatility	

Appendix Table 3 lists the independent varibales that are considered as possible determinants of segmentation. In any given specification, we include either Equity Market Openness or Capital Account Openness, but not both. We also consider three additional variables, Local Equity Market Illiquidity, MYY R^2 Synchronicity, and the Abs. Difference in Real Interest Rates for which some country years are missing. Variables marked with * are time-invariant. In all specifications, we include an intercept term. For a detailed description of all variables, see Appendix Table 2.

Table Appendix 4
Model reduction algorithm

Steps	Significance Levels
1 Formulate and estimate a general model (G1)	
a Test significance of individual coefficient estimates: t-test If all estimates are individually significant, G1 is the final model.	0.025
b Test G1 against the null of "all coefficients are zero" and the null of "all coefficient but constant are zero": F-test If the null is not rejected, it is the final model.	0.500
2 Pre-search tests	
a Top-down tests	
Test joint significance of expanding list of coefficient estimates (from smallest to largest t-statistic): F-tests If F-test does not reject, remove variables. Reduced model is the new general model (G2).	0.500
b Estimate new general model (G2) and repeat top-down tests.	
Test joint significance of expanding list of coefficient estimates (from smallest to largest t-statistic): F-tests If F-test does not reject, remove variables.	0.250
c Bottom-up tests	
Test joint significance of decreasing list of coefficient estimates (from largest to smallest t-statistic) : F-test	0.025
d Test whether model can be reduced to those variables that the bottom-up tests finds to be jointly significant: F-test If F-test does not reject, remove additional variables identified by bottom-up test. The reduced model is the new general model (G3).	0.025
3 Multiple-path tests	
a Estimate the new general model (G3). If all estimates are individually significant, G3 is the final model: t-test	0.025
b Otherwise, initiate search paths. Remove blocks of variables with increasing p-values of t-statistics and reestimate model: – Check groups with t-p-values $>$ 0.90 – Check groups with t-p-values $>$ 0.70 – Check groups with t-p-values $>$ 0.50 – Check groups with t-p-values $>$ 0.25 – Check groups with t-p-values $>$ 0.10 – Check groups with t-p-values $>$ 0.05 – Check groups with t-p-values $>$ 0.01 – Check groups with t-p-values $>$ 0.001 Remove one insignificant variable at time until all insignificant variables have "commenced" a path.	
c Continue search paths:	
As long as insignificant estimates survive, drop the least significant one and reestimate: t-test	0.025
A search path is abandoned if no coefficients are significant: t-test	0.025
A path arrives at a terminal model if all coefficient estimates are significant: t-test	0.025
4 Encompassing	
If all search paths are abandoned, G3 is the final model. If there is only one terminal model, it is the final model.	
If there are multiple terminal models, each is tested against the union of all terminal models: F-test – If all models are rejected, the union is the final model. – If only one model is not rejected, it is the final model. – If multiple models are not rejected, they are tested against their union (after removing any rejected models): * If only one model is not rejected, it is the final model. * If all models are rejected, the union is the final model. * If no model is rejected, their union is the new general model (G4).	0.025

(*continued*)

Table Appendix 4
Continued

Steps	Significance Levels
5 Repeat steps 3 and 4 for the new general model (G4)	
If there is only one terminal model, it is the final model.	
If there are multiple terminal models, they are again tested against their union:	
– If only one model is not rejected, it is the final model.	
– If all models are rejected and their union equals G4, then G4 is the final model.	
– If several models are not rejected and their union does not equal G4, their union is the new general model (G5) and steps 3 and 4 are repeated again.	
– If several models are not rejected and their union equals G4, the model with the smallest Schwarz criterion is the final model.	

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