

Essays in Emerging Market Finance and Integration

Andrea Kiguel

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
under the Executive Committee
of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2019

©2019

Andrea Kiguel

All Rights Reserved

ABSTRACT

Essays in Emerging Market Finance and Integration

Andrea Kiguel

Financial integration is often perceived to lead to convergence of asset prices, as well as higher comovements across countries, with the idea that the dependence on world factors should increase as markets integrate. This dissertation focuses on analyzing how integration has changed over time in developed and, especially, emerging markets. In particular, the chapters tackle different aspects of how integration has changed over time and the relevance of particular global factors in pricing.

In [Chapter 1](#), I study the link between globalization and asset returns. Here, I provide a comprehensive analysis of the impact of economic and financial globalization on asset return comovements over the past 35 years. The globalization indicators draw a distinction between *de jure* openness that results from changes in the regulatory environment and *de facto* or realized openness, as well as between capital market restrictions across different asset classes. Although globalization has trended positively for most of the sample, the global financial crisis and its aftermath have provided new headwinds. Equity, bond, and foreign exchange returns often have different responses to globalization. I generally find weak evidence of comovement measures reacting to globalization and often find other economic factors to be equally or more important determinants.

In [Chapter 2](#), I analyze variance risk in global markets. Innovations in volatility constitute a potentially important asset pricing risk factor that can be easily tested through the return on variance swaps. I characterize the exposure of the returns on three asset classes (equities, bonds and currencies) in all regions of the world to United States based equity variance risk. I explore the implications for global risk premiums and asset return comovements using both developed and emerging markets. I first find that regional portfolios across all three asset classes and practically all countries exhibit negative loadings with respect to the variance risk factor. This exposure is not only statistically but also economically significant representing for most assets we consider around 50% of the global risk premiums implied by a simple three-factor model with global equity, bond, and variance risks. Second, this simple three-factor model also explains a substantive fraction of the comovements between international assets, but the fit is best for international eq-

uity correlations and is worse for currency returns and across asset correlations.

In [Chapter 3](#), I study the link between time-varying integration and asset pricing. Emerging markets are subject to constant integration shocks, which can make markets more integrated or more segmented. Changes in integration have dynamic effects that are difficult to accommodate in valuation models, as both time-varying betas and risk premium are needed to capture the direct and indirect effects of changes in integration on dividend yields. Here, I develop a novel present value model to value cash flows with time-varying expected returns, where integration affects the cost of capital in a time-varying fashion. This framework prices expectations about future integration, which is modeled as a mean reverting process. I calibrate the model using a segmentation shock in Argentina in 2011 as a case study, and find that the model is able to capture part of the increase in dividend yields as markets became more segmented. By assuming that investors perceive the shock as permanent and thus price lower mean integration following the segmentation shock, I am able to model the full extent of the change in dividends.

The three chapters show that, while integration has broadly increased over time, different asset classes have different responses to globalization. I find that integration is time-varying and that markets can become more segmented; that is, integration is not a one-way street, as many models have assumed in the past. Finally, I show that global factors matter in emerging markets in all asset classes, and identify variance risk as a new risk factor which helps explain why global capital asset pricing models tend to yield low discount rates in these economies. Therefore, researchers and practitioners should take into account the importance of both local and global factors when valuing emerging market assets and take into account that the relative importance of each factor varies over time.

Contents

List of Tables	v
List of Figures	vi
Acknowledgements	vii
1 Globalization and Asset Returns	1
1.1 Introduction	2
1.2 Globalization	5
1.3 Asset Return Comovements	10
1.3.1 Theory	10
1.3.2 Measurement	13
1.3.3 Empirical Results on the Time Variation in Comovements	17
1.3.3.1 First versus Second Sample Half Results	18
1.3.3.2 The Time Variation in Convergence Statistics	20
1.4 Asset Return Convergence, Globalization and Other Factors	22
1.4.1 Convergence Measures and their Determinants	22
1.4.1.1 Empirical Framework	22
1.4.1.2 Equity Returns	26
1.4.1.3 Bond Returns	28
1.4.1.4 Foreign Exchange Returns	29
1.4.1.5 Return Dispersion	31
1.4.2 A Parametric Model and Time-varying Betas	32

1.4.2.1	The Model and Empirical Results	32
1.4.2.2	Interpreting the Results	34
1.4.3	Risk Premium Results	37
1.4.3.1	Risk Premiums in a Parametric Model	37
1.4.3.2	Risk Premium Dispersion	39
1.5	Additional Analysis and Robustness Checks	42
1.5.1	Local Currency Returns	42
1.5.2	Global Cycles	43
1.5.3	Corporate Governance	44
1.5.4	Effect of Unbalanced Samples	45
1.6	Conclusions	46
2	Variance Risk in Global Markets	74
2.1	Introduction	75
2.2	Data	77
2.3	Measuring Global Volatility Risk in Equity, Bond, and Currency Markets	79
2.3.1	Empirical Results for Equities	82
2.3.2	Empirical Results for Bonds	84
2.3.3	Empirical Results for Currencies	84
2.4	The Economic Importance of Global Volatility Risk	85
2.5	Comovements of Returns	88
2.5.1	Proportion of Correlations Explained	89
2.5.2	Root Mean Squared Error Correlation Analysis	91
2.6	Variance Betas: Dollar versus Local Currency	92
2.7	Conclusions	93
3	Time-Varying Integration and Valuation in Emerging Markets	110
3.1	Introduction	111
3.2	Dividend Yields and Integration	113
3.2.1	The role of financial integration	117
3.3	Data	121

3.4	Case Study: Argentina 2011	124
3.5	Calibration	125
3.5.1	Parameters	125
3.5.2	Results	127
3.6	Conclusion	130
Bibliography		137
Appendix		148
	Appendix for Chapter 1	148
	Appendix for Chapter 2	157
	Appendix for Chapter 3	159
C1	Mapping Cash Flows and Expected Returns to State Variables	159
C1.1	Mapping Cash Flows and Expected Returns to X_t and ν_{t+1}	159
C1.2	Mapping Expected Returns to X_t in Simplified Model	161
C2	The Pricing Equation	162
C3	The Pricing Equation: Simplified Model	165

List of Tables

1.1	Openness Summary Statistics	50
1.2	Asset Prices - Difference in Means Tests	51
1.3	Equity Kernel Weighted Regressions	54
1.4	Bond Kernel Weighted Regressions	56
1.5	Exchange Rate Kernel Weighted Regressions	58
1.6	Equity Returns, Globalization, Political Risk, Cycles and Crises	60
1.7	Bond Returns, Globalization, Political Risk, Cycles and Crises	61
1.8	Exchange Rate Returns, Globalization, Political Risk, Cycles and Crises	62
1.9	Equity Beta: Effect of Changes in Openness, Political Risk, Cycle and Crises	63
1.10	Bond Beta: Effect of Changes in Openness, Political Risk, Cycle and Crises	63
1.11	Exchange Rates Beta: Effect of Changes in Openness, Political Risk, Cycle and Crises	64
1.12	Cross-Sectional Dispersion in Risk Premiums	65
1.13	Cross-Sectional Dispersion in Equity Risk Premiums and Globalization	66
1.14	Cross-Sectional Dispersion in Bond Risk Premiums	67
1.15	Cross-Sectional Dispersion in Exchange Rate Risk Premiums	68
2.1	Summary Statistics - Regional Index Returns	99
2.2	Summary Statistics for Risk Factors	100
2.3	Global Equity Market Returns Priced by Their Exposures to U.S. Equity Market, Bond Market, and Variance Risks	101
2.4	Global Bond Market Returns Priced by Their Exposures to U.S. Equity Market, Bond Market, and Variance Risks	102

2.5	Global Foreign Exchange Market Returns Priced by Their Exposures to U.S. Equity Market, Bond Market, and Variance Risks	103
2.6	Regional Risk Premiums: Does Global Volatility Matter?	104
2.7	Pricing Errors	105
2.8	Model-Implied Relative to Realized Regional Correlations for Equity, Bond and For- eign Currency Markets	106
2.9	Correlations of Regional Equity, Bond and Foreign Exchange Markets	107
2.10	Correlations for Equities, Bonds, and Foreign Exchange within Regions	108
2.11	Model Fit: Root Mean Square Error	109
3.1	Argentina 2011-2105 Capital Controls Timeline	132
3.2	Calibration parameters	134
3.3	Dividend yields under different values of financial integration	135
3.4	The Cepo Shock: Permanent versus Temporary Changes in Financial Integration	135
A.1	Data Description	148
A.2	Country Start Dates and Classifications	155
A.3	Openness Measures Correlations	156
B.1	Countries and Assets	157

List of Figures

1.1	Openness Measures	69
1.2	Correlations, Betas and Idiosyncratic Risk: First Half versus Second Half	70
1.3	Time-Varying Correlations, Betas and Idiosyncratic Risk	73
2.1	The <i>VIX</i> and the Variance Swap Return	95
2.2	Excess equity returns and global variance by region	95
2.3	Excess bond returns and global variance by region	96
2.4	Excess foreign currency returns and global variance by region	96
2.5	Excess equity returns and global variance by region and global equity market state	97
2.6	Excess bond returns and global variance by region and global equity market state	97
2.7	Excess foreign currency returns and global variance by region and global equity market state	98
2.8	Variance Betas: Dollar versus Local Currency	98
3.1	Capital Controls 2011	136

Acknowledgements

I would like to thank my committee, fellow students and faculty and staff at Columbia for the support offered during the writing of this dissertation. First of all, I would like to express my gratitude to Geert Bekaert and Bob Hodrick for their guidance and encouragement, without their help this dissertation would not have been possible. I would like to especially thank my advisor, Geert, for always guiding me when I did not know what direction to follow, going through every little detail of each paper with me, pushing me to think from another perspective, and for all his time and dedication. I would also like to thank Bob for all his advice and support to become a better empirical researcher, and for all his helpful comments over the years. I am also grateful to Andrey Ermolov, Michael Gavin and Jesse Schreger for their valuable comments and helpful feedback. It has been amazing to have the opportunity to work with these amazing professors and people.

I would also like to thank the practitioners who gave me advise along the way and encouraged and inspired me to pursue my Ph.D; without their guidance, I may not have had the courage to go down this fulfilling path. A special thanks to Guillermo Mondino, Eduardo Levy Yeyati, Rodrigo Valdes, Piero Ghezzi, Jimena Zuniga, Mauro Roca and Claudio Irigoyen.

I am also deeply grateful to my amazing classmates and friends. I would especially like to thank Patricia Navarro Palau and Andrés Ayala for their encouragement, motivation and help. Patricia, the Ph.D. would have been a very different experience without you and your support has been invaluable. I would also like to thank Mariana Garcia Schmidt, Jorge Mejia-Licona, Shaowen Luo, Xing Xia, Zhongjin Liu, Guojun Chen, and all my cohort for all their help and advice during this process.

Finally, I would like to thank my family, since they were the ones who made this experience possible. Without the emotional support of my parents, Miguel and Claudia Kiguel, and my brother, Sebastian Kiguel, my son, Elliot Baker and especially, my husband, Eric Baker, this dissertation would not be completed. Thanks for believing in me and for your unconditional love and encouragement.

To Eric, for all his support.

Chapter 1

Globalization and Asset Returns

1.1 INTRODUCTION

Much ink has flowed in discussing effects of globalization on the terms of trade, asset returns, and the real economy. The literature is so voluminous that providing a comprehensive survey is nearly impossible. Fortunately, a number of summary articles already exist. [Bekaert and Harvey \(2003\)](#) survey both the real and the financial effects of financial openness, mostly focusing on equity markets. The evidence on the real side remains controversial. The survey articles by [Eichengreen \(2001\)](#) and [Kose, Prasad, Rogoff, and Wei \(2009\)](#) conclude that the empirical evidence on the costs and benefits of capital account liberalization remains mixed, whereas Henry's (2007) interpretation of the literature supports [Bekaert and Harvey's \(2003\)](#) view that capital account liberalization has promoted growth. Studies incorporating the dynamics of liberalization, such as those by [Bekaert, Harvey, and Lundblad \(2005\)](#), [Quinn and Toyoda \(2008\)](#), and [Gupta and Yuan \(2009\)](#), do find robust positive growth effects. Because the temporary effects of financial openness are likely small (see [Gourinchas and Jeanne \(2006\)](#)), recent work has focused on the effects of financial openness on factor productivity, mostly finding positive effects ([Bonfiglioli \(2008\)](#); [Bekaert, Harvey, and Lundblad \(2011\)](#)). The evidence linking financial openness to both real volatility and a country's vulnerability to crises remains mixed (see [Bekaert, Harvey, and Lundblad \(2006\)](#); [Kose, Prasad, and Terrones \(2006\)](#)). Nevertheless, there is a growing consensus that the relation between financial openness and economic growth and volatility is subject to threshold effects, with countries with better macroeconomic policies and institutions (including better-developed financial sectors) responding more positively to reforms (e.g., [Kose, Prasad, and Taylor \(2011\)](#)).

Although the bulk of cross-country studies find that trade openness and liberalization increase growth and factor productivity (see, e.g., [Sachs and Warner \(1995\)](#)), others criticize these findings (see, e.g., [Harrison and Hanson \(1999\)](#), [Rodriguez and Rodrik \(2000\)](#)). However, recent research has confirmed the positive effects using microeconomic data and more convincing econometric identification (see, e.g., [Amiti and Konings \(2007\)](#), [Topalova and Khandelwal \(2011\)](#)). The effect of trade openness and growth volatility is the topic of a large literature, with many studies finding that trade openness increases output volatility (see, e.g., [Rodrik \(1998\)](#), [Di Giovanni and Levchenko \(2009\)](#)). [Bekaert and Popov \(2016\)](#) find that de facto trade openness increases aggregate consumption volatility but trade liberalization (policy reforms) reduces it.

One important channel through which financial globalization affects the real sector is its impact on asset prices. [Stulz \(1999\)](#) concludes that opening a country to portfolio flows decreases its cost of capital without adverse effects on its security markets; [Karolyi and Stulz \(2003\)](#) argue that despite globalization, standard international asset pricing theory fails to explain the portfolio holdings of investors, equity flows, and the time-varying properties of correlations across countries. Both of these survey articles, as well as the survey by [Bekaert and Harvey \(2003\)](#), primarily focus on equity markets, as does the bulk of the academic literature. Trade links have also been shown to affect equity market correlations and asset prices across countries (see, e.g., [Bekaert and Harvey \(1997\)](#)).

In this article, we characterize the link between the globalization process and the comovement of asset returns. To do so, we start by providing a simple quantitative definition of globalization, distinguishing between economic and financial globalization and between *de jure* (regulatory) and *de facto* (realized) integration. For *de jure* financial openness, we measure the degree to which international capital flows and foreign holdings of domestic assets are unencumbered by regulations; for *de jure* trade openness, we measure the extent to which trade and service flows are free of regulatory restrictions. The *de facto* measures attempt to quantify the extent to which securities are actually held by foreign investors (as a result of international capital flows) or the magnitude of actual trade flows.

Conventional wisdom suggests that integration should lead to convergence of asset prices (projects of similar risk command the same price per unit of cash flow in integrated countries), as well as higher comovement of returns across countries. Using a large panel of data, we examine several measures of convergence and comovement and their link to quantitative measures of globalization. We cast a wider net than the existing literature by examining equity, bond, and foreign exchange returns. We also use several different measures of globalization, contrasting the effects of trade and financial openness as well as *de jure* and *de facto* integration measures, and we differentiate between openness measures applicable to equity, bond, and money markets. Our comprehensive examination may shed light on why many studies fail to document strong evidence of convergence using returns data (see the discussion by [Pukthuanthong and Roll \(2009\)](#)). The distinction between different asset classes is also important given recent findings that the real effects of liberalization may be positive for equity flows [foreign direct investment (FDI) and port-

folio equity flows] but negative for bond and money market flows (Kose, Prasad, and Terrones (2009); Aizenman, Jinjark, and Park (2013)).

The survey article by Stulz (1999) and much of the literature focus on expected returns. We do not address the important question of whether globalization has reduced the cost of capital, and we do not provide a comprehensive survey of this literature. For emerging markets, several studies (Bekaert and Harvey (2000), Henry (2000), Kim and Singal (2000)) find that stock market liberalization decreases the cost of capital, although the estimated magnitudes differ. Evidence from American Depositary Receipts announcements corroborates these findings (see, for example, Foerster and Karolyi (1999)). These studies avail themselves of several broad liberalization programs introduced in many emerging markets at a particular point in time. When globalization happens more gradually, documenting the cost of capital effects is considerably more difficult. Some limited evidence suggests that the cost of capital decreases when there is an increase in the degree of globalization (see, e.g., De Jong and de Roon (2005)), which is also the case in terms of efforts toward increased regional integration such as the European Union (see Bekaert, Harvey, Lundblad, and Siegel (2013)).

The global financial crisis of 2008–2009 has opened new research paths, given that globalization may have halted or even reversed course. In terms of trade, the World Trade Organization's Doha Round of multilateral trade negotiations, launched in 2001, has come to a standstill, and the global financial crisis has led to many protectionist tendencies in national policies that are evident, for example, in the Buy America program in the United States and in the imposition of local content requirement measures in many countries. The global financial crisis has also spurred research on financial macromanagement and macroeconomic stability, leading various researchers and policymakers, most notably the International Monetary Fund (IMF), to defend capital controls (Jeanne, Subramanian, and Williamson (2012); Rey (2015)). Brazil implemented controls on inflows in the face of currency appreciation, and Iceland introduced controls on outflows in the wake of its banking crisis. The after effects of the global financial crisis are still being felt, with political sentiment against the perceived negative consequences of globalization being voiced in many developed countries.

The remainder of this article is organized as follows. Section 1.2 defines our globalization measures and examines whether the degree of globalization has changed over the past 30 years. We

find that globalization has generally increased, with an important exception for debt markets in emerging countries. Although most measures trend upward, tests show little significance. Section 1.3 summarizes asset return data, reflects on where we should expect convergence and where not, and shows initial results on the convergence of asset returns. Importantly, we find that results differ across asset classes. For equities, we observe an increase in correlations and global betas and a decrease in idiosyncratic risk over the sample period. Similar conclusions hold for foreign exchange returns. Bond returns behave differently in developed markets, with correlations with the global bond market decreasing for a large number of countries, primarily driven by increases in country-specific risk. The various comovement measures do not show a consistent upward trend but reflect cyclical behavior. The dispersion of risk premiums seems to have consistently trended downwards. Section 1.4 links convergence measures to globalization and other factors, including political risk, business cycle variation, and crises. We generally find weak evidence of convergence linked to globalization, with the results often differing across empirical specifications, across asset classes, across country groups (developed versus emerging), and across convergence measures. Correlations are strongly impacted by movements in the variance of global asset returns, and for bond markets political stability is often an important determinant of return comovements. The dispersion of equity and bond risk premiums does seem to have fallen with increased financial openness. A number of robustness checks are presented in Section 1.5. The final section offers some concluding remarks.

1.2 GLOBALIZATION

We are interested in two aspects of globalization: economic integration, brought about by trade links, and financial integration, brought about by free capital flows. Measuring integration is fraught with difficulty and is the topic of a large literature in itself. In particular, de jure openness may not mean that markets are fully integrated because other factors, such as political risk and poor liquidity, may cause segmentation (for related analyses, see [Bekaert \(1995\)](#), [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#)); conversely, investment barriers may not prevent actual capital flows. [Aizenman and Noy \(2009\)](#) also show that there are important links between trade openness and financial openness, arguing that capital controls in trade-open countries are likely ineffectual.

Our primary interest is de jure measures of globalization. This focus is important because, ultimately, whether the trend toward globalization continues is mostly in the hands of policymakers. Also, [Bekaert, Harvey, and Lumsdaine \(2002\)](#) identify endogenous dates of market integration from economic and financial data, finding them to be mostly later than dates of market reforms, suggesting that de jure financial openness leads to de facto integration, albeit with a lag.

For trade openness, we create an annual current account openness measure following [Quinn and Toyoda \(2008\)](#). The measure, denoted by $TI_{i,t}^{QT}$ (trade integration, Quinn–Toyoda), varies from 0 to 8, with 8 indicating a country’s full compliance with the IMF’s Article VIII obligations regarding the absence of restrictions on the international trade of goods and services. We rescale the measure to be between 0 and 1 and update the data from 2011 to 2014 using a regression approach described in [Table A.1](#). An alternative measure is the trade liberalization indicator of [Wacziarg and Welch \(2008\)](#), which builds on the classification by [Sachs and Warner \(1995\)](#) of countries as either open or closed on the basis of five criteria, such as the magnitude of tariffs and nontariff barriers. Being a 0/1 indicator variable, the Wacziarg–Welch measure displays very little cross-sectional variation toward the end of the sample, and actually may not fully reflect the ongoing trend toward more openness. To help capture the reversal in trade openness observed since the start of the 2008–2009 global financial crisis, we also employ a de facto measure: exports plus imports divided by GDP of the current calendar year, denoted by $TI_{i,t}^{df}$.

There are substantially more data available on de jure financial globalization. We first consider the measure of capital account openness compiled by [Quinn and Toyoda \(2008\)](#), which is based on IMF data. They assess the degree of capital account openness on the basis of, inter alia, the presence of taxes on foreign investment, leading to an index between 0 and 4.¹ This capital account openness measure does not differentiate between restrictions particularly relevant for equity, bond, or foreign exchange markets. However, it is conceivable that capital market restrictions differ across these various markets. [Fernández, Klein, Rebucci, Schindler, and Uribe \(2015\)](#) use IMF data to create various subindices of de jure restrictions on a $[0, 1]$ scale for individual asset categories, such as bond securities, money market instruments, etc. It covers 91 countries from 1995 to 2013. We employ several subindices, namely mm (average money market restrictions; most

¹We thank Dennis Quinn for sending updated data through 2011; we rescale the measure between 0 and 1 and extend it through 2014 using a quantitative procedure described in [Table A.1](#).

relevant for the foreign exchange market), bo (average bond restrictions), and eq (average equity restrictions). Table A.1 describes the resulting measures, $FI_{i,t}^{Smm}$, $FI_{i,t}^{Sbo}$, and $FI_{i,t}^{Seq}$ (financial integration), in more detail. We refer to these measures as the Schindler measures, as Schindler (2009) was the first to compile them from information in the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). The literature has employed alternative measures, such as that of Chinn and Ito (2008), which essentially represents the first principal component of four dummy variables on the restrictions on external accounts drawn from the IMF’s AREAER. It is therefore highly correlated with the Quinn–Toyoda openness measures. Various measures exist that focus on equity market openness (see Bekaert (1995), Edison and Warnock (2003)), but they are mostly not up to date. We extend the Schindler indicators to 1980 using a regression procedure and information from the measures of Quinn and Toyoda (2008) and Chinn and Ito (2008).²

As a measure of de facto financial openness, we use the measure proposed by Lane and Milesi-Ferretti (2007): the ratio of foreign assets and foreign liabilities to GDP. Their gross measure adds up the stocks of direct investment, portfolio equity, debt assets (liabilities), and foreign exchange reserves, thereby covering all securities in the IMF’s International Investment Position, and divides the aggregate numbers by annual GDP.³ Because of our focus on various asset classes, we split the measure into a measure focusing on equity, $FI_{i,t}^{df,eq}$, and a measure focusing on debt, $FI_{i,t}^{df,debt}$, which we use for both bond and foreign exchange markets.

Our sample consists of 58 countries, with varying histories and different coverage across asset classes. Table A.2 provides the start dates for the various countries and asset classes. The sample ends in December 2014. All data sources and variable definitions are provided in Table A.1.

Figure 1.1 shows the openness measures averaged over developed and developing countries separately over time. The openness level is generally substantially higher in developed than in emerging markets. The QT capital market openness measures trend upward. For developed countries, financial openness is at about 0.8 by the beginning of our sample, but still continues to increase during the 1985–1990 period, when countries such as New Zealand, Japan, France, Italy, and Belgium further liberalized their capital markets. For emerging markets, a wave of

²Karolyi (2015) analyzes nine different de jure measures including four tax measures from Deloitte.

³Also see Karolyi (2015, ch. 6) for a list of de facto measures.

liberalizations occurred in the late 1980s and early 1990s, and our sample does miss some of these changes. The Schindler measures for emerging markets show no trend for the money market openness measure, a negative trend for the bond measure, and an upward trend for equity market integration until the onset of the global financial crisis. For developed markets, the same patterns are visible for both bond and equity measures, but for money markets, the integration measure decreases in the late 1990s before increasing after the global financial crisis. The decrease in the late 1990s occurs mostly because first the Czech Republic and then Korea enter the sample with very low openness values. Hence, this stems from the unbalanced nature of the sample. This is one reason why most of our empirical analysis uses country-fixed effects, which mitigate this problem.

For the de facto measures, there is a steep upward trend for both bond and equity assets and liabilities for developed but not for emerging markets, where the bond asset and liability measure actually decreases over time. IMF reports suggest that there has been a slowdown of capital inflows into emerging markets since 2010, ascribing the slowdown primarily to reduced growth prospects in many emerging markets. The renewed capital controls, which were especially binding for fixed-income investments (see above), may have played a role as well. At the same time, a number of emerging economies have built up substantial foreign reserves, which should increase gross international asset positions.

The QT trade openness measure generally trends up sharply at the beginning of the sample for both developed and emerging countries, with the trend weakening and being halted or even reversed (for emerging markets) toward the end of the sample. There is some volatile behavior early on, for example, a sharp increase and decrease of trade openness in the early 1990s for emerging markets, which was partially influenced by the entry of countries in early 1990 and late 1992 especially. The same pattern is evident for the de facto measure for emerging markets, which starts trending up after 1995, as does the measure for developed markets. Both measures show a steep fall during the global financial crisis as international trade collapsed.

Table 1.1 reports summary statistics for the openness measures for developed and emerging markets. Focusing first on the de jure $[0, 1]$ measures, for developed markets, the measures fluctuate between 0.5 and 1, with the medians all at 1. For emerging markets, in contrast, there is much more cross-country variation, with the 90% range between 0 and 1 for the Schindler measures and

between 0.25 and 1 for the QT measures. The medians are much lower for emerging than for developed markets. The de facto measures of trade (exports plus imports) and of financial openness (equity and debt) show a similar pattern.

Table 1.1 also reports averages for the first part versus the second part of the sample and tests whether the difference is significantly different from zero. The midpoint of the sample is country-specific. For developed markets, we observe in general an increase in integration, both in financial and trade terms and for both the de jure and de facto measures. For emerging markets, equity market integration (both de facto and de jure) and trade integration increase. However, for emerging markets, we observe a decrease in integration for both the de jure and de facto measures for debt markets. Several emerging markets reintroduced capital controls following the global financial crisis. We observe decreases in bond market openness for more than 15 countries, including Brazil, Indonesia, Russia, and Turkey. Despite this dissimilar variation, the openness measures are highly positively correlated, with correlations exceeding 0.5 and as high as 0.85 among the de facto and de jure measures (see Table A.3).⁴ The de facto and de jure measures are less correlated, with correlations mostly in the 0.3–0.4 range.

In addition to the informal visual inspection of graphs, we formally test whether there is a significant trend in globalization over the past 35 years. The benchmark model for the trend test is

$$y_t = \beta_1 + \beta_2 t + u_t, \quad (1.1)$$

where y_t represents the average globalization measures, and t is a linear time trend. We use the test developed by [Bunzel and Vogelsang \(2005\)](#), which is robust to $I(0)$ and $I(1)$ error terms and uses a Daniell kernel to nonparametrically estimate the error variance needed in the test. Our relatively small sample necessitates the use of a powerful test, and the Bunzel–Vogelsang test has optimal power properties. Perhaps not surprisingly, given our discussion of the Figures above, the trend tests only detect one statistically significant upward trend, namely for de facto equity integration, but (somewhat surprisingly) for emerging, not developed, markets. However, the trend coefficients are almost always positive, with the only exceptions occurring for bond and money market openness.

⁴Correlations across openness variables are calculated over the whole panel.

1.3 ASSET RETURN COMOVEMENTS

In this section, we consider what should be expected regarding the relation between asset return comovements and globalization, and we review the extant literature. We then discuss the convergence measures we employ and finally report how asset return comovements have varied over time.

1.3.1 Theory

Generally, we are interested in measuring the effects of globalization on returns on three asset classes: equities, bonds, and foreign exchange. How should globalization impact the comovement of these asset returns across countries? We study excess log returns, measured in dollars, so the perspective is that of a US investor. A first important point is that there is a strong link between bond and equity returns on the one hand and foreign exchange returns on the other. That is,

$$r_{i,t+1}^j = rr_{i,t+1}^{j,LC} + s_{i,t+1} - i_{US,t} = r_{i,t+1}^{j,LC} + r_{i,t+1}^{fx}, \quad (1.2)$$

with $j = e$ (equities), b (bonds), and where s_{t+1} is the change in the dollar per unit of foreign currency in country i , fx is foreign exchange, r is excess returns, rr is the actual (not excess) return, $i_{US,t}$ is the US short rate, and LC is local currency return. Note that the foreign exchange return is the change in the currency plus the interest rate differential and is proportional to the return on going long a forward contract in the foreign currency. Therefore, changes in the comovements of foreign exchange returns can surely lead to more or less comovement in dollar-based bond and stock excess returns. For this reason, we also investigate local returns in Section 1.5.

The main theoretical restriction of market integration on international pricing is that the pricing kernel is identical for each country's returns, whereas the cash flows are country-specific, but may be affected by trade integration through, for example, business cycle effects. Asset returns reflect valuation changes, driven by changes in interest rates, in risk premiums, and in (expected) cash flows. Fundamental factors driving bond prices and exchange rates such as inflation thus also play a role. Examining convergence of these components lies beyond the scope of this article, but is the subject of a voluminous and varied literature. Importantly, such convergence may have only

an indirect effect on many of the comovement measures that we examine, as these involve second moments, not first moments.⁵

In reflecting on the fundamentals behind the pricing of asset returns, a first framework to consider is that of interest rate parity. Let us start with real interest rate parity, which implies that real interest rates are equalized across countries. However, real interest rate parity requires strong and somewhat unpalatable assumptions to hold: uncovered interest rate parity, purchasing power parity, and the Fisher hypothesis in both countries. That is, full money market integration does not suffice, as it does not preclude the existence of currency and country risk premiums. Nevertheless, one would expect globalization to contribute to real rate convergence across the world, as open financial markets help equalize real returns to capital invested. Although financial market integration should be the major force affecting interest rates, under imperfect integration, trade openness may have important effects. Imagine a closed-economy world, in which real rates reflect expected real growth rates and local precautionary savings motives. Theoretically, the effect of trade openness is not clear. Trade integration might lead to specialization, which should lower output correlations across countries and thus would likely imply real rate divergence, but it might also lead to synchronization of business cycles through demand spillover effects. The evidence on real interest rate convergence is mixed but mostly focused on developed markets (see [Gagnon and Unferth \(1995\)](#); [Jorion \(1996\)](#); [Phylaktis \(1997\)](#); [Breedon, Henry, and Williams \(1999\)](#); [Goldberg, Lothian, and Okunev \(2003\)](#)).

For nominal interest rates, the uncovered interest rate parity condition holds: The nominal interest rate in one country equals the interest rate in another country plus expected exchange rate depreciation. These exchange rate expectations may then be linked to inflation expectations through purchasing power parity. The relationship may be weak because of the presence of currency risk and country risk premiums. Importantly, open financial markets and free trade need not lead to equalization of interest rates (see also [Frankel \(1989\)](#)), but they should lead to the disappearance of country premiums, induced by capital controls. The creation of a monetary union, as happened in the context of the European Union in 1999, is expected to lead to a convergence of

⁵See [Baele, Bekaert, and Inghelbrecht \(2010\)](#) for an application of a factor model to bond and stock returns correlations depending on the second moments of the factors; and [Dumas, Harvey, and Ruiz \(2003\)](#) for examining international stock return correlations as a function of output correlations within an equilibrium pricing model.

nominal interest rates, and it mostly did so within Europe (see [Baele, Ferrando, Hördahl, Krylova, and Monnet \(2004\)](#), [Jappelli and Pagano \(2008\)](#)). One may still observe some divergence for long-term bond yields, which is driven by variation in default risks or illiquidity across countries. Comparing short- versus long-term real interest rates, country-specific monetary policy should exert more of an influence on short-term interest rates, making convergence more likely to be observed for longer-term interest rates. However, if capital flows are unrestricted and the exchange rate is fixed, the trilemma hypothesis would suggest that independent monetary policy is impossible.

An alternative perspective on the convergence of nominal interest rates is a Fisherian world, where nominal interest rates equal real interest rates plus inflation expectations (and perhaps inflation risk premiums). Inflation is, of course, also an important state variable driving bond returns (and, to a lesser extent, equity returns). Globalization may impact the inflation process through a variety of channels. Trade openness generally increases the level of competition in both product and labor markets. Openness means increased tradability and substitutability of products and services across countries; increased contestability of both output and input markets; and increased availability of low-cost production in previous command economies, such as China. [Rogoff \(2003\)](#) and [Lane \(1997\)](#) argue that globalization decreases the central bank's incentive to inflate. [Chen, Imbs, and Scott \(2009\)](#) and [Cox \(2007\)](#) agree that globalization raises productivity growth, which is followed by inflation. On balance, these effects may contribute to inflation convergence across countries (see [Chen, Imbs, and Scott \(2009\)](#)). For example, one interesting recent hypothesis is that international trade has made it possible for many countries to import low inflation from China, withstanding the strong inflationary forces coming from commodity price shocks. Globalization should make country-specific inflation more sensitive to global excess demand conditions, although this, of course, also depends on exchange rate movements. [Borio and Filardo \(2007\)](#) show that, especially since the early 1990s, the role of global economic slack in explaining domestic inflation has substantially increased.

Globalization, together with improved central bank coordination, may also have played an important role in the shift toward lower inflation (see [Rogoff \(2003\)](#)). Inflation volatility (as well as output volatility) has decreased since the mid-to-late 1980s in a phenomenon known as the Great Moderation (see [McConnell and Perez-Quiros \(2000\)](#)). Indeed, there is a debate in macroeconomics about the causes of the break in volatility, which has not been settled even now that it

is becoming clear that this Great Moderation has come to an end (see, e.g., [Baele, Bekaert, Cho, Inghelbrecht, and Moreno \(2015\)](#)). The lower level and variability of inflation are important for us because they may affect comovement measures. At first glance, a substantially lower level of inflation may lead to convergence; decreased variability at the world level, however, may lead to decreased comovement if it is caused by the lower variability of global inflation shocks.

An important part of the variation in bond returns and, even more so, of equity returns comes from variation in risk premiums. Here, we expect financial market integration to be the main driver behind the convergence of term and equity premiums across countries. In integrated economies, securities of similar risk should command the same risk premium and we should likely observe risk premiums converge.

Finally, how should globalization affect the correlation of cash flows across countries? Here the debate on the effects of openness on business cycle convergence is relevant again. Assume that cash flows are positively correlated with output. The effect of openness on business cycle convergence has been studied extensively in the literature, but mostly with a focus on financial openness. Indeed, most theoretical models predict that financial market integration leads to business cycle divergence, through either specialization toward higher return projects [Obstfeld \(1994\)](#) or the attraction of capital to positive productivity shocks [Baxter and Crucini \(1995\)](#). The empirical evidence is mixed (compare the work of [Kalemli-Ozcan, Papaioannou, and Peydró \(2013\)](#), who find divergence, with that of [Imbs \(2004\)](#), who finds convergence). Thus, the theoretical literature would suggest that financial market integration may lead to business cycle divergence and hence to lower cash flow correlations. Recall that trade openness has ambiguous effects on output growth correlations. Of course, how output translates into cash flows is an entirely different matter, which may depend on the competitive structure in particular countries. [Ammer and Mei \(1996\)](#), for example, find that cash flow growth rates are more highly correlated across countries than are output growth rates.

1.3.2 Measurement

To investigate whether we observe a pattern of cross-country convergence/comovement in returns, we require a measure of convergence. The most obvious convergence statistic is the correlation. There is a long tradition in finance of examining the links between globalization and return

correlations. (An alternative statistic to examine the correlation for a group of countries would be the variance ratio proposed by [Ferreira and Gama \(2005\)](#).) [Bekaert and Harvey \(2000\)](#), [Kim and Singal \(2000\)](#), and [Bekaert, Harvey, and Lumsdaine \(2002\)](#) use the stock market openings of emerging markets at the end of the 1980s and the beginning of the 1990s to trace the effects of (a shock to) integration on asset prices, typically using event study-type methodologies. They find that liberalizations increase the correlation with world market returns. [Longin and Solnik \(1995\)](#) detect an upward trend in correlations across the G7 countries using a multivariate GARCH model, but [Bekaert, Hodrick, and Zhang \(2009a\)](#) only find a significant trend within Europe. Of course, correlations have well-known limitations, especially when one is looking for low-frequency changes in comovement. The reason is that correlations vary considerably over time, particularly in response to movements in the volatilities of underlying factors. Consider a simple one-factor model for a variable $r_{i,t}$ for country i :

$$r_{i,t} = \beta_i f_t + \varepsilon_{i,t}. \quad (1.3)$$

Imagine that f_t is the world factor. An example of such a model would be the world capital asset pricing model (CAPM), where $r_{i,t}$ would be the country's equity (excess) market return and f_t the world (excess) market return. It is easy to show that, in such a model, the correlation between $r_{i,t}$ and f_t equals

$$\rho_{i,f} = \beta_i \frac{\sigma_f}{\sigma_i}, \quad (1.4)$$

where σ_i is the volatility of the variable $r_{i,t}$ and σ_f the volatility of the factor. Consequently, all else being equal, if the volatility of the factor increases, it increases the correlation between $r_{i,t}$ and the global factor, and, given that the $\varepsilon_{i,t}$ are idiosyncratic, increases the correlations among all country variables correlated with f , provided they have positive betas. (For related discussions, see [Boyer, Gibson, and Loretan \(1999\)](#); [Forbes and Rigobon \(2002\)](#); [Bekaert, Harvey, and Ng \(2005\)](#); [Bekaert, Hodrick, and Zhang \(2009a\)](#).) It is well known that the volatility of well-diversified equity portfolios varies substantially over time without showing significant permanent changes. Macro variables show distinct cyclical variation in volatility, being higher in recessions (for consumption growth, see, e.g., [Bekaert and Liu \(2004\)](#)). Consequently, there is much scope for correlations to show substantial temporary movements that make it difficult to detect the possible underlying trends caused by the globalization process. In particular, they may temporarily increase when

factor volatilities are temporarily high, a phenomenon we call the volatility bias.

The volatility bias for equity markets is worse in bear markets. [Erb, Harvey, and Viskanta \(1994\)](#), [Longin and Solnik \(1995\)](#), and [Ang and Bekaert \(2002\)](#) show that stock markets are unusually highly correlated in bear markets, even beyond what can be attributed to the higher variance of market factors in such market conditions. Consequently, the incidence of bear markets may play a role in measuring changes in correlations. In our empirical work, we control for global recessions and crises to mitigate the volatility bias, but this may not suffice; we therefore also control for it directly using a volatility measure.

Considering Equation 1.3, one sees that financial market and trade integration is most likely to manifest itself in the betas. As markets integrate, the dependence on world factors presumably increases. The literature here is large. Articles that have parameterized betas as a function of integration indicators (most frequently, measures of trade integration) include [Harvey \(1995\)](#), [Bekaert and Harvey \(1997\)](#), [Chen and Zhang \(1997\)](#), [Ng \(2000\)](#), [Fratzscher \(2002\)](#), [Bekaert, Harvey, and Ng \(2005\)](#), and [Baele and Inghelbrecht \(2009\)](#).

Some caution needs to be exercised; if the global factor simply aggregates the country-specific variables (which would be the case in a strict application of the world CAPM), then the betas must add up to 1 and, hence, cannot increase for all countries. However, the bulk of the articles we mention apply variants of Equation 1.3 in such a way that these constraints do not apply, for example, by using the United States as the global benchmark. Likewise, we use GDP-weighted returns for the G7 countries as the benchmark. The model can be represented as

$$r_{i,t} = \alpha_i + \beta_i r_{w,t} + \varepsilon_{i,t}, \quad (1.5)$$

where $r_{i,t}$ denotes returns in country i at time t and $r_{w,t}$ denotes the global benchmark. Given that the United States has a dominant weight in the G7 benchmark, we exclude it from the set of countries in our panel sample, as comovements would be severely upward biased for the United States. The benchmarks are asset class-specific and are further described in Table A.1. The regressions are estimated country by country using Ordinary Least Squares (OLS).

In the context of this one-factor model, the correlation has three main determinants (for more discussion, see [Baele, Bekaert, and Schäfer \(2015\)](#)): a volatility bias (the ratio of global to local

volatility), the beta, and the idiosyncratic (country-specific) volatility. We also examine the time variation in country-specific volatilities.

Our framework does have a shortcoming, as it restricts attention to one factor. [Pukthuanthong and Roll \(2009\)](#) propose using the R^2 of a multifactor model to measure market integration. Using a principal-components approach with 10 factors to compute time-varying R^2 s, they uncover a marked increase in measured integration for most countries, which is not revealed by simple correlations among country indices.

The last convergence measure we examine is cross-sectional dispersion:

$$CS_t^2 = \frac{1}{N} \sum_{i=1}^N \left(x_{i,t} - \frac{1}{N} \sum_{i=1}^N x_{i,t} \right)^2. \quad (1.6)$$

This statistic measures how dispersed a variable (in this case, $x_{i,t}$) is around its cross-sectional mean at each point in time. The measure has obvious appeal, as we would expect that full market integration might induce low cross-sectional return dispersion, and the statistic can be computed at each point in time without any historical time series. One concern about the cross-sectional dispersion measure is that it may be mechanically increasing in overall volatility even if that volatility is global in nature. To get more insight into this issue, we decompose the expected value of the cross-sectional dispersion as follows:

$$E[CS_t^2] = E \left[\frac{1}{N} \sum_{i=1}^N (x_{i,t} - \bar{x}_t)^2 \right] = \frac{1}{N} \sum_{i=1}^N \text{var}(x_{i,t}) + \overline{CS}^2 - \text{var}(\bar{x}_t), \quad (1.7)$$

where $\overline{CS}^2 = (1/N) \sum_{i=1}^N (\bar{x}_i - \bar{\bar{x}})^2$ is the cross-sectional variance applied to country means, \bar{x}_t is the cross-sectional mean at time t , and $\text{var}(\bar{x}_t)$ denotes a time-series variance. Hence, the cross-sectional dispersion comprises the cross-sectional dispersion of country means and also pure volatility terms: the difference between average total volatility and the volatility of the cross-sectional mean at time t , where the latter can be viewed as the global factor. Consequently, volatility only increases dispersion to the extent that it does not reflect volatility of the global factor, that is, to the extent that it is idiosyncratic. Although this appears intuitive, there is some evidence that overall volatility and global systematic volatility may be (highly) correlated (see [Bekaert, Hodrick, and Zhang \(2012\)](#)). Therefore, we also correct for volatility bias in regressions that involve

cross-sectional dispersion. For our regression analysis, we transform the dispersion measure into an annualized volatility measure, which facilitates its economic interpretation.

1.3.3 Empirical Results on the Time Variation in Comovements

Unless we make strong parametric assumptions, our comovement measures, with the exception of cross-sectional dispersion, require windows of time-series observations to be quantified. Using short windows likely increases noise, but using long windows prevents a full characterization of their time variation. We therefore follow a two-pronged approach. In Figure 1.2 and Table 1.2, we investigate the values of the various statistics (correlation, beta, and idiosyncratic risk) in the first versus the second half of the sample. Again, note that the sample halves are country-specific. Such an approach is perhaps coarse, but it provides a robust nonparametric view on whether the past 15 years have witnessed increases in asset return comovements. In Figure 1.3, we investigate the time variation in the various statistics. To do so, we must create time-varying measures of the various statistics. Our approach is to start from a particular data point, say time t_0 , split the sample into five-year subsamples, and use 30 data points before and after this data point. Within subsamples, we use a normal kernel to downweight observations further away from time t_0 .⁶ In particular, we compute the time-varying correlations, betas, and idiosyncratic risk as follows:

$$\text{corr}_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j)(r_{i,t+j} - \bar{r}_{i,t})(r_{w,t+j} - \bar{r}_{w,t})}{\sqrt{\sum_{j=-30}^{j=30} K_h(j)(r_{i,t+j} - \bar{r}_{i,t})^2} \sqrt{\sum_{j=-30}^{j=30} K_h(j)(r_{w,t+j} - \bar{r}_{w,t})^2}}, \quad (1.8)$$

$$\beta_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j)(r_{i,t+j} - \bar{r}_{i,t})(r_{w,t+j} - \bar{r}_{w,t})}{\sum_{j=-30}^{j=30} K_h(j)(r_{w,t+j} - \bar{r}_{w,t})^2}, \quad (1.9)$$

$$\text{var}_{i,t}^{\varepsilon} = \sum_{j=-30}^{j=30} K_h(j)(\varepsilon_{i,t+j} - \bar{\varepsilon}_{i,t})^2, \quad (1.10)$$

where $\bar{r}_{i,t} = \sum_{j=-30}^{j=30} K_h(j)r_{i,t+j}$, $\varepsilon_{i,t} = r_{i,t} - \beta_{i,t}r_{w,t}$, $\bar{\varepsilon}_{i,t} = \sum_{j=-30}^{j=30} K_h(j)\varepsilon_{i,t+j}$, and $K_h(j) \equiv K(j/h)/(hT)$ is a kernel with bandwidth $h > 0$. We use a two-sided Gaussian kernel with an

⁶Note that with this method, we lose the first and last 30 observations of each country's sample. In order to recover the first 30 observations, we start with an asymmetric kernel that uses 30 forward-looking observations for the first data point. As we move forward in the sample, we incorporate all the possible backward-looking observations. We apply the same methodology, in the opposite direction, to the last 30 observations.

18-month bandwidth, $K(z) = (1/\sqrt{2\pi}) \exp(-z^2/2)$, where $z = (t/T - \tau)/h$, $\tau = t_0/T$, and h is expressed as a fraction of the sample size T . We divide by the sum to ensure the weights add to 1 in a finite sample. Note that 76% of the observations are within 18 months of the base observations.

1.3.3.1 First versus Second Sample Half Results

Figure 1.2 shows the average (correlation, beta, and idiosyncratic risk) in the first and second halves of the sample period. The sample midpoint averages differ for developed and for emerging countries and across asset classes and are reported in Table 1.2a. We depict the average statistic for the first half of the sample on the x -axis and for the second half of the sample on the y -axis. If the country dots are mostly above the 45° line, the statistic increases in the second half of the sample relative to the first half. In Table 1.2, we report averages across the developed and emerging markets for the two sample halves and a test of the significance of their difference. We first discuss the correlation statistics, followed by the beta statistics, the idiosyncratic risk statistics, and finally the dispersion statistics.

In terms of correlations, the equity return results show that return correlations invariably increase from the first part to the second part of the sample, with the correlation increases often being very substantial. On average, the correlation increases from 0.56 to 0.79 for developed and from 0.31 to 0.62 for emerging markets, with both changes highly statistically significant. Bond returns offer a more mixed picture. For emerging markets, the correlations still generally increase, with Hungary and Lebanon being the only exceptions. On average, the correlation increases from 0.13 to 0.45, which is economically and statistically significant. However, for developed markets, correlations decrease for several countries, and the average increase is economically trivial (from 0.70 to 0.71) and statistically insignificant. One potential partial reason for this phenomenon is the European sovereign debt crisis post-2010, which may explain the presence of Greece, Ireland, and Portugal among the countries whose correlations decreased. We more formally examine the link between correlation and crises in Section 1.4. For foreign exchange returns, we observe a more general increase, with the only currencies that correlate less with the world foreign exchange return more recently being the yen and the Argentinean peso. Unusual country-specific policies in these countries are likely to blame. In Japan, substantial monetary easing associated with Abenomics, introduced in 2012, caused a dramatic weakening of the yen. In Argentina, Cristina Kirch-

ner introduced currency controls in 2011, after which the peso depreciated steadily; by the end of 2015, the gap between the overvalued official and the parallel rate was reported to be nearly 70%. For developed markets, correlations increase from 0.48 to 0.68, with the change significant at the 10% level, whereas for emerging markets, correlations increase from 0.22 to 0.50, with the change significant at the 1% level.

It is possible that the increase in correlation we observe stems simply from the volatility bias, induced by the recent global financial crisis, which we discussed above. Investigating betas and idiosyncratic risk can shed some initial light on this. An increase in betas is more likely to be permanent, as it cannot stem from volatility bias. It is plausible that country-specific risk permanently decreases with globalization. What happens in a global crisis is unclear. It is possible that idiosyncratic risk temporarily increases in crisis times together with systematic volatility, counteracting the volatility bias. It is also possible that a global crisis causes investors to focus on global macro factors rather than on the pricing of country-specific factors.

For equity returns, only a small minority of the countries (5 out of 25 developed countries and 4 out of 22 emerging countries) experience a decrease in beta relative to the global benchmark. On average, betas increase from 0.97 to 1.18 for developed and from 0.90 to 1.19 for emerging markets. Both changes are statistically significant. In addition, idiosyncratic risk also decreases for virtually all countries, with the average changes being 6% (in annualized volatility terms) for developed markets and a very substantial 16% for emerging markets, both of which are highly statistically significantly different from 0.

For emerging bond returns, betas invariably increase, consistent with the general observed increase in correlations. The increase is economically large, from 0.09 to 0.94, and generally statistically significant. For developed markets, betas only decrease for three countries (Norway, the United Kingdom, and Japan), and betas increase on average from 1.27 to 1.50, the change being significant at the 5% level. Average idiosyncratic risk increases insignificantly for developed markets, but decreases by 6% for emerging markets, the change being significant at the 10% level. Therefore, the decrease in bond return correlations observed for many developed countries can likely be attributed to an increase in country-specific risk, which may even counteract increases in global betas.

For foreign exchange returns, Figure 1.2 shows that betas mostly increase and thus can be a

reason for observing increased correlations, but the idiosyncratic risk changes show no pattern. Table 1.2 reveals that the increase in betas exceeds 0.45 for both emerging and developed countries. For idiosyncratic risk, we indeed do not observe any significant changes. Hence, the observed increases in correlations are because of increased global betas.

Table 1.2e shows results regarding cross-sectional dispersion, which significantly and substantially decreases for equity returns in both developed and emerging markets. For bonds, it increases slightly but significantly for developed markets, but decreases significantly by 5% for emerging markets. For foreign exchange returns, dispersion decreases significantly for emerging markets by about 4%, whereas for developed markets there is a small increase that is significant at the 5% level. Eun and Lee (2010) investigate distance measures in returns and volatility of equity returns and also document strong convergence.

1.3.3.2 The Time Variation in Convergence Statistics

We start with a graphical view of the evolution of the convergence statistics over time. Figure 1.3 depicts the correlations, betas, and idiosyncratic volatilities for equity returns, bond returns, and foreign exchange returns. To produce the exhibits, we average the kernel-weighted statistics over respectively, emerging and developed markets.

In Figure 1.3a, with some exceptions, return correlations follow a similar pattern across country categories and across asset classes: flat or decreasing in the beginning of the sample, showing a sharp upward trend from about the end of the 1990s through the global financial crisis before decreasing again. These results are somewhat in contrast with those of Eiling and Gerard (2015), who find that emerging market correlations increase (both within regional groups and with developed markets) for most of their sample, and those of Christoffersen, Errunza, Jacobs, and Langlois (2012), who find that correlations increase for both developed and emerging markets. Both papers use different methodologies but rely on certain parametric restrictions to derive their results. Importantly, their sample ends in 2009, missing the downturn in correlations that we observe.

Figure 1.3 examines the time variation in the global betas. Many studies, mostly focusing on equity markets, have observed that betas with respect to global factors increased over time. Baele (2005) and Baele, Ferrando, Hördahl, Krylova, and Monnet (2004) have documented increases in shock spillovers with respect to the global market, and Bekaert and Harvey (2000) show that stock

market liberalizations increase betas. The graphs suggest a somewhat more mixed pattern, similar to that observed for correlations, at least for bond and foreign exchange returns. For equities, we see little trend for developed markets, with slow increases only happening toward the end of the 1990s. For emerging markets, the increase is sharp until about 2000, but then shows more cyclical movements varying between 1.0 and 1.5. For idiosyncratic volatility in emerging markets, we observe a sharp downward trend, interspersed with some cyclical movements for all asset returns. The same pattern, but much weaker, is visible for equity returns in developed markets, whereas for bonds and exchange rates, cyclical movements dominate, with the recent global and European sovereign crises causing a spike in volatility.

To detect quasi-permanent movements in convergence/divergence measures, we use trend tests. This may appear strange at first, as it is quite possible that some measures may move to a point where they can no longer converge further. Also, if *de jure* liberalizations drive changes in the measures, a break analysis around the liberalization dates would appear superior. However, recall that we are interested in the convergence of returns across countries. Consequently, the convergence measures are affected by liberalizations in all the countries in the sample. Given sufficient cross-sectional and temporal variation in the liberalizations over time, the pattern could look like a slow trend over time, which might coincide with the trends in the globalization process itself, even though these are somewhat weak (see Figure 1.1 and Table 1.1). Therefore, the test must have the power to detect a slow trend, even if the break in one country is sudden and abrupt. Nevertheless, in many countries or regional groups (such as the European Union), integration itself has been gradual. For instance, Korea relaxed foreign ownership restrictions starting in 1991, in slow increments, to finally become totally open in 2002. The use of trend analysis is also widespread in the literature (see, e.g., [Bekaert, Hodrick, and Zhang \(2009a\)](#); [Eiling and Gerard \(2015\)](#)).

The results are reported in Table 1.2. For correlations, we find positive trend coefficients for all asset classes and country groups, except for bonds in developed markets, where the trend coefficient is essentially 0. None of the coefficients is significantly different from 0. A similar picture emerges for betas, where the coefficient is always positive but, again, no coefficient is significant. For idiosyncratic risk, the coefficient is negative except for bond and foreign exchange returns in developed markets. Again, statistical significance is elusive. This may be because of

a lack of power of the tests or may simply reflect that many of the comovement measures show too much cyclical behavior for an underlying trend to shine through. In Section 1.4, we attempt to control for some of the potential determinants of these cyclical movements. Table 1.2e shows the tests for cross-sectional dispersion, and these tests prove more powerful. We find negative trend coefficients in all cases (except for bonds in developed markets), which are all statistically significant for emerging markets.

1.4 ASSET RETURN CONVERGENCE, GLOBALIZATION AND OTHER FACTORS

We now directly investigate the link between our return convergence measures and our openness variables. We use two approaches. Our first approach is informal, linking the convergence measure examined in the previous section to globalization measures and other control variables using a simple panel model. Our second approach estimates a parametric factor model that allows for the conditional mean and the beta exposure to the global factor to vary through time with various determinants. It therefore focuses on the global factor exposure as a convergence measure but also allows us to extract time-varying risk premiums.

1.4.1 Convergence Measures and their Determinants

We now explore the link between our convergence measures and both trade and financial openness.

1.4.1.1 Empirical Framework

To explore the link between globalization and the convergence of asset returns, we specify multivariate regressions of the form

$$\text{Conv}_{i,t} = \alpha_i + \beta_1 \text{TI}_{i,t} + \beta_2 \text{FI}_{i,t} + \gamma' Z_{i,t} + \varepsilon_{i,t}, \quad (1.11)$$

where $\text{Conv}_{i,t}$ is the convergence measure (correlation, beta, or idiosyncratic risk), $\text{TI}_{i,t}$ is the trade openness measure, $\text{FI}_{i,t}$ is the financial openness measure, and $Z_{i,t}$ are control variables that we

discuss below. We use only one globalization measure in each regression, as they are highly correlated. To accommodate the serial correlation in the error terms, we use country-clustered standard errors in our main specifications. We also check whether a trend variable survives in such a specification. Finally, note that the regressions feature country-fixed effects, so that they are truly picking up (common) time variation in our sample.

We use four control variables that may *ex ante* have a significant effect on convergence but that may not be directly related to openness. The first is a country-specific business cycle variable, denoted by $\text{Cycle}_{i,t}$. To measure the stage of the business cycle, we subtract a moving average of past GDP growth (over the last five years) from current GDP growth. However, we only have quarterly or end-of-year annual GDP growth. To turn this into a monthly variable, $\text{Cycle}_{i,t}$ is constructed using the weighted average of the quarterly or annual business cycle variable $\text{Cycle}_{i,s,a}$ in the current quarter or year and last quarter or year. For example, assuming we only have annual GDP growth, in t , the m -th month of year s ,

$$\text{Cycle}_{i,t} = \frac{12-m}{12}\text{Cycle}_{i,s-1,a} + \frac{m}{12}\text{Cycle}_{i,s,a}. \quad (1.12)$$

It is well known that, in recessions, all asset returns are more variable, which may lead to higher asset return comovements to the extent that the variability increase is systematic rather than country-specific. In a robustness check, we replace the country-specific cycle variable with its global counterpart (a weighted average of the G7 countries' growth rates). The country-specific business cycle variable is mildly negatively correlated with the openness variables.

The second variable is a crisis measure, denoted by $\text{Crisis}_{i,t}$. When crises are isolated to a few countries or one region, they may actually decrease the comovement with global returns. However, if the crises are global in nature, comovements may increase. We use the crisis variable of [Reinhart and Rogoff \(2009\)](#), who investigate seven varieties of crisis, including banking and currency crises, for a large panel of countries. We map their $[0, 7]$ score onto the $[0, 1]$ interval. Overall, the crisis variable is negatively correlated with the openness measures. It is conceivable that governments face pressure in times of crisis to impose capital controls. [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#) suggest that in times of crisis, markets become more effectively segmented. We further comment on the different nature of the crisis variable for developed versus developing

countries when discussing the results.

The work of [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#) is part of a large literature that stresses the difference between *de jure* and *de facto* integration as reflected in asset prices. For instance, [Bekaert \(1995\)](#) argues that indirect barriers to investment (such as poor liquidity, poor corporate governance, political and substantial macroeconomic risks, etc.) may keep institutional investors out of certain emerging markets and prevent *de facto* integration, even though these markets are legally open. [Nishiotis \(2004\)](#) shows how these indirect barriers are more important than direct barriers using a sample of closed-end funds. [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#) develop a measure of *de facto* equity market segmentation and find that, apart from equity market openness, a measure of the quality of institutions, stock market development and certain global risk variables (proxied for by US credit spreads and the US equity market volatility measure, VIX) also greatly matter in explaining the temporal and cross-sectional variation in *de facto* segmentation.

As a third explanatory variable, we use a variable that consistently shows up as a strong determinant of effective segmentation, namely political risk. We use data on the political risk ratings of the International Country Risk Guide (ICRG; for more information, see [Table A.1](#)), which are available for a large panel of countries. Political risk measures the attitude of a government toward FDI, and [Bekaert, Harvey, Lundblad, and Siegel \(2014\)](#) show that high political risk repels FDI. Because several components of the ICRG political risk measure attempt to reflect the quality of a government's institutions and its attitude to businesses more generally, it may be correlated with measures of corporate governance.

The use of international data in the corporate finance literature has expanded, yet few try to control for the degree of openness. There is an implicit assumption that cross-country differences in corporate governance are of first-order importance. This implicit argument was recently made eloquently explicit by [Stulz \(2005\)](#). He argues that a twin agency problem of rulers of sovereign states and corporate insiders, pursuing their own interests at the expense of outside investors, limits the beneficial effects of financial globalization. In other words, corporate governance at the firm and country level, not financial openness, is the main factor driving cross-country differences in returns. Unfortunately, panel data on corporate governance for a large set of countries are not available, but our political risk measure may allow an informal test of Stulz's theory. Although we

believe this measure is likely correlated with the quality of corporate governance, we may obtain a better proxy by focusing on subindices of the overall rating. For a robustness check, we create an index of the quality of institutions from three of the overall rating's components, Corruption, Law and Order, and Bureaucracy Quality, following [Bekaert, Harvey, and Lundblad \(2005\)](#). Note that the political risk rating varies between 0 and 100, where 100 represents perfect political stability. We transform the measure to a [0,1] scale but keep the political stability scaling. The correlation between political stability and our openness measures is far from perfect, hovering around 0.50.

Finally, we also control for the volatility bias we discussed before by adding a monthly measure of the realized global equity variance (for details of the computation, see [Table A.1](#)).

Our empirical results are organized in [Tables 1.3, 1.4, and 1.5](#) for equities, bonds, and foreign exchange returns, respectively. We consider two alternative specifications for our independent variables. The approach discussed here applies the same kernel to our control variables as we use for the dependent variables. Alternatively, we can simply use the control variable observation at time t . Each table has three panels, with regression results for correlations, betas, and idiosyncratic volatility, respectively. The first four columns in each table report results for developed and for emerging markets, first for a *de jure* and then for a *de facto* openness measure. The last four columns repeat these results, adding a trend term to the specification. The last two lines of each table produce the coefficients on the trade openness measures in regressions where the financial openness measures are replaced with trade openness. Because of the relatively high correlations between these two measures, the other coefficients do not change much and are therefore not reported.

Note that we run a large number of different specifications and therefore should expect some coefficients to be significant just by chance (for a discussion of the effect of data mining on statistical inference, see [Harvey, Liu, and Zhu \(2016\)](#)). To mitigate this problem, we focus our discussion on results that are statistically significant and robust across two different specifications. That is, the asterisks in [Tables 1.3–1.5](#) refer to 1%, 5% and 10% significance using the kernel-weighted specification of the control variables. However, we only view a coefficient as robust if it has the same sign and is at least significant at the 10% level in the alternative specification using the independent variables simply at time t . Such coefficients are bolded.

1.4.1.2 Equity Returns

We start our discussion with the equity return correlations. For developed markets, equity return correlations are not significantly affected by *de jure* financial globalization, but they do increase significantly with *de jure* trade integration. The coefficient of 0.65 indicates an economically very significant increase of correlation; when trade integration increases from its 5% to 95% value (a move of 0.47), correlations would be expected to increase by $0.47 \times 0.65 = 0.31$. The coefficient is much reduced in value and loses statistical significance when a time trend is introduced. For *de facto* integration, the financial and trade openness measures are both positive but marginally statistically significant (at the 5% and 10% levels, respectively), but all lose statistical significance when a trend is introduced. For emerging markets, we find positive coefficients for almost all openness measures, which are significant in about half of the specifications. The effect is economically and statistically strongest for *de facto* equity market integration. When a trend is introduced, the effects lose significance for the *de facto* measures.

In all specifications, the trend coefficient is highly significant, that is, correlations have trended upward, even when we control for variables potentially accounting for their time variation. Note that the significance of the trend coefficient may not mean that openness does not matter. As Table 1.1 indicates, most openness measures show positive trend behavior, which is, however, only statistically significant for the *de facto* financial measure for emerging markets.

As to the other variables, their signs are robust across the different specifications, but only a minority of the coefficients are statistically significantly different from 0. Political stability is associated with higher global correlations, but the coefficient is only significant in one specification, namely for developed markets and *de jure* financial openness. Its economic effect implies an increase in the correlation of $0.24 \times 0.74 = 0.18$ when political stability goes from the 5% to the 95% level in the sample (a change of 0.24 in the measure). The cycle variable does not have a significant effect on equity return correlations. The crisis variable is only significant for emerging markets and has a negative coefficient. The negative sign may be surprising if the crisis variable predominately measures global crises, during which we would expect correlations to increase. However, although the crisis variable, on average, peaks in the global financial crisis, its average value is higher for emerging markets in the early and late 1990s, whereas for developed markets there are

a number of occasional peaks (with the variable indeed being highest during the global financial crisis). Finally, the global variance coefficient is positive and very significant in all specifications, suggesting that the volatility bias is a key driver of correlations.

In Table 1.3b, we show the same specifications for the time-varying global betas. For developed markets, the coefficients on openness are mostly small and insignificant, with the exception of the coefficient on *de jure* trade openness. Some coefficients even become negative when a trend is introduced, but the *de jure* trade measure retains its statistical (at the 10% level) and economic significance. A 90% range increase in the trade openness variable would generate a $0.51 \times 0.83 = 0.42$ increase in beta. For emerging markets, we find a statistically significant effect only for *de facto* financial and trade openness. The political stability variable again obtains a positive coefficient, significant in half of the specifications that we show. The cycle variable again is never significant. Interestingly, the crisis variable coefficient is now positive and, for the developed market specifications, significant. This is likely induced by the recent global recession, when betas of developed equity markets relative to the global market may have increased. [Bekaert, Ehrmann, Fratzscher, and Mehl \(2014a\)](#) suggest that the global financial crisis changed betas in a country-specific way, with the US-originated crisis hitting countries with bad fundamentals the most. Consistent with the intuition that the realized variance captures a volatility bias present in correlations, it does not affect betas for developed markets, with coefficients that are mostly not significant. For emerging markets, it does appear that in times of high global volatility, betas increase, but the effect is only statistically significant when no trend is included. The trend coefficient remains positive and significant in all specifications.

For the idiosyncratic volatility regressions in Table 1.3c, we find no significant effect of *de jure* financial openness. However, *de facto* financial globalization leads to lower idiosyncratic risk in both developed and emerging markets, with the significance disappearing when a trend is introduced. The effects are stronger for trade openness, especially for developed markets. The coefficients are always negative, with the exception of the last specification (emerging markets, *de facto* integration, with trend). High GDP growth decreases idiosyncratic risk for emerging markets, which is only significant when a trend is included in the regression. Crises invariably increase idiosyncratic risk, with the effect being mostly significant. The effect of the variance variable on idiosyncratic risk mimics its effect on betas but with the opposite sign.

1.4.1.3 Bond Returns

Given that we do not have daily data on bond and foreign exchange returns, we use the equity return realized variance in both the bond and foreign exchange return regressions. Although there is likely positive correlation between realized variances across all three asset classes, it is also possible that in certain market scenarios (e.g., flights to safety), the correlation is relatively low. Therefore, this variable can serve as only an imperfect volatility bias control and may, in part, simply reflect priced global equity volatility risk.

We now move to Table 1.4, which focuses on bond return regressions. The bond financial openness variables do not have a significant impact on bond return correlations. The lack of significance is also observed for trade openness but, in this case, the effect turns significantly negative when a trend is included for developed markets for the *de jure* measure. The political risk variable now has a more robust and significant effect on correlations across countries. Its coefficient is mostly positive and statistically significant for developed markets, whereas it is only significant for emerging markets when a trend is allowed for. The effect is economically large (a coefficient of 2.0 means a $0.48 = 2.0 \times 0.24$ increase in correlation for a 90% range improvement in political stability). This is not surprising from the perspective of the literature on sovereign bond pricing, where political risk is a key determinant of sovereign spreads (for empirical results and a survey of the literature, see [Bekaert, Harvey, Lundblad, and Siegel \(2016\)](#)). To the extent that political risk is idiosyncratic, its presence would induce more country-specific pricing of sovereign bonds. The cycle variable again is never statistically significant. The crisis variable has a negative effect, which is significant for emerging markets, again indicating that, for these countries, crises are dominated by country-specific events. The realized equity variance has no significant effect on global bond return correlations.

The effect of financial and trade openness on local bond return betas mimics their effect on correlations, with one single positive significant coefficient (*de facto* debt openness) and even a few significantly negative ones. Political stability increases betas for developed markets but reduces betas for emerging markets. The latter effect is surprising but does not survive when a trend is allowed for, even though political stability does not show much trending behavior for emerging markets. The results for the cycle variable are very similar to those for the political risk variable,

but with the coefficient signs reversed. That is, for developed (emerging) markets, betas increase (decrease) in recessionary times. This may partly pick up the upward trend in betas in the second half of the sample when the global crisis hits, an event which may dominate the developed market business cycle, whereas emerging market business cycles are more country-specific.⁷ The crisis variable mostly follows the coefficient pattern of the political stability variable and is significant for emerging markets for all specifications. In developed markets, perhaps the higher crisis incidence during the global financial crisis caused bond betas to increase, whereas for emerging markets the crises are mostly country-specific, making them decouple from global bond markets in times of crisis. The equity variance variable is positive and significant at the 5% level when no trend is included for emerging markets.

For idiosyncratic risk, there are no significant effects due to globalization. Here again, political stability generates stronger effects, mostly decreasing idiosyncratic risk, with the effects being similar in magnitude and statistically significant for developed markets and for emerging markets when a trend is allowed for. Although the cycle variable does not have a significant effect on idiosyncratic risk, it is not surprising that crises invariably increase it significantly for both emerging and developed markets. Global equity variance risk is also associated with higher idiosyncratic bond risk, but only for emerging markets.

1.4.1.4 Foreign Exchange Returns

In Table 1.5, we investigate the convergence statistics for exchange rate returns. For financial and trade openness, only 3 coefficients (out of 16) are statistically significant at the 5% or 10% level. *de jure* financial integration for developed markets and *de jure* trade integration for emerging markets are associated with higher foreign exchange correlations. Political stability increases correlations, but only for developed markets, with the effect weakening when a trend is included; for emerging markets, in contrast, this effect surfaces only when a trend is included. The cycle variable is not significant, and the crisis variable significantly decreases correlations only for emerging markets when no trend is included. The realized variance variable has a positive coefficient only for emerging markets, an effect which is always statistically significant. There does appear to be a

⁷Levy Yeyati and Williams (2012) show that emerging economies decoupled from the business cycle of developed countries during the 2000s.

positive trend in foreign exchange correlations, but it is significant only for emerging markets.

Regarding betas, *de jure* financial openness significantly increases betas for developed markets, and *de jure* trade openness does so for emerging markets; there are no other significant effects. Thus, the link between globalization and higher return correlations is at least partially driven by higher global betas. There are very few significant coefficients for the political risk, cycle, crisis, and realized variance variables. The trend term is here more pronounced and significant than for correlations.

Openness is mostly associated with increases in idiosyncratic risk. The effects are significant for *de jure* financial openness and for *de jure* trade openness, but only for developed markets. Political stability and cycles have no effect on idiosyncratic foreign exchange risk. Because crises in emerging markets are mostly idiosyncratic and often currency-related, it is not surprising that we find significantly positive coefficients for the crisis variable. Global equity variance risk always has a positive and statistically significant positive coefficient, but only for developed markets.

The foreign exchange results show that currency movements are not likely driving the major results we observe for bond equity returns; we verify this more formally in Section 5. Regarding equities, we do not confirm Stulz's hypothesis, as the globalization variables seem to have a more important effect on our convergence measures than do political risk measures, although the globalization effects are far from strong in statistical terms. These results are reminiscent of the results of [Bekaert, Harvey, Lundblad, and Siegel \(2007\)](#), who argue that the literature on the channels of growth ignores openness in favor of financial development and institutional factors, but that financial openness plays a much more important role than these other factors in aligning growth opportunities with actual growth. Here we show, as do [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#) with an entirely different approach, that financial openness is more important than corporate governance and (the lack of) political risk in integrating financial markets. However, these results do not extend to bond markets. For bond markets, political stability is a much more important determinant of correlations and idiosyncratic risk than is globalization. Political stability is also a very significant determinant of global bond betas, but increases global betas for developed markets while decreasing them for emerging markets, a result that deserves further scrutiny.

1.4.1.5 Return Dispersion

In Section 1.3, we found strong evidence of negative trends in cross-sectional dispersion. We now examine whether the cross-sectional dispersion movements over time are related to the dispersion and levels of our fundamental variables, including globalization, political risk, business cycle variation, and crises. To conserve space, we provide a detailed discussion and detailed results in the Supplemental Appendix. Here, we simply summarize the salient and robust results. We start with equity return dispersion. First, *de jure* financial and trade openness significantly reduce dispersion for both developed and emerging markets. Second, the dispersion of the political stability measure is positively associated with return dispersion, as is the dispersion of the crisis variables. The latter variable thus explains peaks in return dispersion due to country-specific crises. Third, dispersion is positively linked to realized equity variances, so there is a positive volatility bias, despite the decomposition in Equation 8. Finally, the trend survives in most but not all regressions.

This equity volatility effect is also present for bond returns, but there are fewer robust and significant effects than for equities. Financial globalization, both *de jure* and *de facto*, increases dispersion, which is perhaps surprising, but may be related to the openness reversal for bond markets we witnessed at the end of the sample. There are two more significant effects, but they apply only to developed markets. First, there is more return dispersion in good economic times (measured by the cycle variable); returns in good times are more likely to be country-specific than are returns during bad times. Second, the cross-sectional dispersion of crises is also positively linked with the dispersion of the crisis variable.

For foreign exchange returns, the cross-sectional dispersion of *de jure* financial globalization is positively correlated with return dispersion for emerging markets, whereas for *de facto* financial globalization, this effect is significant only for developed markets. For emerging markets, the level effect for *de jure* financial globalization is also positive (but recall that money market openness goes down slightly over the sample). For trade openness, there are robust effects only across specifications for developed markets and *de facto* trade openness. Again, there are positive dispersion and level effects. Other robust significant effects include the positive effect of the realized variance variable and the negative trend for emerging markets.

1.4.2 A Parametric Model and Time-varying Betas

We now explore a model whereby the sensitivity of the asset return to the world factor is a time-varying function of openness, the business cycle, political risk as well as crises.

1.4.2.1 The Model and Empirical Results

Our second model attempts to more directly deal with the volatility bias critique and focuses on how openness affects the beta with respect to the global factor. We estimate the following panel factor model:

$$\begin{aligned}
 r_{i,t+1}^j &= \alpha_{i,t} + \delta'_{i,t} Z_{i,t} + \beta_{i,t} r_{w,t+1}^j + \varepsilon_{i,t+1}, \\
 \alpha_{i,t} &= \alpha_i + \alpha_{\text{open}} \text{Open}_{i,t} + \alpha_{\text{pr}} \text{PR}_{i,t} + \alpha_{\text{cycle}} \text{Cycle}_{i,t} + \alpha_{\text{crisis}} \text{Crisis}_{i,t}, \\
 \delta_{i,t} &= \delta_0 + \delta_{\text{open}} \text{Open}_{i,t} + \delta_{\text{pr}} \text{PR}_{i,t} + \delta_{\text{cycle}} \text{Cycle}_{i,t} + \delta_{\text{crisis}} \text{Crisis}_{i,t}, \\
 \beta_{i,t} &= \beta_0 + \beta_{\text{open}} \text{Open}_{i,t} + \beta_{\text{pr}} \text{PR}_{i,t} + \beta_{\text{cycle}} \text{Cycle}_{i,t} + \beta_{\text{crisis}} \text{Crisis}_{i,t},
 \end{aligned} \tag{1.13}$$

where r^j denotes excess returns for $j = e, b, fx$; $Z_{i,t}$ is a vector of instruments that help determine the expected return for market i (specifically, dividend yields $DY_{i,t}$ and short-term interest rates $i_{i,t}$); and $\text{Open}_{i,t}$ is either financial openness (FI) or trade openness (TI). All the coefficients vary over time with the independent variables we introduced before (that is, a country-specific openness measure, $\text{Open}_{i,t}$; a political risk indicator, $\text{PR}_{i,t}$; a business cycle variable, $\text{Cycle}_{i,t}$; and a crisis indicator, $\text{Crisis}_{i,t}$). The constant term (α_i) depends on a country-specific fixed effect, and the remaining coefficients are constrained to be the same across countries for identification. The coefficient in which we are most interested is β_{open} . Standard errors are clustered at the country level.

Although conditional mean effects are not the main focus in this article, we investigate the behavior of risk premiums in Section 1.4.3. Therefore, we use a set of predictive instruments to capture time variation in the conditional mean. As before, we include only one openness variable in each regression we run. Also, although the country-specific betas showed some cross-country variation, they did not add much to the fit of the model, so we focus on a model without country-specific betas. All variation in betas must therefore be generated by the exposures to the four

control variables.

Tables 1.6, 1.7, and 1.8 report the results for equity, bond, and foreign exchange returns, respectively. Each table has eight columns, looking at two financial openness measures (*de jure* and *de facto*) and two trade openness measures (*de jure* and *de facto*) and splitting the sample over developed and emerging markets. The first set of rows include the conditional mean parameters, which we discuss in Section 4.3. We first focus on the beta exposures, and provide a discussion across asset classes.

Given the multiple interaction effects, the constant beta is hard to interpret, but we report it for completeness. The first result is that financial and trade openness have no significant positive effects on the conditional beta for any asset class. It is true that we have estimated some alternative specifications where some of the positive coefficients turned out stronger and significant. For example, for foreign exchange, joint samples across developed and emerging markets provide more powerful results. Political stability shows somewhat stronger results in that for equity returns, political stability in emerging markets increases betas significantly, whereas for foreign exchange returns, it does so only for developed markets. The cycle variable is never significant. The crisis variable, in contrast, is positive and significant for both equity and bond returns, but only in developed markets for foreign exchange returns.

To get a sense of the economic importance of the effects we estimate here, Tables 1.9–1.11 show the change in beta when moving from the 5th to the 95th percentile of the variable in question, leaving the other variables at their overall means. Although many of the coefficients are insignificant, it is interesting to obtain an economic picture of the effects implied by the regressions. Given relatively large standard errors, we define a beta difference of 0.20 as economically significant. Assuming a global equity premium of 6%, such a change in beta is associated with an increment in the country risk premium of 1.2% attributable to global risk. For bond and foreign exchange returns, the risk premium changes would, of course, be smaller.

First, if we consider global betas as capturing potentially permanent effects of globalization, the results differ across types of openness and across asset classes. For equity returns, there is only one economically significant result: Financial globalization in emerging markets would increase betas from 1.05 to 1.33 when moving from low to high openness. For bond returns, among financial globalization measures, only *de facto* financial globalization increases global betas sub-

stantially, and this only for developed markets. However, trade openness is generally associated with substantially higher bond betas. There is an almost significant decline in bond betas with higher financial openness for emerging markets. For foreign exchange returns, globalization is mostly associated with relatively large decreases (increases) in world betas for developed (emerging) markets.

Second, the effect of political risk is a bit more robust across asset classes and openness measures. When it is associated with a major change in beta, it is almost always an increase in beta, and the increase in beta is often very large. For equities, global betas in emerging markets increase by 0.5–0.6 moving from the 5th percentile to the 95th percentile of the political stability variable; for bond returns, the effect is about 0.20, but only for developed (not emerging) markets, whereas for foreign exchange, the effect is generally very large but largest for developed markets. This is also the case for the crisis variable, which increases betas substantially for all asset classes and country groups, with the exception of bond returns in emerging markets. The cycle variable does not generate meaningful economic results.

1.4.2.2 Interpreting the Results

There are a number of possible interpretations for the weak links we find between globalization and global betas. First, regional integration may be stronger than global market integration; that is, we may observe strong within-region convergence, but weaker integration across regions.⁸ The past 35 years have witnessed several strong regional economic and financial integration initiatives, including free trade arrangements in North America (NAFTA) and Asia (ASEAN), with the most momentous change taking place within the European Union, which established an economic and monetary union with one currency in 1999. There is a substantial literature on European integration (for recent surveys, see [Baele, Ferrando, Hördahl, Krylova, and Monnet \(2004\)](#), [Jappelli and Pagano \(2008\)](#)), but most of the formal academic literature has focused on equity returns. [Baele, Ferrando, Hördahl, Krylova, and Monnet \(2004\)](#) document a clear increase in regional and global betas, with the regional increase stronger than the global one. [Baele \(2005\)](#) also finds a

⁸[Kose, Otrok, and Prasad \(2008\)](#) find convergence of business cycle fluctuations among developed countries and among emerging economies, but nevertheless find the relative importance of the global factor to have declined over the previous 20 years, suggesting decoupling between developed and emerging economies.

larger increase in regional than in global effects (betas and variance ratios), with spillover intensities (betas) increasing most strongly in the second half of the 1980s and the first half of the 1990s. He links these changes to many structural determinants, such as trade integration, equity market development, and inflation. [Hardouvelis, Malliaropoulos, and Priestley \(2004\)](#) document strong convergence in the cost of equity across different countries in the same sector, but much less convergence across different sectors. They list the launch of the single currency as a major factor. [Bekaert, Harvey, Lundblad, and Siegel \(2013\)](#), focusing on valuation differentials, find that the European Union (but not the Euro) strongly contributed to European equity market integration. For Asia, [Ng \(2000\)](#) uses a conditional GARCH model to investigate spillovers from Japan and the United States to Pacific Basin markets. She finds evidence of both regional and global spillover effects, but the effects of measures of trade and financial integration are not always significant or of the correct sign. These results are consistent with ours. She also finds that the proportions of the Pacific Basin market volatility captured by regional and world factors are small. [Eiling and Gerard \(2015\)](#) document strong within-region increases in correlations, which are partially due to financial and trade openness. Although our model could be easily adapted to account for regional integration, we defer this to further research. In a precursor to this article, [Bekaert and Wang \(2009\)](#) found regional betas to be larger than global betas in Europe but not in Asia.

Second, our beta model may suffer from an omitted variable problem. There are many factors affecting comovements, and without properly controlling for them, we may fail to pick up the effects of globalization. One variable for which we fail to control is industry structure. Whereas the early literature (see [Heston and Rouwenhorst \(1994\)](#)) suggested that country factors dominated the variation of firm returns relative to industry factors, more recent work (see, e.g., [Cavaglia, Brightman, and Aked \(2000\)](#)) argues that industry factors have become at least as important as country factors, likely because of financial integration, and can no longer be ignored. [Campa and Fernandes \(2006\)](#) directly link the relative importance of industry and country factors to measures of economic and financial international integration and development. Their results suggest that industrial structure may matter too and that countries with a more specialized production structure will have more country-specific risk. Nevertheless, several results in the literature suggest that our failure to create industry factors is not critical. First, several studies show that country factors are still more important than industry factors (see [Bekaert, Hodrick, and Zhang \(2009a\)](#));

Eiling, Gerard, Hillion, and de Roon (2012)). One reason that several studies overestimate the importance of industry factors is simply sample selection; their sample periods end around the year 2000, a time of huge technology-sector volatility. Brooks and Del Negro (2004) ascribe the relative change of importance of industry versus country factors to the 1998–1999 stock market bubble. Further, Baele and Inghelbrecht (2009) correct directly for industry misalignment in a study of stock return comovements without finding much of an effect. Finally, Bekaert, Hodrick, and Zhang (2009a) show that parsimonious risk-based models are better at capturing comovements than are models with multiple country and industry factors for developed countries, whereas Phylaktis and Xia (2006) show that country factors remain dominant in emerging markets.

Third, a potential sampling problem is that the end of our sample period is dominated by the global financial crisis, in which globalization was halted or even reversed. We have argued before that crises may lead to temporary higher comovements that have nothing to do with liberalizations. However, in much of our analysis, we control for global recessions (typically associated with higher volatility of asset prices) and for crises. Our focus on betas in the parametric model bypasses the volatility bias critique. Yet, we find that the crisis variable is associated with large increases in global betas, especially for developed markets. This implicitly suggests that the time-varying beta model does not fit crisis returns well. Bekaert, Ehrmann, Fratzscher, and Mehl (2014a) measure such changes in betas for the global financial crisis and other crises and, building on an intuition first laid out by Bekaert, Harvey, and Ng (2005), suggest they constitute crisis contagion, representing the unexpected comovements from the perspective of the asset pricing model. Such contagion also happened, to a lesser extent, during the LTCM/Russia crisis in 1998, but did not happen at all during the technology-sector bust at the end of the 1990s. They analyze the sources of the beta changes, finding a strong role for country-specific policy factors over and above measures of integration or even international banking links. The crisis may therefore represent a nonlinear shift in exposures not well captured by our linear parametric model.

Finally, several articles have attempted to estimate more dynamic models, specifying an asset pricing model, linking the second moments to the first moments, and then examining the degree of integration over time (see Bekaert and Harvey (1995); Carrieri, Errunza, and Hogan (2007); Carrieri, Chaieb, and Errunza (2013)). This research finds that the evolution toward more integrated markets is not always a smooth process for each country, and our linear model may not

capture these dynamics very well.

We conclude that parametric models of global betas do not uncover strong links with globalization measures and that other factors (such as political stability and crises) often matter more. This contrasts somewhat with the results for the nonparametric kernel-weighted regressions. There we did find that equity rerun correlations increased with openness measures and this increase was attributable to increases in beta (and partly also to lower country-specific risk). Interestingly, we find the results typically to be stronger for trade, rather than for financial globalization, and typically also stronger for *de facto* rather than *de jure* openness. Somewhat weaker but similar results apply to foreign exchange returns. However, for bond returns, the globalization measures are not as important as the other variables, especially political risk, even in the kernel-weighted regressions. It is conceivable that the recent period dominated by a severe sovereign bond crisis in Europe may be partially to blame.

1.4.3 Risk Premium Results

We now explore both the relation between our openness measures and risk premiums as well as the dispersion in risk premiums.

1.4.3.1 Risk Premiums in a Parametric Model

We now investigate briefly the conditional mean results. We already pointed out that it is not obvious that financial openness (and even less so trade openness) will lead to stronger comovements of asset returns. However, under most dynamic pricing models, risk premiums should become more highly correlated when markets integrate. It is notoriously difficult to estimate risk premiums from asset return data. The regression model we formulated above implies proxies for risk premiums through its conditional mean function. [Bekaert \(1995\)](#) and [Campbell and Hamao \(1992\)](#) use similar methods to extract expected equity returns and argue that in a one-factor model, these expected returns should be perfectly correlated under perfect market integration. Note that the conditional mean function that we estimate is quite complex, as it involves each variable we use to model the time variation in betas and the interaction of each of those variables with instruments. The instruments we use are the local dividend yield and the short-term interest rate, as in [Ang and Bekaert \(2007\)](#). Table [A.1](#) describes the data sources for these variables. The slope

coefficients are reported in Tables 1.6, 1.7, and 1.8, for equity, bond, and foreign exchange returns, respectively.

For equity returns, the crisis variable, not surprisingly, has an overall negative and significant coefficient, but for the other variables, significance is not consistent across specifications. The direct effect of trade integration is negative and significant, but trade integration also increases the dependence on the short-term interest rate. For developed markets, *de jure* financial globalization surprisingly has a positive direct effect, but also decreases the dependence of the equity premium on the local dividend yield. For *de facto* equity integration, the effect is reversed, with the direct effect being negative, but the interaction effect being positive for the short rate for developed markets and for the dividend yield for emerging markets. Political stability has a negative direct effect on expected returns in emerging markets, and there are no significant interaction terms.

For bond returns, we do not observe significant coefficients for the financial globalization variables or their interactions with the instruments. We do find a significant negative direct effect of *de jure* trade integration for developed markets. There are no significant direct effects for the other three variables, but a few significant interaction effects. For example, the cycle variable has a positive interaction effect with the short rate for developed markets. That is, the dependence of the risk premium on the short rate increases in good times. It has a negative interaction with the local dividend yield for emerging markets, however. For developed markets, the crisis variable now has a negative significant interaction effect with the local dividend yield. Such an effect can implicitly ensure that during a global crisis, the bond premium becomes more global. These effects are robust across the various specifications.

For foreign exchange returns, globalization measures do not feature significant coefficients for developed markets. In emerging markets, *de jure* financial globalization increases the expected exchange rate return directly, but the interaction effect with both the local dividend yield and the interest rate is negative. The interest rate itself has mostly a significant negative coefficient for emerging markets; that is, high short-term interest rates reduce the expected return on foreign exchange, which would appear to be inconsistent with standard unbiasedness hypothesis regressions. However, [Bansal and Dahlquist \(2000\)](#) show that the deviations from unbiasedness, which typically suggest that expected returns increase in the interest differential with the dollar, are confined to (a subset of) developed countries, whereas foreign exchange risk premiums in emerging

markets depend on various local factors, as we document here as well. The negative interaction effect with the short rate is also present for *de jure* trade integration. Political stability in emerging markets increases the dependence of the expected foreign exchange return on the short rate. The cycle and crisis variables do not have significant direct effects on expected foreign exchange returns, but have significant negative interaction effects with the local interest rate for emerging markets (cycle variable) and developed markets (crisis variable).

Examining the regression coefficients does not suffice to appreciate the full effect of globalization on expected returns. The market integration process is likely to change many relationships in the economy and may serve as a structural break for the return generating process.⁹ We partially accommodate this by allowing for interaction effects between the predictive instruments and the globalization variables, but our instruments (dividend yields and interest rates) are themselves affected by the globalization process. We therefore conduct further analysis, extracting the risk premiums from the predictive regression framework and examining whether these premiums have undergone comovement changes correlated with globalization and our other variables. Of course, we make the strong implicit assumption that time-invariant parameters on our factors such as globalization and political stability capture all the changes in the predictive relationship between the instruments and returns. Moreover, we have not included global instruments in the relationship (for early work on foreign and domestic instruments predicting equity and foreign exchange returns, see [Bekaert and Hodrick \(1992\)](#)), which would have greatly complicated the already heavily parameterized model.

1.4.3.2 Risk Premium Dispersion

To examine convergence of risk premiums, we simply compute the cross-sectional dispersion of our premium estimates at each point in time. Recall that we have eight different specifications for each asset class, and thus eight alternative estimates of risk premiums at each point in time. We simply compute the convergence measures for all specifications. In [Table 1.12](#), we report Bunzel–Vogelsang trend tests on these dispersion statistics. With few exceptions, we find strong negative trends for all specifications and all three asset classes. Positive trends are only observed for bond

⁹[Bekaert, Harvey, and Lumsdaine \(2002\)](#) exploit these structural breaks to date the time of integration.

return premiums for developed markets. For both bond and equity premiums, we find only one trend coefficient to be statistically significant, but for foreign exchange risk premiums, the trend coefficients are significant for five out of eight specifications.

It is interesting that we find the strongest evidence of convergence in an asset class that has received considerably less attention in the market integration literature, which has mostly focused on equities. Of course, these findings may simply reflect the limited power of trend tests and the fact that foreign exchange returns are less noisy than equity returns.

The downward trend in the dispersion of risk premiums across countries raises the question whether this convergence is linked to any of our fundamental variables, including globalization, political risk, business cycle variation, or crises. It is not necessarily only the level of these variables that ought to matter, but also their cross-sectional dispersion. For example, we indicated before that business cycle convergence may impact the return convergence, whereas global recessions may also impact risk premiums worldwide. We therefore use both the (average) levels and cross-sectional dispersion of our four variables as independent variables. For the cycle and crisis variables, we do use global versions of the level variables, as the incidence of global recessions or crises may affect return comovements. Unfortunately, we cannot include the cross-sectional dispersion and levels of the globalization measures in one regression, as in many instances they are too negatively correlated. That is, as the degree of globalization increases, the dispersion of openness measures unsurprisingly decreases (e.g., for equity *de jure* openness, the correlation is -0.93).

We begin with equity risk premiums (see Table 1.13). The table reports the specification with a trend term. Bolded coefficients indicate that the coefficient is significant at the 10% level or lower and has the same sign in a regression without the trend term. We focus on robust findings. For *de jure* financial globalization, we find its cross-sectional dispersion to positively affect the dispersion of equity risk premiums and its level to decrease dispersion, but this is only robustly true for developed markets. Surprisingly, for *de facto* openness, we find a negative effect of its dispersion on return dispersion. However, the dispersion of *de facto* openness shows a strong upward trend over time, which may explain this result. For trade openness, we only find significant robust results for *de jure* trade openness in emerging markets. Here the signs are again unexpected, with the dispersion having a negative effect (this may be explained by the volatile period in the early

1990s) and the level a positive effect. In terms of the other variables, we find a positive effect of both the dispersion and level of political stability, with the latter perhaps being surprising. This effect is only present for emerging markets. Dispersion in the cycle variable is overwhelmingly negatively related to risk premium dispersion in emerging markets. Perhaps high cycle dispersion is observed in normal times when country-specific shocks (as opposed to global recession shocks) drive the economy. In such periods, risk premiums may be relatively normal and not very dispersed. The cycle level is negatively related to equity premium dispersion, but only in developed markets. In global recessionary periods, risk premiums likely rise substantially, which may be accompanied by more dispersion across different countries. The realized variance variable is positively related to premium dispersion for developed markets.

For bond return risk premiums, there are very few globalization effects that are significant and robust across specifications in Table 1.14. Both the level and dispersion of *de jure* financial openness lower bond premium dispersion. The cross-sectional dispersion of *de facto* trade openness increases the dispersion of bond premiums for developed markets, whereas its level increases premium dispersion in both developed and emerging markets. In terms of other effects, the level of the cycle variable affects dispersion negatively in both emerging and developed markets; that is, bad times are associated with mostly higher and thus more dispersed risk premiums. This may be exacerbated by the fact that in bad times, flights to safety may make benchmark bonds (such as US and German bonds) have very low or negative risk premiums. The global crisis variable decreases dispersion of bond risk premiums in emerging markets, and the realized variance variable increases dispersion in both developed and emerging markets.

For foreign exchange return risk premium dispersion in Table 1.15, we find that both level and dispersion of all financial globalization measures increase their dispersion in emerging markets. For developed markets, only the dispersion of *de facto* openness increases premium dispersion robustly and significantly. For trade openness, we find more significant results for developed markets. The cross-sectional dispersion of both *de jure* and *de facto* trade openness increases the dispersion of foreign exchange risk premiums in developed markets, but in terms of level, *de jure* openness decreases and *de facto* trade openness increases dispersion. For emerging markets, only the *de jure* openness measures are significant with the expected positive (negative) sign for dispersion (level). We also find that political stability in developed markets contributes to lower

dispersion of foreign exchange risk premiums, and bad times (negative cycle variables) increase dispersion in emerging markets. The cross-sectional dispersion of GDP growth decreases the dispersion of exchange rate premiums in developed markets.

1.5 ADDITIONAL ANALYSIS AND ROBUSTNESS CHECKS

Here we report on some additional analyzes we conducted.

1.5.1 Local Currency Returns

One potential problem with our analysis for equity and bond returns is that we expressed all returns in dollars, and they thus feature a common currency component across countries. Because foreign exchange return correlations increased over time, they may be partially responsible for higher global correlations for bond and equity returns. To verify this, we computed local currency bond and equity returns (for details, see Table A.1). The panel correlation between dollar and local currency equity returns is 0.85, but it is only 0.35 for the corresponding bond returns. This is obviously because of the variability of equity markets dominating that of currency changes, whereas the latter dominates the variability of fixed-income instruments.

Note that we consider the correlation, betas, and idiosyncratic volatility relative to the global dollar-denominated benchmark as before. Although the implicit regressions use two different currencies, the idea here is to decompose the previous findings in components due to local currency returns and due to the joint dollar component. While removing the common currency component must reduce the beta and correlation statistics, we focus on how the changes in these statistics are related to globalization measures and other determinants.

Here we survey which results are different from the dollar-denominated results, and detailed results are relegated to the Supplemental Appendix. First, we investigate results from the first half versus the second half of the sample. Significant increases for return correlations are still observed for both equity and (only for emerging markets) bond returns from the first to the second half of the sample, but the result does weaken for bonds. For betas, the beta increases for equities weaken considerably, and in fact are no longer significant for emerging markets. For bond returns, the beta increases are smaller but remain significant. The idiosyncratic volatility results (decreases for

equities and for bonds, but only for emerging markets in the latter case) are entirely robust.

Second, we redo the panel regressions on the kernel-weighted comovement statistics. For equities, the significant correlation increases under *de facto* openness remain robust, whereas the trade openness results weaken somewhat, especially when a trend coefficient is included in the regression. Interestingly, the positive effect of political stability on correlations is more uniformly significant; this is also true of its effect on betas. For financial openness, we do not observe any significant effects on betas, but *de jure* trade openness continues to positively affect betas for developed markets. The idiosyncratic volatility results are entirely robust. For bonds, we see in fact somewhat stronger, more significant, and more positive results for the effect of *de facto* financial integration, and of both *de facto* and *de jure* trade integration, on correlations. These results extend to betas. Globalization did not have much effect on idiosyncratic bond volatility, and that remains true for local bond returns. In terms of the other coefficients, the main change is that for emerging markets, the cycle variable now has a strong significant and positive effect on correlations and betas, which was much weaker when convoluted with currency changes. Similarly, it now has a robust negative effect on the idiosyncratic bond return variability. The results for the parametric model largely mimic the beta results from the panel regressions, with, for example, trade openness now having a positive and significant effect on bond betas.

In sum, while there are some small changes, the dollar denomination did not spuriously induce an effect of globalization on convergence. For example, the results for idiosyncratic volatility are completely robust.

1.5.2 Global Cycles

In the main regression, we used a country-specific business cycle variable. However, it is conceivable that the global business cycle is more important in driving cross-country correlations. As we argued before, the sign of the effect is *ex ante* unclear. More generally, in bad times, higher global volatility increases the volatility bias, but our regressions control for this. Nonetheless, much research suggests that there may be more home bias in bad times ([Ang and Bekaert \(2002\)](#); [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#)), so that *de facto* integration may reverse.

When we rerun the kernel-weighted regression, replacing the country-specific with the global business cycle variable, the variable mostly has a strongly positive and significant effect on equity

return correlations, which only disappears for developed markets when a trend is accounted for. This is also true for equity betas, suggesting again that bad times are associated with more segmentation, once one controls for volatility biases. The results on idiosyncratic volatility are very sensitive to whether one controls for a trend, suggesting that the negative trend in idiosyncratic volatility may be linked to the increased prevalence of global recessions over time. The parametric model largely confirms this result, but the interaction between the global cycle variable and the global beta is only statistically significant for developed markets.

For bond returns, the cycle variable generates robustly significant effects only in developed markets, with global recessions increasing bond return correlations, a result that was not significant before. It is also not entirely driven by the exchange rate component in bond returns. One possible explanation is that global bond markets jointly reacted to the global recession and the ensuing unusual monetary policies that were exported from the United States to other countries (see [Rey \(2015\)](#)). However, the effect does not survive for betas (except when one controls for a trend), which suggests that it may also be because we imperfectly control for volatility bias in these regressions, having no available measure of global bond return volatility. This lack of robustness is further confirmed by the parametric regression, where the interaction effects with the cycle variable are negative for emerging markets but positive for developed markets.

For currency returns, the global cycle variable has a robust significantly positive effect on correlations for emerging markets, which is also present for global foreign exchange betas. Thus, as for equities, there is more comovement in good times. This is confirmed in the parametric model results, but the interaction coefficient is only significant in one specification.

1.5.3 Corporate Governance

Here we investigate the effect of replacing the general political risk index by a quality of institutions variable, combining corruption, law and order, and quality of bureaucracy subindices. This measure may prove a better indication of the corporate governance framework in a country, but it is far from a perfect measure. The panel correlation with the political risk index is only 0.62 for developed markets, but it is 0.70 for emerging markets. However, there are many countries for which both indices show very low correlation across time (e.g., Brazil, India, Poland, Russia, and Thailand among emerging markets and Canada, Denmark, New Zealand, and Sweden among

developed markets). Thus, it is conceivable that this variable generates different results from our main results.

In the previous panel regressions, political stability mostly increased global equity correlations and betas without significantly affecting idiosyncratic volatility. Although the other coefficients mostly remain robust, the coefficient on the corporate governance variable is negative for developed markets in the correlation regressions and mostly loses significance in the beta regressions. In the idiosyncratic volatility regressions, the coefficients for developed markets (when no trend is included) turn positive. For bond return correlations, the signs on the corporate governance variable are also mostly negative, but this time are only significant for emerging markets when no trend is allowed. The pattern is even stronger for betas, where it holds for both bonds and equities, but only when no trend is included in the regression. For idiosyncratic volatility, the corporate governance variable does not have much of an effect. For exchange rates, the signs are still predominantly negative on the corporate governance variable for both correlations and betas, but only one coefficient is statistically significant in 16 different specifications. In the parametric regressions, the corporate governance variable never enters significantly.

These results are somewhat surprising. If corporate governance is an effective segmenting factor, one would not expect improvements in corporate governance to lower comovements with the global market. The results also appear inconsistent with the Stulz hypothesis, which suggests that corporate governance is a main driver of international asset returns. It is therefore likely that the positive association we found before between the more general index of political stability and correlations/betas does not reflect a corporate governance effect, but may be an indirect openness effect because political stability, in general, is highly correlated with FDI.

1.5.4 Effect of Unbalanced Samples

All of our results make use of an unbalanced sample, with countries added on as data become available. We selected the starting point of the sample requiring a minimum number of countries to minimize the problem as much as possible. There may be a negative correlation between incomplete data and globalization, so that the unbalanced sample may actually bias the results against finding increased comovement over time as a result of globalization, as less integrated countries enter the sample. To verify this, we rerun our kernel-weighted regressions, adding an independent

variable measuring the change in the number of countries. Hence, if the addition of countries affects our results, this variable may capture the bias, and the other coefficients may change as well. In the Supplemental Appendix, we show that changes in the number of countries often have a significant effect on comovements, but not always in the expected direction. For example, for equities, an increase in the number of countries decreases correlations in all specifications; decreases betas in emerging markets but has a non-robust effect on betas in developed markets; and has little effect on idiosyncratic variability. Importantly, whatever the bias, the addition of the variable does not change the other coefficients in any meaningful way, with all significant coefficients remaining significant and the magnitudes barely altered.

1.6 CONCLUSIONS

In this article, we examine whether globalization has been associated with increased comovement of asset returns across the world, focusing on equity, bond, and foreign exchange returns. We start the analysis by measuring the globalization process in developed and emerging markets over the past 35 years. We investigate measures of *de jure* and *de facto* financial and trade openness. Perhaps surprisingly, for our sample period, globalization does not invariably trend upward. Two factors may play a role here. First, the recent global financial crisis halted the globalization process in some countries and even reversed it for some. This is particularly evident from regulatory actions applied to bond and money markets, as well as from actual trade flows that collapsed during the crisis. Second, our sample may have missed the biggest globalization wave by starting too late. For developed countries, it is conceivable that trade openness generated most globalization effects before 1980. It is hard to imagine financial openness generating large effects then, as it only began in earnest in the 1980s for most countries. For emerging markets, capital market liberalizations were mainly concentrated in the late 1980s and early 1990s. Our average starting date for emerging markets is September 1991 for equities and even later for the other asset classes, so it is possible that we have missed some liberalization effects.

Our analysis focuses on comovements relative to a global benchmark return for each asset class (representing G7 countries). The evidence shows that global comovements have increased substantially over our sample period. Correlations between country returns and a global benchmark

return are higher in the second half versus the first half of our sample. Time-varying correlations show both trending behavior and cyclical movements. Exceptions are developed market bonds, where global correlations often decreased.

Correlations can increase because global betas increase, because the variability of global factors increases, or because country-specific variances decrease. The volatility bias is particularly important for our analysis, as our sample period witnessed several economic crises. Controlling for such a bias, we still find that betas increased and idiosyncratic volatilities decreased, with some notable exceptions. In particular, country-specific volatilities increased substantially in developed bond markets, and bond return correlations therefore do not display an upward trend. However, financial and trade globalization seem to only weakly correlate with these movements. We use a regression model linking rolling correlations, betas, and country-specific volatilities to our globalization measures and other determinants of comovements as well as a parametric time-varying global beta model. Although the latter model yields few significant and robust results, there are some important associations between globalization measures and convergence measures in the regression framework, especially for equity returns and for the de facto openness measures.

Much of the existing evidence focuses only on equity returns and has used correlations as a measure of comovement, with some research foreshadowing our results. [Karolyi \(2003\)](#) calls the evidence on trends in correlations linked to stronger real and financial linkages remarkably weak. [Bekaert, Hodrick, and Zhang \(2009a\)](#) examine return correlations between developed countries and find a significant trend only among the European countries, and no trend at all in the Far East. The literature on international factor models applied to individual stocks has also yielded results consistent with our findings. The extant literature (see, e.g., [Griffin \(2002\)](#); [Hou, Karolyi, and Kho \(2011a\)](#); [Fama and French \(2012\)](#)) typically finds that local models outperform global ones. [Petzev, Schrimpf, and Wagner \(2016\)](#) attempt to characterize the time variation in fit of local versus global models. They confirm our finding that the R^2 of global factor models has increased and has reduced the gap with the explanatory power of local models (even when controlling for the volatility bias). However, the pricing errors of global models are still much larger than those for local models and have failed to converge. [Petzev, Schrimpf, and Wagner \(2016\)](#) speculate that the increased comovement must therefore stem from real rather than financial integration, in contrast to, e.g., [Baele and Soriano \(2010\)](#). Our direct tests reveal a much more nuanced picture, in which,

for example, increased return correlations in developed markets are positively associated with trade integration, but in emerging markets also depend significantly on financial globalization.

There are several possible explanations for the weak links between globalization and the comovement of asset returns. First, regional integration could dominate world integration. Our framework can be easily generalized to accommodate regional betas. We expect that such an exercise would generate a strong comovement increase within certain regions (see also [Eiling and Gerard \(2015\)](#)), but that the recent worldwide and European crises may weaken the link between regional globalization measures and return comovements.

Second, because of the increased incidence of crises, we may find stronger results focusing on tails in asset return distributions, rather than on the linear measures we have employed here (for efforts in this line, see [Bae, Karolyi, and Stulz \(2003\)](#); [Beine, Cosma, and Vermeulen \(2010\)](#); [Christoffersen, Errunza, Jacobs, and Langlois \(2012\)](#)).

Third, given that we included a number of alternative comovement determinants in our analysis, it does not appear that our results are driven by the omission of relevant factors in our regressions. This is reminiscent of the results of [King, Sentana, and Wadhvani \(1994\)](#), who put forward a long list of observable economic factors to explain covariances among stock market returns, but find that these factors explain very little. This state of affairs may also help explain the strong results of [Pukthuanthong and Roll \(2009\)](#), who document a marked increase in the degree of integration in equity markets over time. They explain global equity returns using a 10-factor principal component analysis. Because they extract factors from the return data, their integration measure is not affected by the poor explanatory power of observable factors. Their method also nicely circumvents the problem that integration may well decrease comovements under certain types of events; e.g., competitive pressure or supply shocks (e.g., commodity price shocks) may benefit certain countries but hurt others more swiftly in an integrated market.

Fourth, the challenge of documenting strong effects of globalization on the convergence of asset returns was already apparent in some early studies of the dynamics of market integration. [Bekaert and Harvey \(1995\)](#), for example, argue that integration is a nonsmooth process that may actually reverse, and is only weakly linked to *de jure* openness.

We do believe it is possible to devise more powerful tests. [Pukthuanthong and Roll \(2009\)](#) are not the only researchers who find strong convergence in measures of *de facto* financial integration.

[Bekaert, Harvey, Lundblad, and Siegel \(2007\)](#) characterize each country by a vector of industry weights (measured using stock market capitalization weights) and then compute the (logarithmic) difference between a country's price to earnings (PE) ratio and the PE ratio for the country's basket of industries at world multiples. [Bekaert, Harvey, Lundblad, and Siegel \(2007, 2011\)](#) show that under some strong assumptions of real and financial integration, this measure should be close to zero. Although their measure confounds economic and financial integration, they show that *de jure* globalization, especially financial globalization, has a strong negative effect on these valuation differentials, which tend to decrease over time. They also show that they diverge again in crises, a result that also holds true within the European Union (see [Bekaert, Harvey, Lundblad, and Siegel \(2013\)](#)).

This article and earlier work by [Bekaert and Harvey \(2000\)](#) has suggested that the focus on returns may prevent powerful econometric tests of the effects of globalization. A focus on prices instead of returns may be necessary to detect more powerful links. In addition, it would be fascinating to decompose returns and prices in their various economic components. Equity returns have a valuation and cash flow component. Bond returns reflect interest rate changes which, in turn, reflect real and inflation components. Foreign exchange returns reflect the pure currency and a carry component. Finer decompositions of returns may yield valuable insights.

Our analysis can be expanded in other directions. First, we have focused on three major asset classes, but omitted others such as real estate. Second, the growth of the Chinese stock market and its dramatic gyrations in 2015 suggest that in the future, we may have to include some of the larger emerging markets in our factor models. Third, we have focused on comovements within an asset class, and not across asset classes. Recent work on the demand for global safe assets ([Bruno and Shin \(2015\)](#)) suggests that this may create spillover effects between Federal Reserve policies (and thus US bond returns), the dollar, and asset returns across the world.

TABLES AND FIGURES

Table 1.1: Openness Summary Statistics

This table reports summary statistics for the openness measures for developed (Panel A) and emerging markets (Panel B). Columns two to seven report summary statistics for the whole sample, while columns eight and nine divide the sample in half and report averages for the first part versus the second part of the sample. Given the unbalanced nature of the panel, the midpoint of the sample is country-specific. Start dates for each country can be found in Appendix ???. The penultimate column (difference) shows a difference in means test to find out if the first half of the sample is significantly different from the second half. Whereas the summary statistics are calculated over the pooled sample, here we calculate the country means and then run a cross-sectional test to compare the first and second halves. Asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The last column shows the results of the [Bunzel and Vogelsang \(2005\)](#) trend tests conducted on regional measures, which are constructed as equally-weighted averages across countries. This trend test is based on the series model $y_t = \beta_1 + \beta_2 t + u_t$, where y_t is the variable of interest and t for the linear time trend, and uses a Daniell kernel to nonparametrically estimate the error terms. We test for the null hypothesis that $\beta_2 = 0$. A number in bold font indicates that the trend beta is significantly different from zero at the 5% significance level. See Appendix ??? for details on variable definitions and sources.

Variable	N	Mean	Median	sd	p5	p95	Mean Half 1	Mean Half 2	Diff	Trend
<i>Panel A: Developed Markets</i>										
FI_i^{Seq}	9562	0.90	1.00	0.18	0.50	1.00	0.87	0.93	0.06	0.10
FI_i^{Sbo}	6127	0.93	1.00	0.16	0.71	1.00	0.92	0.93	0.00	0.09
FI_i^{Smm}	3725	0.93	1.00	0.15	0.50	1.00	0.92	0.94	0.04	-0.02
FI_i^{QT}	9562	0.90	1.00	0.14	0.62	1.00	0.84	0.96	0.13***	0.24
$FI_i^{df,eq}$	9562	0.56	0.27	1.09	0.01	2.02	0.17	0.95	0.11***	1.44
$FI_i^{df,debt}$	6127	2.47	1.69	2.62	0.58	6.07	1.59	3.34	0.14	3.39
TI_i^{QT}	9562	0.93	1.00	0.12	0.62	1.00	0.88	0.99	0.78**	0.21
TI_i^{df}	9380	0.74	0.51	0.69	0.26	2.61	0.66	0.82	1.72**	0.31
<i>Panel B: Emerging Markets</i>										
FI_i^{Seq}	6142	0.37	0.25	0.33	-0.00	1.00	0.35	0.39	0.06	0.13
FI_i^{Sbo}	5561	0.51	0.50	0.37	0.00	1.00	0.53	0.48	0.00	-0.15
FI_i^{Smm}	3514	0.38	0.25	0.34	0.00	1.00	0.39	0.37	0.04	0.01
FI_i^{QT}	6142	0.61	0.62	0.23	0.25	1.00	0.58	0.64	0.13***	0.16
$FI_i^{df,eq}$	6142	0.10	0.06	0.12	0.01	0.36	0.06	0.14	0.11***	0.16
$FI_i^{df,debt}$	5561	0.75	0.58	0.63	0.24	2.25	0.82	0.67	0.14	-0.30
TI_i^{QT}	6142	0.71	0.77	0.24	0.25	1.00	0.68	0.74	0.78**	0.13
TI_i^{df}	6142	0.53	0.45	0.35	0.17	1.37	0.47	0.59	1.72**	0.22

Table 1.2: Asset Prices - Difference in Means Tests

This table reports the difference in means tests for the correlation between country returns and world returns, the beta with world returns, idiosyncratic risk, and cross-sectional dispersion in the first half of the sample versus the second half. The sample midpoint and start dates differ across countries, given the unbalanced nature of the panel, and are presented in panel *a*. Panel *b* reports correlations, and panels *c* and *d* report betas and annualized idiosyncratic risk, respectively, calculated from the following country-specific regressions for each half: $r_{i,t} = \alpha_i + \beta_i r_{w,t} + \varepsilon_{i,t}$. Panel *e* presents the difference in means test for cross-sectional dispersion. This is calculated using a balanced sample and is defined as

$$CS_t = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(r_{i,t} - \frac{1}{N} \sum_{i=1}^N r_{i,t} \right)^2}.$$

Note that we report the cross-sectional dispersion in annualized volatility units. For the difference in means tests, asterisks (***, **, and *) represent statistical significance at the 1%, 5%, and 10% levels, respectively. This table also reports the results of the trend tests of [Bunzel and Vogelsang \(2005\)](#) conducted on time-varying correlations, betas, and idiosyncratic risk for equity, bond, and exchange rate returns using a kernel method and on the cross-sectional standard dispersions. This trend test is based on the series model $y_t = \beta_1 + \beta_2 t + u_t$, where y_t is the variable of interest and t is a linear time trend, and uses a Daniell kernel to nonparametrically estimate the error terms. We test for the null hypothesis that $\beta_2 = 0$. A bold number means that the trend beta is significantly different from 0 at the 5% significance level. All results are presented for developed and emerging markets, which are grouped according to International Monetary Fund classifications (for details, see [Table A.2](#)).

		Developed	Emerging
<i>Panel A: Country-Specific Midpoints and Start Dates</i>			
Equities	Average Middle Date	1998m12	2003m3
	Average Start Date	1983m2	1991m9
Bonds	Average Middle Date	2002m9	2005m8
	Average Start Date	1990m8	1996m9
Exchange Rates	Average Middle Date	2002m12	2006m11
	Average Start Date	1991m2	1998m11
<i>Panel B: Correlations</i>			
Equities	First Half	0.56	0.31
	Second Half	0.79	0.62
	Difference	0.23***	0.30***
	Trend Test	0.34	0.56
Bonds	First Half	0.70	0.13
	Second Half	0.71	0.45
	Difference	0.01	0.32***
	Trend Test	0.02	0.72

continued

Table 1.2 – *Continued*

		Developed	Emerging
Exchange Rates	First Half	0.48	0.22
	Second Half	0.68	0.50
	Difference	0.20*	0.28***
	Trend Test	0.27	0.52
<i>Panel C: Betas</i>			
Equities	First Half	0.97	0.90
	Second Half	1.18	1.19
	Difference	0.21***	0.30**
	Trend Test	0.36	0.79
Bonds	First Half	1.27	0.09
	Second Half	1.50	0.94
	Difference	0.23**	0.85***
	Trend Test	0.48	1.90
Exchange Rates	First Half	0.55	0.38
	Second Half	0.98	0.87
	Difference	0.43**	0.49***
	Trend Test	0.69	0.77
<i>Panel D: Idiosyncratic Risk</i>			
Equities	First Half	0.21	0.40
	Second Half	0.15	0.24
	Difference	-0.06***	-0.16***
	Trend Test	-0.10	-0.31
Bonds	First Half	0.08	0.18
	Second Half	0.09	0.12
	Difference	0.02	-0.06**
	Trend Test	0.00	-0.15
Exchange Rates	First Half	0.07	0.13
	Second Half	0.07	0.11
	Difference	0.00	-0.02
	Trend Test	0.02	-0.10

*Panel E: Cross-Sectional Dispersion**continued*

Table 1.2 – *Continued*

		Developed	Emerging
Equities	First Half	0.17	0.29
	Second Half	0.13	0.19
	Difference	-0.047***	-0.102***
	Trend Test	-0.07	-0.18
Bonds	First Half	0.05	0.12
	Second Half	0.06	0.07
	Difference	0.015***	-0.050***
	Trend Test	0.02	-0.12
Exchange Rates	First Half	0.06	0.12
	Second Half	0.07	0.08
	Difference	0.010**	-0.038***
	Trend Test	0.00	-0.08

Table 1.3: Equity Kernel Weighted Regressions

This table reports the results of time-varying correlation, beta, and idiosyncratic risk regressions for equities. We create time-varying measures using a kernel method. For each country, given any date t_0 , we split the sample into five-year subsamples and use the 30 data points before and after that point. Within these subsamples, we use a normal kernel to assign weights to the individual observations according to how close they are to t_0 . We then compute kernel-weighted correlations, betas, and idiosyncratic risk as follows:

$$corr_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t}) (r_{w,t+j} - \bar{r}_{w,t})}{\sqrt{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t})^2} \sqrt{\sum_{j=-30}^{j=30} K_h(j) (r_{w,t+j} - \bar{r}_{w,t})^2}},$$

$$\beta_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t}) (r_{iw,t+j} - \bar{r}_{w,t})}{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t})^2},$$

$$var_{i,t}^{\varepsilon} = \sum_{j=-30}^{j=30} K_h(j) (\varepsilon_{i,t+j} - \bar{\varepsilon}_{i,t})^2.$$

where $\bar{r}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) r_{i,t+j}$, $\varepsilon_{i,t} = r_{i,t} - \beta_{i,t} r_{w,t}$, and $\bar{\varepsilon}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) \varepsilon_{i,t+j}$, and $K_h(j) \equiv K(j/h)/h$ is a kernel with bandwidth $h > 0$. We use a two-sided Gaussian kernel, $K(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$, and divide by the sum to ensure the weights add to one in a finite sample. We link these measures to openness and other control variables using variations of the following panel regression:

$$x_{i,t+1} = \alpha_i + \beta_1 \overline{Open}_{i,t} + \beta_2 \overline{PR}_{i,t} + \beta_3 \overline{Cycle}_{i,t} + \beta_4 \overline{Crisis}_{i,t} + \beta_5 \overline{RV}_{w,t+1} + \beta_6 trend + \varepsilon_{i,t+1}$$

where $x_{i,t+1}$ reflects correlation, beta, or idiosyncratic risk and $\overline{Open}_{i,t}$ represents either financial integration (FI) or trade integration (TI). Note that the same kernel approach is applied to the independent variables (i.e., we use the time-varying means of these variables, which are calculated as $\bar{z}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) z_{i,t+j}$). All regressions have country level fixed effects and clustered standard errors. Panel *a* presents the results for correlations, panel *b* for betas, and panel *c* for idiosyncratic risk. In each panel, there are two rows labeled $TI_{i,t}^{QT}$ and $TI_{i,t}^{df}$. These are the coefficients on the trade openness measures in regressions where financial openness is replaced with trade openness. The remaining coefficients in these regressions are robust and therefore are not reported. Coefficients in bold represent variables that are also significant and have the same signs in regressions where the independent variables are taken at one point in time. Asterisks (***, **, and *) represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Table A.1.

Panel A: Correlations

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$
$FI_{i,t}^{Seq}$	0.035 [0.17]	0.15 [1.11]			-0.032 [-0.20]	0.18** [2.64]		
$FI_{i,t}^{df,eq}$			0.085** [2.74]	0.79*** [4.05]			-0.031 [-1.36]	0.073 [0.41]
$PR_{i,t}$	0.74*** [2.97]	0.36 [1.02]	0.40 [1.45]	0.35 [1.13]	0.26 [1.07]	0.40 [1.02]	0.34 [1.45]	0.53 [1.37]
$Cycle_{i,t}$	0.22 [0.26]	0.37 [0.72]	-0.14 [-0.15]	0.59 [1.20]	-0.66 [-0.84]	0.67 [1.55]	-0.64 [-0.79]	0.70 [1.54]
$Crisis_{i,t}$	0.27 [1.05]	-0.69*** [-5.40]	0.18 [0.71]	-0.57*** [-4.18]	-0.088 [-0.47]	-0.25* [-1.83]	-0.085 [-0.45]	-0.28* [-1.97]
$RV_{w,t+1}$	42.3*** [7.51]	62.7*** [10.1]	37.0*** [5.75]	56.1*** [8.55]	25.0*** [5.22]	44.8*** [8.59]	25.1*** [4.92]	46.1*** [8.28]
Time Trend					0.088*** [7.11]	0.12*** [6.64]	0.096*** [5.84]	0.12*** [4.66]
$TI_{i,t}^{QT}$	0.65*** [3.61]	0.28** [2.31]			0.16 [0.74]	0.23** [2.16]		
$TI_{i,t}^{df}$			0.30* [1.93]	0.33* [1.90]			0.095 [0.96]	-0.059 [-0.52]
Observations	7,047	5,676	7,047	5,676	7,047	5,676	7,047	5,676
Adjusted R-squared	0.535	0.623	0.571	0.660	0.698	0.732	0.701	0.721
Region	DM	EM	DM	EM	DM	EM	DM	EM

Panel B: Betas

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}
$FI_{i,t}^{Seq}$	0.15 [0.36]	0.42 [1.01]			0.055 [0.14]	0.47 [1.38]		
$FI_{i,t}^{df,eq}$			0.064 [0.68]	1.01** [2.30]			-0.14** [-2.34]	-0.57 [-0.93]
$PR_{i,t}$	1.29** [2.13]	2.13** [2.12]	1.05 [1.46]	2.30** [2.21]	0.58 [0.80]	2.21** [2.17]	0.95 [1.27]	2.71** [2.39]
$Cycle_{i,t}$	-0.46 [-0.19]	0.16 [0.059]	-0.57 [-0.23]	0.48 [0.17]	-1.76 [-0.76]	0.73 [0.28]	-1.46 [-0.64]	0.72 [0.27]
$Crisis_{i,t}$	2.43*** [3.98]	-0.062 [-0.11]	2.35*** [3.77]	0.061 [0.10]	1.91*** [2.89]	0.75 [1.22]	1.89*** [2.97]	0.71 [1.15]
$RV_{w,t+1}$	5.62 [0.37]	47.9** [2.83]	2.69 [0.19]	40.7** [2.38]	-19.7 [-1.59]	14.5 [1.12]	-18.2 [-1.50]	18.6 [1.27]
Time Trend					0.13*** [3.24]	0.23*** [3.22]	0.17*** [3.75]	0.26** [2.83]
$TI_{i,t}^{QT}$	1.42*** [3.68]	0.10 [0.38]			0.83* [1.88]	-0.0011 [-0.0047]		
$TI_{i,t}^{df}$			0.25 [0.76]	0.66* [1.95]			-0.080 [-0.31]	-0.038 [-0.13]
Observations	7,047	5,676	7,047	5,676	7,047	5,676	7,047	5,676
Adjusted R-squared	0.346	0.360	0.349	0.363	0.438	0.420	0.455	0.411
Region	DM	EM	DM	EM	DM	EM	DM	EM

Panel C: Idiosyncratic Volatility

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$
$FI_{i,t}^{Seq}$	-0.0057 [-0.13]	0.039 [0.60]			0.021 [0.98]	0.027 [0.76]		
$FI_{i,t}^{df,eq}$			-0.042*** [-5.42]	-0.23*** [-3.16]			0.0010 [0.065]	0.12 [1.03]
$PR_{i,t}$	-0.14 [-0.77]	0.052 [0.28]	0.029 [0.14]	0.12 [0.84]	0.052 [0.29]	0.034 [0.18]	0.051 [0.28]	0.032 [0.18]
$Cycle_{i,t}$	-0.19 [-0.71]	-0.86** [-2.54]	0.0059 [0.025]	-0.91** [-2.65]	0.17 [0.76]	-0.98** [-2.78]	0.19 [0.89]	-0.96** [-2.76]
$Crisis_{i,t}$	0.20 [1.27]	0.76*** [11.2]	0.25 [1.60]	0.71*** [11.0]	0.34** [2.47]	0.58*** [7.99]	0.34** [2.40]	0.57*** [7.69]
$RV_{w,t+1}$	-2.70 [-0.95]	-7.90*** [-3.25]	-0.023 [-0.0084]	-5.40** [-2.47]	4.22* [1.80]	-0.60 [-0.35]	4.33* [1.84]	-0.48 [-0.29]
Time Trend					-0.035*** [-7.93]	-0.050*** [-5.71]	-0.035*** [-5.52]	-0.058*** [-4.50]
$TI_{i,t}^{QT}$	-0.31*** [-4.26]	-0.093 [-1.38]			-0.13 [-1.66]	-0.070* [-1.79]		
$TI_{i,t}^{df}$			-0.14*** [-3.41]	-0.13** [-2.44]			-0.060** [-2.56]	0.038 [0.70]
Observations	7,047	5,676	7,047	5,676	7,047	5,676	7,047	5,676
Adjusted R-squared	0.540	0.763	0.591	0.774	0.695	0.819	0.694	0.820
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.4: Bond Kernel Weighted Regressions

This table reports the results of time-varying correlation, beta, and idiosyncratic risk regressions for bonds. We create time-varying measures using a kernel method. For each country, given any date t_0 , we split the sample into five-year subsamples and use the 30 data points before and after that point. Within these subsamples, we use a normal kernel to assign weights to the individual observations according to how close they are to t_0 . We then compute kernel-weighted correlations, betas, and idiosyncratic risk as follows:

$$corr_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t}) (r_{w,t+j} - \bar{r}_{w,t})}{\sqrt{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t})^2} \sqrt{\sum_{j=-30}^{j=30} K_h(j) (r_{w,t+j} - \bar{r}_{w,t})^2}},$$

$$\beta_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t}) (r_{iw,t+j} - \bar{r}_{w,t})}{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t})^2},$$

$$var_{i,t}^{\varepsilon} = \sum_{j=-30}^{j=30} K_h(j) (\varepsilon_{i,t+j} - \bar{\varepsilon}_{i,t})^2.$$

where $\bar{r}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) r_{i,t+j}$, $\varepsilon_{i,t} = r_{i,t} - \beta_{i,t} r_{w,t}$, and $\bar{\varepsilon}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) \varepsilon_{i,t+j}$, and $K_h(j) \equiv K(j/h)/h$ is a kernel with bandwidth $h > 0$. We use a two-sided Gaussian kernel, $K(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$, and divide by the sum to ensure the weights add to one in a finite sample. We link these measures to openness and other control variables using variations of the following panel regression:

$$x_{i,t+1} = \alpha_i + \beta_1 \overline{Open}_{i,t} + \beta_2 \overline{PR}_{i,t} + \beta_3 \overline{Cycle}_{i,t} + \beta_4 \overline{Crisis}_{i,t} + \beta_5 \overline{RV}_{w,t+1} + \beta_6 trend + \varepsilon_{i,t+1}$$

where $x_{i,t+1}$ reflects correlation, beta, or idiosyncratic risk and $\overline{Open}_{i,t}$ represents either financial integration (FI) or trade integration (TI). Note that the same kernel approach is applied to the independent variables (i.e., we use the time-varying means of these variables, which are calculated as $\bar{z}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) z_{i,t+j}$). All regressions have country level fixed effects and clustered standard errors. Panel *a* presents the results for correlations, panel *b* for betas, and panel *c* for idiosyncratic risk. In each panel, there are two rows labeled $TI_{i,t}^{QT}$ and $TI_{i,t}^{df}$. These are the coefficients on the trade openness measures in regressions where financial openness is replaced with trade openness. The remaining coefficients in these regressions are robust and therefore are not reported. Coefficients in bold represent variables that are also significant and have the same signs in regressions where the independent variables are taken at one point in time. Asterisks (***, **, and *) represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Table A.1.

Panel A: Correlations

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$
$FI_{i,t}^{Sbo}$	0.068 [0.50]	-0.16 [-1.16]			0.049 [0.37]	-0.087 [-0.80]		
$FI_{i,t}^{df,debt}$			0.016* [1.96]	-0.089 [-0.69]			-0.0062 [-0.22]	0.00049 [0.0043]
$PR_{i,t}$	2.37*** [4.34]	-0.51 [-0.80]	2.41*** [4.34]	-0.67 [-0.91]	2.35*** [4.20]	0.97* [1.94]	2.40*** [4.28]	0.94* [1.95]
$Cycle_{i,t}$	-1.58 [-1.46]	1.23 [1.50]	-1.68 [-1.35]	1.44 [1.56]	-1.89 [-1.49]	1.24* [1.82]	-1.82 [-1.38]	1.30* [1.76]
$Crisis_{i,t}$	-0.22 [-1.00]	-1.37*** [-5.76]	-0.32 [-1.28]	-1.34*** [-5.17]	-0.34 [-1.16]	-0.61*** [-4.25]	-0.31 [-1.14]	-0.62*** [-4.01]
$RV_{w,t+1}$	2.89 [0.43]	10.9 [1.58]	0.73 [0.11]	11.9 [1.64]	-1.23 [-0.18]	-6.42 [-1.17]	-1.09 [-0.16]	-5.86 [-1.08]
Time Trend					0.024 [1.12]	0.26*** [8.70]	0.029 [0.72]	0.26*** [9.12]
$TI_{i,t}^{QT}$	-0.43 [-1.26]	0.29 [0.95]			-0.78** [-2.19]	0.18 [1.15]		
$TI_{i,t}^{df}$			-0.034 [-0.39]	0.36 [1.39]			-0.29* [-1.84]	-0.050 [-0.33]
Observations	5,414	4,310	5,414	4,310	5,414	4,310	5,414	4,310
Adjusted R-squared	0.634	0.584	0.637	0.579	0.643	0.791	0.642	0.789
Region	DM	EM	DM	EM	DM	EM	DM	EM

Panel B: Betas								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}
$FI_{i,t}^{Sbo}$	0.066 [0.24]	-0.55 [-1.09]			-0.068 [-0.28]	-0.37** [-2.36]		
$FI_{i,t}^{df,debt}$			0.064* [1.89]	-0.45 [-1.06]			-0.14* [-1.88]	-0.23 [-1.32]
$PR_{i,t}$	2.69*** [2.89]	-3.43** [-2.45]	2.65** [2.84]	-4.08** [-2.41]	2.54** [2.17]	0.23 [0.31]	2.53** [2.16]	-0.12 [-0.13]
$Cycle_{i,t}$	-5.40*** [-3.95]	3.09 [1.61]	-6.06*** [-4.38]	3.98* [1.79]	-7.47*** [-4.05]	3.13 [1.65]	-7.33*** [-4.56]	3.65* [1.91]
$Crisis_{i,t}$	1.58** [2.40]	-2.81*** [-6.14]	1.13 [1.56]	-2.66*** [-5.18]	0.76 [0.72]	-0.95** [-2.55]	1.23 [1.37]	-0.88** [-2.27]
$RV_{w,t+1}$	10.3 [0.48]	54.6** [2.53]	1.32 [0.061]	57.7** [2.17]	-17.4 [-0.76]	12.0 [0.53]	-15.0 [-0.63]	14.1 [0.58]
Time Trend					0.16** [2.46]	0.64*** [9.37]	0.26** [2.33]	0.64*** [9.66]
$TI_{i,t}^{QT}$	0.41 [1.26]	0.36 [0.45]			-1.35* [-1.93]	0.079 [0.19]		
$TI_{i,t}^{df}$			0.42 [1.30]	0.98 [1.49]			-0.90* [-1.82]	-0.028 [-0.086]
Observations	5,414	4,310	5,414	4,310	5,414	4,310	5,414	4,310
Adjusted R-squared	0.450	0.482	0.463	0.474	0.537	0.751	0.563	0.746
Region	DM	EM	DM	EM	DM	EM	DM	EM

Panel C: Idiosyncratic Risk								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$
$FI_{i,t}^{Sbo}$	-0.068 [-1.06]	0.017 [0.63]			-0.067 [-1.03]	0.0070 [0.18]		
$FI_{i,t}^{df,debt}$			-0.0048 [-1.26]	0.064* [1.72]			-0.0086** [-2.60]	0.052 [1.55]
$PR_{i,t}$	-0.37*** [-3.43]	-0.14 [-1.28]	-0.43*** [-2.92]	-0.077 [-0.68]	-0.37*** [-3.34]	-0.35** [-2.50]	-0.43*** [-2.93]	-0.29* [-2.04]
$Cycle_{i,t}$	-0.72 [-1.33]	-0.075 [-0.27]	-0.75 [-1.16]	-0.16 [-0.53]	-0.71 [-1.22]	-0.077 [-0.29]	-0.78 [-1.18]	-0.14 [-0.51]
$Crisis_{i,t}$	0.15 [1.68]	0.32*** [6.91]	0.17*** [2.93]	0.29*** [5.34]	0.15* [2.09]	0.22*** [4.46]	0.17*** [3.07]	0.20*** [3.42]
$RV_{w,t+1}$	1.02 [0.44]	10.2** [2.78]	1.55 [0.56]	10.2*** [2.90]	1.12 [0.40]	12.6*** [3.54]	1.24 [0.44]	12.6*** [3.55]
Time Trend					-0.00058 [-0.14]	-0.036*** [-3.79]	0.0050 [1.40]	-0.035*** [-4.28]
$TI_{i,t}^{QT}$	-0.0014 [-0.019]	-0.059 [-1.07]			0.012 [0.17]	-0.044 [-1.00]		
$TI_{i,t}^{df}$			-0.0063 [-0.16]	-0.045 [-0.82]			0.0029 [0.078]	0.012 [0.28]
Observations	5,414	4,310	5,414	4,310	5,414	4,310	5,414	4,310
Adjusted R-squared	0.512	0.719	0.505	0.727	0.512	0.759	0.507	0.764
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.5: Exchange Rate Kernel Weighted Regressions

This table reports the results of time-varying correlation, beta, and idiosyncratic risk regressions for exchange rates. We create time-varying measures using a kernel method. For each country, given any date t_0 , we split the sample into five-year subsamples and use the 30 data points before and after that point. Within these subsamples, we use a normal kernel to assign weights to the individual observations according to how close they are to t_0 . We then compute kernel-weighted correlations, betas, and idiosyncratic risk as follows:

$$corr_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t}) (r_{w,t+j} - \bar{r}_{w,t})}{\sqrt{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t})^2} \sqrt{\sum_{j=-30}^{j=30} K_h(j) (r_{w,t+j} - \bar{r}_{w,t})^2}},$$

$$\beta_{i,t} = \frac{\sum_{j=-30}^{j=30} K_h(j) (r_{i,t+j} - \bar{r}_{i,t}) (r_{iw,t+j} - \bar{r}_{w,t})}{\sum_{j=-30}^{j=30} K_h(j) (r_{2,t+j} - \bar{r}_{w,t})^2},$$

$$var_{i,t}^{\varepsilon} = \sum_{j=-30}^{j=30} K_h(j) (\varepsilon_{i,t+j} - \bar{\varepsilon}_{i,t})^2.$$

where $\bar{r}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) r_{i,t+j}$, $\varepsilon_{i,t} = r_{i,t} - \beta_{i,t} r_{w,t}$, and $\bar{\varepsilon}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) \varepsilon_{i,t+j}$, and $K_h(j) \equiv K(j/h)/h$ is a kernel with bandwidth $h > 0$. We use a two-sided Gaussian kernel, $K(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$, and divide by the sum to ensure the weights add to one in a finite sample. We link these measures to openness and other control variables using variations of the following panel regression:

$$x_{i,t+1} = \alpha_i + \beta_1 \overline{Open}_{i,t} + \beta_2 \overline{PR}_{i,t} + \beta_3 \overline{Cycle}_{i,t} + \beta_4 \overline{Crisis}_{i,t} + \beta_5 \overline{RV}_{w,t+1} + \beta_6 trend + \varepsilon_{i,t+1}$$

where $x_{i,t+1}$ reflects correlation, beta, or idiosyncratic risk and $\overline{Open}_{i,t}$ represents either financial integration (FI) or trade integration (TI). Note that the same kernel approach is applied to the independent variables (i.e., we use the time-varying means of these variables, which are calculated as $\bar{z}_{i,t} = \sum_{j=-30}^{j=30} K_h(j) z_{i,t+j}$). All regressions have country level fixed effects and clustered standard errors. Panel *a* presents the results for correlations, panel *b* for betas, and panel *c* for idiosyncratic risk. In each panel, there are two rows labeled $TI_{i,t}^{QT}$ and $TI_{i,t}^{df}$. These are the coefficients on the trade openness measures in regressions where financial openness is replaced with trade openness. The remaining coefficients in these regressions are robust and therefore are not reported. Coefficients in bold represent variables that are also significant and have the same signs in regressions where the independent variables are taken at one point in time. Asterisks (***, **, and *) represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Table A.1.

Panel A: Correlations								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$	$corr_{it+1}$
$FI_{i,t}^{Smm}$	0.44*** [3.34]	0.043 [0.29]			0.34*** [3.73]	-0.0048 [-0.042]		
$FI_{i,t}^{df,debt}$			-0.0021 [-0.35]	-0.11 [-0.49]			-0.024 [-1.69]	0.055 [0.33]
$PR_{i,t}$	2.30** [2.28]	-0.62 [-0.72]	2.13* [2.20]	-0.56 [-0.71]	1.72 [1.60]	1.33* [1.99]	1.31 [1.15]	1.34** [2.17]
$Cycle_{i,t}$	-0.47 [-0.27]	0.17 [0.12]	-0.81 [-0.42]	0.40 [0.32]	-1.81 [-0.85]	0.13 [0.17]	-2.55 [-1.09]	0.011 [0.013]
$Crisis_{i,t}$	0.65 [0.90]	-0.80*** [-3.30]	0.39 [0.48]	-0.72*** [-3.16]	0.78 [1.06]	-0.20 [-1.06]	0.61 [0.79]	-0.23 [-1.07]
$RV_{w,t+1}$	2.40 [0.12]	35.4*** [3.56]	5.35 [0.26]	35.0*** [3.53]	-15.3 [-0.94]	27.1*** [3.39]	-14.6 [-0.86]	27.2*** [3.37]
Time Trend					0.078 [1.77]	0.27*** [6.33]	0.11* [1.93]	0.28*** [6.85]
$TI_{i,t}^{QT}$	-0.46 [-0.31]	0.75** [2.38]			-1.56 [-0.98]	0.28 [1.38]		
$TI_{i,t}^{df}$			0.038 [0.28]	0.48 [1.08]			-0.039 [-0.24]	-0.22 [-1.54]
Observations	3,265	3,453	3,265	3,453	3,265	3,453	3,265	3,453
Adjusted R-squared	0.592	0.568	0.572	0.570	0.631	0.791	0.632	0.792
Region	DM	EM	DM	EM	DM	EM	DM	EM

Panel B: Betas								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}	β_{it+1}
$FI_{i,t}^{Smm}$	1.05** [2.59]	0.42 [1.43]			0.75** [2.42]	0.33 [1.12]		
$FI_{i,t}^{df,debt}$			0.028 [1.54]	-0.034 [-0.070]			-0.024 [-0.81]	0.28 [0.67]
$PR_{i,t}$	2.82 [1.38]	-2.03 [-1.00]	2.53 [1.46]	-1.51 [-0.82]	1.16 [0.53]	1.63 [0.83]	0.54 [0.24]	2.14 [1.23]
$Cycle_{i,t}$	-1.47 [-0.68]	-1.47 [-0.58]	-2.20 [-0.91]	-1.51 [-0.69]	-5.25* [-1.98]	-1.53 [-0.80]	-6.44** [-2.28]	-2.26 [-1.08]
$Crisis_{i,t}$	0.87 [0.60]	0.031 [0.058]	0.33 [0.21]	0.21 [0.30]	1.23 [0.79]	1.16** [2.17]	0.84 [0.53]	1.15 [1.35]
$RV_{w,t+1}$	32.9 [0.95]	28.3* [1.78]	32.1 [0.85]	27.5 [1.66]	-17.1 [-0.60]	12.6 [0.92]	-16.1 [-0.54]	12.4 [0.91]
Time Trend					0.22** [3.05]	0.51*** [4.32]	0.26** [2.89]	0.53*** [4.57]
$TI_{i,t}^{QT}$	1.00 [0.45]	2.34*** [3.85]			-1.70 [-0.65]	1.55*** [3.44]		
$TI_{i,t}^{df}$			-0.15 [-0.70]	1.18 [1.41]			-0.37 [-1.56]	-0.095 [-0.30]
Observations	3,265	3,453	3,265	3,453	3,265	3,453	3,265	3,453
Adjusted R-squared	0.562	0.551	0.534	0.535	0.661	0.753	0.647	0.747
Region	DM	EM	DM	EM	DM	EM	DM	EM

Panel C: Idiosyncratic Risk								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$	$ivol_{it+1}$
$FI_{i,t}^{Smm}$	0.044*** [3.61]	0.049 [0.83]			0.042*** [3.57]	0.054 [1.08]		
$FI_{i,t}^{df,debt}$			-0.00073 [-0.87]	-0.026 [-0.28]			-0.0015 [-1.40]	-0.044 [-0.51]
$PR_{i,t}$	-0.015 [-0.27]	-0.075 [-0.27]	-0.034 [-0.55]	-0.012 [-0.056]	-0.026 [-0.51]	-0.28 [-0.74]	-0.063 [-1.01]	-0.22 [-0.64]
$Cycle_{i,t}$	0.0091 [0.075]	-0.31 [-0.84]	-0.025 [-0.23]	-0.27 [-0.55]	-0.017 [-0.13]	-0.31 [-0.92]	-0.087 [-0.81]	-0.23 [-0.53]
$Crisis_{i,t}$	0.035 [0.68]	0.43** [2.73]	0.0086 [0.19]	0.47** [2.18]	0.038 [0.74]	0.37*** [3.20]	0.016 [0.37]	0.41** [2.47]
$RV_{w,t+1}$	5.81*** [4.13]	1.11 [0.32]	6.23*** [4.02]	0.95 [0.26]	5.47*** [3.68]	2.00 [0.63]	5.52*** [3.61]	1.79 [0.55]
Time Trend					0.0015 [0.56]	-0.029 [-1.40]	0.0038 [1.65]	-0.030 [-1.34]
$TI_{i,t}^{QT}$	0.19*** [3.59]	0.012 [0.11]			0.19** [3.08]	0.071 [0.69]		
$TI_{i,t}^{df}$			-0.012 [-1.56]	-0.11 [-1.40]			-0.015* [-1.88]	-0.046 [-0.80]
Observations	3,265	3,453	3,265	3,453	3,265	3,453	3,265	3,453
Adjusted R-squared	0.798	0.565	0.781	0.557	0.800	0.594	0.788	0.586
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.6: Equity Returns, Globalization, Political Risk, Cycles and Crises

We estimate a panel factor model with betas that vary over time with openness, political risk, cycles and crises. Specifically, we estimate

$$r_{i,t+1}^e = \alpha_i + \alpha_{open} Open_{i,t} + \alpha_{pr} PR_{i,t} + \alpha_{cycle} Cycle_{i,t} + \alpha_{crisis} Crisis_{i,t} + \delta_0' Z_{i,t} + \delta_{open}' Open_{i,t} Z_{i,t} + \delta_{pr}' PR_{i,t} Z_{i,t} + \delta_{cycle}' Cycle_{i,t} Z_{i,t} + \delta_{crisis}' Crisis_{i,t} Z_{i,t} + \beta_0 r_{w,t+1}^e + \beta_{open} Open_{i,t} r_{w,t+1}^e + \beta_{pr} PR_{i,t} r_{w,t+1}^e + \beta_{cycle} Cycle_{i,t} r_{w,t+1}^e + \beta_{crisis} Crisis_{i,t} r_{w,t+1}^e + \varepsilon_{i,t+1}$$

where r^e denotes equity excess returns, $Z_{i,t}$ is a vector of instruments which help estimate the expected return of market i (specifically, dividend yields $DY_{i,t}$ and short-term interest rates $i_{i,t}$), $Open_{i,t}$ is either financial openness (FI) or trade openness (TI), $PR_{i,t}$ is a political risk indicator, $Cycle_{i,t}$ is a business cycle variable and $Crisis_{i,t}$ is a crisis indicator. Note that α_i denotes a country-specific fixed effect, while the remaining coefficients are constrained to be the same across countries. All regressions include fixed effects and standard errors clustered at the country-level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) r_{it+1}^e	(2) r_{it+1}^e	(3) r_{it+1}^e	(4) r_{it+1}^e	(5) r_{it+1}^e	(6) r_{it+1}^e	(7) r_{it+1}^e	(8) r_{it+1}^e
$FI_{i,t}^{Seq}$	0.032* [1.74]	0.010 [0.52]						
$FI_{i,t}^{dj}$			-0.0075* [-1.87]	-0.11** [-2.57]				
$TI_{i,t}^{QT}$					-0.063* [-1.94]	-0.069** [-2.26]		
$TI_{i,t}^{dj}$							-0.0037 [-0.54]	-0.010 [-0.73]
$PR_{i,t}$	-0.017 [-0.46]	-0.13** [-2.90]	-0.0033 [-0.088]	-0.099** [-2.17]	-0.013 [-0.37]	-0.097** [-2.21]	-0.013 [-0.33]	-0.11** [-2.23]
$Cycle_{i,t}$	0.031 [0.46]	0.092 [1.07]	0.019 [0.31]	0.11 [1.42]	-0.0035 [-0.045]	0.073 [0.97]	0.027 [0.44]	0.098 [1.23]
$Crisis_{i,t}$	-0.069** [-2.43]	-0.061 [-1.66]	-0.071** [-2.29]	-0.091* [-2.01]	-0.078** [-2.48]	-0.081** [-2.52]	-0.074** [-2.35]	-0.072* [-1.91]
$DY_{i,t}$	-0.31 [-0.29]	0.70 [0.73]	-0.45 [-0.45]	0.62 [0.63]	-0.72 [-0.71]	0.22 [0.28]	-0.83 [-0.94]	0.52 [0.54]
$FI_{i,t}^{Seq} DY_{i,t}$	-0.96* [-1.88]	-0.21 [-0.51]						
$FI_{i,t}^{df} DY_{i,t}$			0.24 [1.30]	2.35** [2.23]				
$TI_{i,t}^{QT} DY_{i,t}$					-0.13 [-0.24]	0.26 [0.35]		
$TI_{i,t}^{df} DY_{i,t}$							0.16 [0.97]	0.33 [1.44]
$PR_{i,t} DY_{i,t}$	1.38 [1.18]	-0.37 [-0.24]	0.37 [0.29]	-0.73 [-0.55]	0.95 [0.83]	0.014 [0.0098]	0.75 [0.68]	-0.52 [-0.38]
$Cycle_{i,t} DY_{i,t}$	-1.57 [-0.59]	-0.038 [-0.012]	-1.21 [-0.51]	-0.56 [-0.20]	-1.08 [-0.41]	-0.60 [-0.20]	-1.28 [-0.58]	-0.27 [-0.093]
$Crisis_{i,t} DY_{i,t}$	1.14 [1.21]	-0.18 [-0.18]	1.10 [1.14]	0.30 [0.24]	1.28 [1.35]	-0.36 [-0.37]	1.22 [1.27]	-0.072 [-0.072]
$i_{i,t}^S$	0.51*** [3.01]	-0.062 [-1.05]	0.46** [2.74]	-0.042 [-0.72]	0.039 [0.12]	-0.15 [-1.03]	0.45*** [2.93]	-0.023 [-0.24]
$FI_{i,t}^{Seq} i_{i,t}^S$	0.14 [1.69]	0.064 [0.98]						
$FI_{i,t}^{df} i_{i,t}^S$			0.095** [2.19]	0.59 [1.13]				
$TI_{i,t}^{QT} i_{i,t}^S$					0.48* [1.78]	0.19 [1.31]		
$TI_{i,t}^{df} i_{i,t}^S$							-0.046 [-1.36]	0.0067 [0.068]
$PR_{i,t} i_{i,t}^S$	-0.74*** [-3.21]	0.11 [0.95]	-0.57*** [-3.02]	0.031 [0.27]	-0.63*** [-3.85]	-0.018 [-0.16]	-0.53*** [-3.08]	0.061 [0.46]
$Cycle_{i,t} i_{i,t}^S$	-0.24 [-0.49]	-0.26 [-1.24]	-0.076 [-0.22]	-0.17 [-1.15]	0.15 [0.37]	-0.18 [-0.88]	-0.24 [-0.61]	-0.26 [-1.63]
$Crisis_{i,t} i_{i,t}^S$	-0.50** [-2.17]	-0.036 [-0.41]	-0.38* [-1.85]	0.067 [0.86]	-0.35* [-1.91]	0.071 [0.99]	-0.39* [-1.94]	0.0050 [0.089]
$r_{w,t+1}$	1.00** [2.46]	-0.20 [-0.62]	0.96** [2.57]	-0.21 [-0.74]	0.82* [2.00]	-0.13 [-0.33]	0.91** [2.25]	-0.20 [-0.63]
$FI_{i,t}^{Seq} r_{w,t+1}$	-0.075 [-0.33]	0.28 [1.28]						
$FI_{i,t}^{df} r_{w,t+1}$			0.024 [0.43]	-0.30 [-0.78]				
$TI_{i,t}^{QT} r_{w,t+1}$					0.24 [0.79]	-0.10 [-0.37]		
$TI_{i,t}^{df} r_{w,t+1}$							0.029 [1.23]	-0.068 [-0.30]
$PR_{i,t} r_{w,t+1}$	0.090 [0.18]	1.72*** [3.21]	0.030 [0.067]	1.95*** [4.24]	-0.048 [-0.092]	1.87*** [3.79]	0.082 [0.16]	1.93*** [3.52]
$Cycle_{i,t} r_{w,t+1}$	0.60 [0.83]	-1.31 [-1.20]	0.59 [0.76]	-1.30 [-1.23]	0.66 [0.92]	-1.33 [-1.26]	0.62 [0.79]	-1.34 [-1.25]
$Crisis_{i,t} r_{w,t+1}$	1.31*** [3.94]	1.17*** [3.93]	1.31*** [3.89]	1.15*** [3.41]	1.30*** [3.81]	1.17*** [3.36]	1.33*** [3.91]	1.18*** [3.59]
Observations	7,520	4,593	7,520	4,593	7,520	4,593	7,388	4,593
Adjusted R-squared	0.484	0.291	0.483	0.290	0.483	0.290	0.483	0.289
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.7: Bond Returns, Globalization, Political Risk, Cycles and Crises

We estimate a panel factor model with betas that vary over time with openness, political risk, cycles and crises. Specifically, we estimate

$$r_{i,t+1}^b = \alpha_i + \alpha_{open} Open_{i,t} + \alpha_{pr} PR_{i,t} + \alpha_{cycle} Cycle_{i,t} + \alpha_{crisis} Crisis_{i,t} + \delta'_0 Z_{i,t} + \delta'_{open} Open_{i,t} Z_{i,t} + \delta'_{pr} PR_{i,t} Z_{i,t} + \delta'_{cycle} Cycle_{i,t} Z_{i,t} + \delta'_{crisis} Crisis_{i,t} Z_{i,t} + \beta_0 r_{w,t+1}^b + \beta_{open} Open_{i,t} r_{w,t+1}^b + \beta_{pr} PR_{i,t} r_{w,t+1}^b + \beta_{cycle} Cycle_{i,t} r_{w,t+1}^b + \beta_{crisis} Crisis_{i,t} r_{w,t+1}^b + \varepsilon_{i,t+1}$$

where r^b denotes bond excess returns, $Z_{i,t}$ is a vector of instruments which help estimate the expected return of market i (specifically, dividend yields $DY_{i,t}$ and short-term interest rates $i_{i,t}$), $Open_{i,t}$ is either financial openness (FI) or trade openness (TI), $PR_{i,t}$ is a political risk indicator, $Cycle_{i,t}$ is a business cycle variable and $Crisis_{i,t}$ is a crisis indicator. Note that α_i denotes a country-specific fixed effect, while the remaining coefficients are constrained to be the same across countries. All regressions include fixed effects and standard errors clustered at the country-level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) r_{it+1}^b	(2) r_{it+1}^b	(3) r_{it+1}^b	(4) r_{it+1}^b	(5) r_{it+1}^b	(6) r_{it+1}^b	(7) r_{it+1}^b	(8) r_{it+1}^b
$FI_{i,t}^{Sbo}$	0.0088 [0.77]	0.015 [0.92]						
$FI_{i,t}^{dj}$			0.00043 [0.72]	0.016** [2.34]				
$TI_{i,t}^{QT}$					-0.049* [-1.75]	-0.014 [-1.14]		
$TI_{i,t}^{dj}$							0.0053 [1.16]	0.0033 [0.32]
$PR_{i,t}$	-0.040 [-1.06]	0.0011 [0.021]	-0.035 [-1.09]	0.0045 [0.077]	-0.039 [-1.03]	-0.011 [-0.23]	-0.038 [-1.13]	-0.0047 [-0.084]
$Cycle_{i,t}$	-0.011 [-0.26]	0.022 [0.80]	-0.019 [-0.47]	-0.014 [-0.29]	-0.012 [-0.28]	0.017 [0.51]	-0.023 [-0.59]	0.015 [0.45]
$Crisis_{i,t}$	-0.0011 [-0.079]	0.0060 [0.19]	0.00050 [0.033]	-0.0077 [-0.30]	-0.0061 [-0.37]	0.0050 [0.17]	-0.0028 [-0.17]	0.0058 [0.23]
$DY_{i,t}$	0.13 [0.34]	1.53 [1.34]	0.091 [0.28]	1.69 [1.59]	-1.24 [-1.48]	1.17 [1.07]	0.13 [0.44]	1.47 [1.24]
$FI_{i,t}^{Sbo} DY_{i,t}$	-0.15 [-0.78]	-0.46 [-0.71]						
$FI_{i,t}^{df} DY_{i,t}$			0.020 [0.81]	-0.062 [-0.17]				
$TI_{i,t}^{QT} DY_{i,t}$					1.35 [1.69]	-0.15 [-0.33]		
$TI_{i,t}^{df} DY_{i,t}$							0.093 [1.44]	0.092 [0.31]
$PR_{i,t} DY_{i,t}$	0.14 [0.43]	-1.70 [-1.06]	-0.031 [-0.092]	-2.21 [-1.28]	0.023 [0.059]	-1.21 [-0.79]	-0.088 [-0.27]	-1.97 [-1.04]
$Cycle_{i,t} DY_{i,t}$	-1.43 [-0.93]	-3.75** [-2.80]	-1.36 [-0.88]	-2.89** [-2.51]	-1.37 [-0.86]	-3.85** [-2.88]	-1.30 [-0.83]	-3.55** [-2.90]
$Crisis_{i,t} DY_{i,t}$	-0.93* [-2.01]	-1.32 [-1.01]	-1.03** [-2.34]	-0.85 [-1.06]	-0.94** [-2.16]	-1.29 [-1.05]	-1.05** [-2.59]	-1.11 [-1.25]
$i_{i,t}^S$	-0.40 [-0.61]	0.0071 [0.062]	-0.47 [-0.66]	-0.080 [-1.17]	-0.47 [-0.59]	-0.012 [-0.11]	-0.49 [-0.68]	-0.060 [-0.86]
$FI_{i,t}^{Sbo} i_{i,t}^S$	-0.067 [-0.39]	-0.048 [-1.49]						
$FI_{i,t}^{df} i_{i,t}^S$			0.0033 [0.30]	-0.022 [-0.83]				
$TI_{i,t}^{QT} i_{i,t}^S$					-0.054 [-0.47]	-0.012 [-0.25]		
$TI_{i,t}^{df} i_{i,t}^S$							-0.13 [-1.29]	-0.015 [-0.27]
$PR_{i,t} i_{i,t}^S$	0.54 [0.59]	0.024 [0.16]	0.57 [0.68]	0.13 [1.03]	0.60 [0.67]	0.013 [0.085]	0.65 [0.72]	0.095 [0.74]
$Cycle_{i,t} i_{i,t}^S$	0.78* [1.74]	0.27 [1.50]	0.96** [2.44]	0.30 [1.09]	0.75* [1.95]	0.30 [1.32]	0.85** [2.15]	0.29 [1.22]
$Crisis_{i,t} i_{i,t}^S$	0.24 [0.50]	0.073 [1.26]	0.24 [0.48]	0.086** [2.54]	0.35 [0.65]	0.068 [1.53]	0.29 [0.58]	0.060 [1.50]
$r_{w,t+1}$	0.15 [0.17]	0.89** [2.88]	0.40 [0.58]	0.88** [2.91]	-0.27 [-0.22]	0.55 [1.57]	0.33 [0.45]	0.91*** [3.88]
$FI_{i,t}^{Sbo} r_{w,t+1}$	0.098 [0.21]	-0.16 [-0.63]						
$FI_{i,t}^{dj} r_{w,t+1}$			0.076 [1.55]	-0.21 [-0.67]				
$TI_{i,t}^{QT} r_{w,t+1}$					0.70 [0.66]	0.48 [1.09]		
$TI_{i,t}^{dj} r_{w,t+1}$							0.25 [1.68]	0.15 [0.82]
$PR_{i,t} r_{w,t+1}$	1.21 [1.60]	-0.32 [-0.78]	0.87 [1.14]	-0.24 [-0.64]	1.02 [1.41]	-0.45 [-1.25]	0.95 [1.21]	-0.56 [-1.35]
$Cycle_{i,t} r_{w,t+1}$	-0.61 [-0.57]	0.32 [0.13]	-0.59 [-0.51]	0.38 [0.16]	-0.52 [-0.49]	0.78 [0.30]	-0.70 [-0.60]	0.45 [0.18]
$Crisis_{i,t} r_{w,t+1}$	1.33*** [3.12]	-0.43 [-0.62]	1.03*** [3.23]	-0.34 [-0.40]	1.26** [2.78]	-0.39 [-0.57]	1.23** [2.85]	-0.46 [-0.67]
Observations	5,702	3,351	5,702	3,351	5,702	3,351	5,667	3,351
Adjusted R-squared	0.446	0.060	0.449	0.059	0.447	0.061	0.446	0.057
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.8: Exchange Rate Returns, Globalization, Political Risk, Cycles and Crises

We estimate a panel factor model with betas that vary over time with openness, political risk, cycles and crises. Specifically, we estimate

$$r_{i,t+1}^{fx} = \alpha_i + \alpha_{open} Open_{i,t} + \alpha_{pr} PR_{i,t} + \alpha_{cycle} Cycle_{i,t} + \alpha_{crisis} Crisis_{i,t} + \delta'_0 Z_{i,t} + \delta'_{open} Open_{i,t} Z_{i,t} + \delta'_{pr} PR_{i,t} Z_{i,t} + \delta'_{cycle} Cycle_{i,t} Z_{i,t} + \delta'_{crisis} Crisis_{i,t} Z_{i,t} + \beta_0 r_{w,t+1}^{fx} + \beta_{open} Open_{i,t} r_{w,t+1}^{fx} + \beta_{pr} PR_{i,t} r_{w,t+1}^{fx} + \beta_{cycle} Cycle_{i,t} r_{w,t+1}^{fx} + \beta_{crisis} Crisis_{i,t} r_{w,t+1}^{fx} + \varepsilon_{i,t+1},$$

where r^{fx} denotes exchange rate excess returns, $Z_{i,t}$ is a vector of instruments which help estimate the expected return of market i (specifically, dividend yields $DY_{i,t}$ and short-term interest rates $i_{i,t}$), $Open_{i,t}$ is either financial openness (FI) or trade openness (TI), $PR_{i,t}$ is a political risk indicator, $Cycle_{i,t}$ is a business cycle variable and $Crisis_{i,t}$ is a crisis indicator. Note that α_i denotes a country-specific fixed effect, while the remaining coefficients are constrained to be the same across countries. All regressions include fixed effects and standard errors clustered at the country-level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $r_{i,t+1}^{fx}$	(2) $r_{i,t+1}^{fx}$	(3) $r_{i,t+1}^{fx}$	(4) $r_{i,t+1}^{fx}$	(5) $r_{i,t+1}^{fx}$	(6) $r_{i,t+1}^{fx}$	(7) $r_{i,t+1}^{fx}$	(8) $r_{i,t+1}^{fx}$
$FI_{i,t}^{Smm}$	-0.0028 [-0.29]	0.046*** [3.16]						
$FI_{i,t}^{dj}$			-0.00028 [-0.42]	-0.0096 [-0.57]				
$TI_{i,t}^{QT}$					-0.031 [-0.82]	0.034* [1.80]		
$TI_{i,t}^{dj}$							-0.00071 [-0.32]	0.011 [0.70]
$PR_{i,t}$	-0.050 [-1.14]	-0.15** [-2.33]	-0.045 [-1.08]	-0.087 [-0.98]	-0.045 [-1.11]	-0.13 [-1.70]	-0.045 [-1.04]	-0.12 [-1.37]
$Cycle_{i,t}$	-0.018 [-0.47]	0.19 [1.00]	-0.015 [-0.44]	0.13 [0.62]	-0.017 [-0.42]	0.16 [0.84]	-0.0048 [-0.14]	0.10 [0.60]
$Crisis_{i,t}$	0.0016 [0.062]	0.0056 [0.47]	0.0033 [0.15]	0.036 [1.14]	-0.0029 [-0.100]	0.030 [1.47]	0.0050 [0.22]	0.034 [1.58]
$DY_{i,t}$	-1.20 [-0.81]	-0.43 [-0.31]	-1.52 [-1.54]	-0.0019 [-0.0013]	-1.42 [-0.65]	-0.56 [-0.39]	-1.41 [-1.31]	-0.27 [-0.19]
$FI_{i,t}^{Smm} DY_{i,t}$	-0.19 [-0.31]	-0.45** [-2.48]						
$FI_{i,t}^{df} DY_{i,t}$			0.015 [0.70]	0.31* [1.86]				
$TI_{i,t}^{QT} DY_{i,t}$					0.077 [0.040]	-0.36 [-0.76]		
$TI_{i,t}^{df} DY_{i,t}$							0.024 [0.38]	0.086 [0.27]
$PR_{i,t} DY_{i,t}$	1.65 [1.31]	0.95 [0.46]	1.77 [1.57]	-0.060 [-0.028]	1.63 [1.46]	1.39 [0.66]	1.67 [1.39]	0.48 [0.21]
$Cycle_{i,t} DY_{i,t}$	0.056 [0.046]	-1.66 [-0.45]	0.20 [0.16]	-0.31 [-0.086]	0.10 [0.086]	-1.19 [-0.34]	-0.065 [-0.051]	-0.14 [-0.039]
$Crisis_{i,t} DY_{i,t}$	-0.28 [-0.37]	-0.62 [-1.07]	-0.30 [-0.50]	-0.76 [-1.31]	-0.17 [-0.23]	-0.80 [-1.16]	-0.34 [-0.53]	-0.67 [-1.01]
$i_{i,t}^S$	0.36* [1.89]	-0.68*** [-4.62]	0.38 [1.31]	-0.75*** [-8.35]	0.40 [1.65]	-0.50*** [-3.48]	0.34 [1.18]	-0.79*** [-6.30]
$FI_{i,t}^{Smm} i_{i,t}^S$	-0.062 [-0.53]	-0.18*** [-4.80]						
$FI_{i,t}^{df} i_{i,t}^S$			0.00081 [0.22]	0.16 [0.93]				
$TI_{i,t}^{QT} i_{i,t}^S$					-0.041 [-0.37]	-0.30* [-1.89]		
$TI_{i,t}^{df} i_{i,t}^S$							-0.0047 [-0.28]	-0.31 [-0.85]
$PR_{i,t} i_{i,t}^S$	-0.32 [-1.23]	1.13*** [5.08]	-0.40 [-1.19]	0.95*** [5.53]	-0.39 [-1.23]	1.04*** [4.83]	-0.36 [-1.07]	1.33*** [3.41]
$Cycle_{i,t} i_{i,t}^S$	0.13 [0.28]	-1.97*** [-3.38]	0.11 [0.24]	-1.84*** [-3.17]	0.091 [0.21]	-1.99*** [-3.42]	0.067 [0.13]	-1.78*** [-4.29]
$Crisis_{i,t} i_{i,t}^S$	-0.45** [-2.80]	0.017 [0.26]	-0.42** [-2.50]	-0.12 [-1.55]	-0.46** [-3.13]	-0.066 [-1.17]	-0.44** [-2.55]	-0.042 [-0.50]
$r_{w,t+1}$	-3.31*** [-3.54]	-0.23 [-0.30]	-2.89** [-3.12]	-0.62 [-0.93]	-2.54** [-2.45]	-0.91 [-1.18]	-2.33** [-2.42]	-0.29 [-0.41]
$FI_{i,t}^{Smm} r_{w,t+1}$	0.25 [0.89]	0.59** [2.67]						
$FI_{i,t}^{dj} r_{w,t+1}$			-0.019 [-1.00]	-0.0070 [-0.015]				
$TI_{i,t}^{QT} r_{w,t+1}$					-0.68 [-0.90]	0.95* [1.93]		
$TI_{i,t}^{dj} r_{w,t+1}$							-0.13* [-2.12]	0.50 [1.59]
$PR_{i,t} r_{w,t+1}$	4.37*** [4.30]	0.83 [0.68]	4.23*** [4.08]	1.74* [1.84]	4.54*** [4.89]	1.08 [0.91]	3.65*** [3.45]	0.79 [0.66]
$Cycle_{i,t} r_{w,t+1}$	0.88 [0.83]	0.40 [0.30]	0.54 [0.49]	0.39 [0.26]	0.66 [0.57]	0.69 [0.49]	0.069 [0.065]	0.39 [0.24]
$Crisis_{i,t} r_{w,t+1}$	2.36*** [5.35]	1.16 [1.53]	2.23*** [4.68]	1.23 [1.51]	2.21*** [5.48]	1.37* [1.75]	1.89** [3.15]	1.40 [1.62]
Observations	3,235	3,135	3,235	3,135	3,235	3,135	3,235	3,135
Adjusted R-squared	0.419	0.262	0.419	0.252	0.419	0.261	0.426	0.257
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.9: Equity Beta: Effect of Changes in Openness, Political Risk, Cycle and Crises

This table characterizes the economic effects of changes in openness, political risk, cycle and crisis levels on the equity beta for developed and emerging markets. The columns in the table correspond to the regression specifications in Table 1.6, which allow betas to vary with the variables mentioned above. The first eight rows report the 5th and 95th percentiles for the instruments. The following rows calculate the total effect on beta. Rows labeled "Low" ("High") compute the total beta using the the 5th (95th) percentile for the variable of interest and the mean level for all other variables.

	FI_1^{Seq}	FI_2^{Seq}	$FI_3^{df,eq}$	$FI_4^{df,eq}$	TI_5^{QT}	TI_6^{QT}	$TI_7^{df,debt}$	$TI_8^{df,debt}$
<i>Open</i> _{p5}	0.50	0.00	0.02	0.01	0.62	0.30	0.26	0.18
<i>Open</i> _{p95}	1.00	1.00	2.05	0.40	1.00	1.00	2.63	1.43
<i>PR</i> _{p5}	0.68	0.47	0.68	0.47	0.68	0.47	0.68	0.47
<i>PR</i> _{p95}	0.92	0.79	0.92	0.79	0.92	0.79	0.92	0.79
<i>Cycle</i> _{p5}	-0.05	-0.06	-0.05	-0.06	-0.05	-0.06	-0.05	-0.06
<i>Cycle</i> _{p95}	0.03	0.05	0.03	0.05	0.03	0.05	0.03	0.05
<i>Crisis</i> _{p5}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
<i>Crisis</i> _{p95}	0.21	0.43	0.21	0.43	0.21	0.43	0.21	0.43
Low Openness	1.11	1.05	1.06	1.18	1.00	1.19	1.06	1.18
High Openness	1.07	1.33	1.11	1.07	1.09	1.12	1.13	1.09
Low Political Risk	1.06	0.84	1.07	0.80	1.08	0.81	1.06	0.80
High Political Risk	1.09	1.39	1.08	1.43	1.07	1.41	1.08	1.42
Low Cycle	1.05	1.23	1.05	1.24	1.04	1.24	1.05	1.24
High Cycle	1.10	1.08	1.10	1.09	1.10	1.08	1.10	1.08
Low Crisis	1.00	1.02	1.00	1.02	1.00	1.02	1.00	1.02
High Crisis	1.28	1.52	1.28	1.52	1.28	1.52	1.28	1.52
Sample	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.10: Bond Beta: Effect of Changes in Openness, Political Risk, Cycle and Crises

This table characterizes the economic effects of changes in openness, political risk, cycle and crisis levels on the bond beta for developed and emerging markets. The columns in the table correspond to the regression specifications in Table 1.7, which allow betas to vary with the variables mentioned above. The first eight rows report the 5th and 95th percentiles for the instruments. The following rows calculate the total effect on beta. Rows labeled "Low" ("High") compute the total beta using the the 5th (95th) percentile for the variable of interest and the mean level for all other variables.

	FI_1^{Seq}	FI_2^{Seq}	$FI_3^{df,eq}$	$FI_4^{df,eq}$	TI_5^{QT}	TI_6^{QT}	$TI_7^{df,debt}$	$TI_8^{df,debt}$
<i>Open</i> _{p5}	0.71	0.00	0.58	0.23	0.88	0.25	0.26	0.18
<i>Open</i> _{p95}	1.00	1.00	6.07	1.15	1.00	1.00	1.18	1.53
<i>PR</i> _{p5}	0.73	0.48	0.73	0.48	0.73	0.48	0.73	0.48
<i>PR</i> _{p95}	0.93	0.80	0.93	0.80	0.93	0.80	0.93	0.80
<i>Cycle</i> _{p5}	-0.04	-0.07	-0.04	-0.07	-0.04	-0.07	-0.04	-0.07
<i>Cycle</i> _{p95}	0.03	0.05	0.03	0.05	0.03	0.05	0.03	0.05
<i>Crisis</i> _{p5}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
<i>Crisis</i> _{p95}	0.23	0.44	0.23	0.44	0.23	0.44	0.23	0.44
Low Openness	1.32	0.63	1.23	0.63	1.27	0.33	1.27	0.52
High Openness	1.34	0.47	1.65	0.44	1.36	0.69	1.51	0.71
Low Political Risk	1.21	0.63	1.29	0.61	1.24	0.65	1.24	0.67
High Political Risk	1.44	0.53	1.46	0.53	1.44	0.50	1.43	0.50
Low Cycle	1.36	0.55	1.40	0.54	1.37	0.52	1.38	0.54
High Cycle	1.32	0.59	1.36	0.58	1.33	0.60	1.32	0.59
Low Crisis	1.26	0.62	1.32	0.60	1.27	0.61	1.27	0.62
High Crisis	1.56	0.43	1.55	0.45	1.55	0.44	1.55	0.42
Sample	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.11: Exchange Rates Beta: Effect of Changes in Openness, Political Risk, Cycle and Crises

This table characterizes the economic effects of changes in openness, political risk, cycle and crisis levels on the exchange rate beta for developed and emerging markets. The columns in the table correspond to the regression specifications in Table 1.8, which allow betas to vary with the variables mentioned above. The first eight rows report the 5th and 95th percentiles for the instruments. The following rows calculate the total effect on beta. Rows labeled "Low" ("High") compute the total beta using the 5th (95th) percentile for the variable of interest and the mean level for all other variables.

	FI_1^{Seq}	FI_2^{Seq}	$FI_3^{df,eq}$	$FI_4^{df,eq}$	TI_5^{QT}	TI_6^{QT}	$TI_7^{df,debt}$	$TI_8^{df,debt}$
<i>Open</i> _{p5}	0.50	0.00	0.51	0.22	0.81	0.38	0.21	0.20
<i>Open</i> _{p95}	1.00	1.00	9.52	0.99	1.00	1.00	3.10	1.35
<i>PR</i> _{p5}	0.67	0.54	0.67	0.54	0.67	0.54	0.67	0.54
<i>PR</i> _{p95}	0.90	0.80	0.90	0.80	0.90	0.80	0.90	0.80
<i>Cycle</i> _{p5}	-0.05	-0.07	-0.05	-0.07	-0.05	-0.07	-0.05	-0.07
<i>Cycle</i> _{p95}	0.03	0.04	0.03	0.04	0.03	0.04	0.03	0.04
<i>Crisis</i> _{p5}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
<i>Crisis</i> _{p95}	0.20	0.36	0.20	0.36	0.20	0.36	0.20	0.36
Low Openness	0.53	0.42	0.69	0.63	0.75	0.28	0.75	0.45
High Openness	0.66	1.01	0.52	0.63	0.62	0.88	0.36	1.02
Low Political Risk	-0.05	0.52	-0.02	0.41	-0.07	0.49	0.08	0.54
High Political Risk	1.00	0.74	0.99	0.86	1.02	0.77	0.95	0.74
Low Cycle	0.60	0.60	0.62	0.61	0.62	0.59	0.65	0.62
High Cycle	0.67	0.65	0.67	0.65	0.67	0.66	0.66	0.66
Low Crisis	0.52	0.53	0.54	0.53	0.54	0.52	0.56	0.53
High Crisis	1.00	0.95	0.99	0.97	0.99	1.01	0.95	1.02
Sample	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.12: Cross-Sectional Dispersion in Risk Premiums

This table reports statistics for expected returns calculated based on Tables 1.6, 1.7, and 1.8 for equity, bond, and exchange rate markets, respectively. Global expected returns are estimated using the following predictive regressions:

$$r_{w,t+1}^e = \alpha + \beta_1 r_{us,t}^e + \beta_2 DY_{us,t} + \beta_3 i_{us,t}^S + \beta_4 term_{us,t} + \varepsilon_{w,t}$$

$$r_{w,t+1}^b = \alpha + \beta_1 r_{us,t}^b + \beta_2 i_{us,t}^S + \beta_3 term_{us,t} + \varepsilon_{w,t}$$

$$r_{w,t+1}^{fx} = \alpha + \beta_1 r_{w,t}^{fx} + \beta_2 i_{us,t}^S + \beta_3 term_{us,t} + \varepsilon_{w,t}$$

where $DY_{us,t}$ is the U.S. dividend yield, $i_{us,t}^S$ is the U.S. short rate and $term_{us,t}$ is the U.S. term premium. Note that expected returns are calculated using a balanced sample. In addition to mean expected returns, this table shows the results of the [Bunzel and Vogelsang \(2005\)](#) trend tests conducted on the cross-sectional dispersion in expected returns. A bold number means that the trend beta is significantly different from zero at the 5% significance level. The cross-sectional dispersion, CS_t is reported in annualized volatility units and is calculated as

$$CS_t = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(r_{i,t} - \frac{1}{N} \sum_{i=1}^N r_{i,t} \right)^2}$$

	Developed mean	CS Trend Test	Emerging mean	CS Trend Test
<i>Panel A: Equities</i>				
FI^{Seq}	0.023	-0.010	0.052	-0.016
$FI_{i,t}^{df,eq}$	0.020	-0.004	0.054	-0.012
$TI_{i,t}^{QT}$	0.022	-0.004	0.070	-0.002
TI^{df}	0.020	-0.003	0.050	-0.015
<i>Panel B: Bonds</i>				
FI^{Sbo}	0.010	0.000	0.024	-0.009
$FI_{i,t}^{df,debt}$	0.011	-0.003	0.025	-0.001
$TI_{i,t}^{QT}$	0.010	-0.004	0.027	-0.015
TI^{df}	0.010	0.000	0.028	-0.004
<i>Panel C: Exchange Rates</i>				
FI^{Smm}	0.016	-0.008	0.030	-0.029
$FI_{i,t}^{df,debt}$	0.013	-0.006	0.022	-0.021
$TI_{i,t}^{QT}$	0.025	-0.007	0.026	-0.033
TI^{df}	0.019	-0.007	0.020	-0.016

Table 1.13: Cross-Sectional Dispersion in Equity Risk Premiums and Globalization

This table reports regressions for the cross-sectional dispersion of the equity risk premium. Expected returns are calculated based on Table 1.6, with global expected returns estimated using the following predictive regression:

$$r_{w,t+1}^e = \alpha + \beta_1 r_{u,s,t}^e + \beta_2 DY_{u,s,t} + \beta_3 i_{u,s,t}^S + \beta_4 term_{u,s,t} + \varepsilon_{w,t}$$

where $DY_{u,s,t}$ is the U.S. dividend yield, $i_{u,s,t}^S$ is the U.S. short rate and $term_{u,s,t}$ is the U.S. term premium. Note that expected returns are calculated using a balanced sample and the cross-sectional dispersion of the equity premium is computed in annualized volatility units. We then estimate

$$CS(E_t[r_{i,t+1}^e]) = \alpha + \beta_1 f(Open_{i,t}) + \beta_2 CS(PR_{i,t}) + \beta_3 \overline{PR_{i,t}} + \beta_4 CS(Cycle_{i,t}) + \beta_5 Cycle_{w,t} + \beta_6 CS(Crisis_{i,t}) + \beta_7 Crisis_{w,t} + \beta_8 RV_{w,t} + \beta_9 t + \varepsilon_{i,t}$$

where $f(Open_{i,t})$ is either the cross-sectional dispersion or the mean across countries of the openness variable. We report the complete results for the financial openness variables. In each specification, there are four rows with $TI_{i,t}^{QT}$ and $TI_{i,t}^{df}$. These are the coefficients on the trade openness measures in regressions where financial openness is replaced with trade openness. The remaining coefficients are robust and therefore not reported. Bolded coefficients are also significant at the 10% level or lower and have the same sign in a regression without the trend term. Asterisks (**, *, and **) indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$	$CS(E_t[r_{i,t+1}^e])$
$CS(FI_{i,t}^{Seq})$	0.036*** [4.51]	0.0042 [1.13]						
$\overline{FI_{i,t}^{Seq}}$								
$CS(FI_{i,t}^{df})$								
$\overline{FI_{i,t}^{df}}$								
$CS(PR_{i,t})$	0.015 [0.39]	0.080*** [7.18]	-0.023 [-0.52]	0.076*** [6.56]	0.021 [1.08]	0.11*** [11.7]	-0.0072 [-0.38]	0.11*** [11.9]
$\overline{PR_{i,t}}$	0.041* [1.73]	0.26*** [6.88]	0.084** [2.57]	0.26*** [6.77]	-0.11*** [-2.63]	0.16*** [4.06]	-0.021 [-0.81]	0.13*** [3.80]
$CS(Cycle_{i,t})$	-0.038*** [-3.33]	-0.025** [-2.57]	-0.049*** [-3.85]	-0.023** [-2.28]	-0.056*** [-3.94]	-0.030*** [-3.41]	-0.041*** [-2.74]	-0.035*** [-4.05]
$Cycle_{w,t}$	-0.0011*** [-3.47]	0.000083 [0.20]	-0.00099*** [-2.97]	0.00011 [0.27]	-0.00073** [-1.99]	0.00016 [0.58]	-0.0012*** [-3.50]	0.00015 [0.54]
$CS(Crisis_{i,t})$	0.069*** [7.09]	0.019*** [4.79]	0.073*** [6.92]	0.019*** [4.79]	0.084*** [8.50]	0.013*** [3.86]	0.073*** [10.6]	0.018*** [4.56]
$Crisis_{w,t}$	-0.047*** [-4.59]	0.025** [2.33]	-0.042*** [-3.46]	0.025** [2.31]	-0.042*** [-2.82]	0.034*** [3.44]	-0.029** [-2.09]	0.037*** [3.71]
$RV_{w,t}$	0.24*** [3.02]	0.38*** [5.74]	0.25*** [2.94]	0.38*** [5.73]	0.16** [2.04]	0.36*** [6.02]	0.27*** [3.32]	0.34*** [6.15]
time trend	-0.0096*** [-6.79]	-0.0022 [-0.76]	-0.012*** [-7.59]	-0.000053 [-0.017]	0.037 [1.95]	-0.017*** [-3.61]	0.00021 [0.020]	-0.015*** [-3.53]
$CS(TI_{i,t}^{QT})$	-0.0072 [-0.34]	-0.15*** [-12.8]						
$\overline{TI_{i,t}^{QT}}$			0.077 [0.75]	0.44*** [9.83]				
$CS(TI_{i,t}^{df})$								
$\overline{TI_{i,t}^{df}}$								
Observations	235	235	235	235	235	235	235	235
Adjusted R-squared	0.618	0.581	0.588	0.581	0.578	0.588	0.532	0.586
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.14: Cross-Sectional Dispersion in Bond Risk Premiums

This table reports regressions for the cross-sectional dispersion of the bond risk premium. Expected returns are calculated based on Table 1.7, with global expected returns estimated using the following predictive regression:

$$r_{w,t+1}^b = \alpha + \beta_1 r_{us,t}^b + \beta_2 i_{us,t}^S + \beta_3 term_{us,t} + \varepsilon_{w,t}$$

where $i_{us,t}^S$ is the U.S. short rate and $term_{us,t}$ is the U.S. term premium. Note that expected returns are calculated using a balanced sample and the cross-sectional dispersion of the risk premium is computed in annualized volatility units. We then estimate

$$CS(E_t[r_{i,t+1}^b]) = \alpha + \beta_1 f(Open_{i,t}) + \beta_2 CS(PR_{i,t}) + \beta_3 \overline{PR}_{i,t} + \beta_4 CS(Cycle_{i,t}) + \beta_5 Cycle_{w,t} + \beta_6 CS(Crisis_{i,t}) + \beta_7 Crisis_{w,t} + \beta_8 RV_{w,t} + \beta_9 t + \varepsilon_{i,t}$$

where $f(Open_{i,t})$ is either the cross-sectional dispersion or the mean across countries of the openness variable. We report the complete results for the financial openness variables. In each specification, there are four rows with $TI_{i,t}^{QT}$ and $TI_{i,t}^{df}$. These are the coefficients on the trade openness measures in regressions where financial openness is replaced with trade openness. The remaining coefficients are robust and therefore not reported. Bolded coefficients are also significant at the 10% level or lower and have the same sign in a regression without the trend term. Asterisks (**, *, and *) indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$	$CS(E_t[r_{i,t+1}^b])$
$CS(FI_{i,t}^{Sbo})$	0.0019 [0.74]	-0.016** [-2.18]						
$\overline{FI}_{i,t}^{Sbo}$			0.0055 [0.40]	-0.13*** [-3.23]				
$CS(FI_{i,t}^{df})$					-0.000021 [-0.088]	0.0013 [0.72]		
$\overline{FI}_{i,t}^{df}$							-0.0014 [-1.55]	-0.016 [-1.62]
$CS(PR_{i,t})$	-0.045*** [-3.36]	0.012 [0.54]	-0.056*** [-4.86]	0.10*** [4.23]	-0.063*** [-5.09]	0.042*** [3.67]	-0.068*** [-5.35]	0.028** [2.04]
$\overline{PR}_{i,t}$	-0.14*** [-5.01]	0.12*** [3.53]	-0.16*** [-6.05]	0.15*** [3.68]	-0.20*** [-6.66]	0.19*** [5.88]	-0.20*** [-6.63]	0.15*** [3.93]
$CS(Cycle_{i,t})$	-0.046*** [-3.35]	0.037** [2.34]	-0.049*** [-3.64]	0.018 [1.08]	-0.038*** [-2.66]	-0.0060 [-0.50]	-0.036** [-2.57]	0.00034 [0.027]
$Cycle_{w,t}$	-0.0011*** [-7.88]	-0.0041*** [-7.86]	-0.0011*** [-7.94]	-0.0044*** [-7.64]	-0.0013*** [-7.90]	-0.0020*** [-7.17]	-0.0012*** [-7.84]	-0.0019*** [-6.94]
$CS(Crisis_{i,t})$	0.0073*** [3.38]	0.032*** [4.42]	0.0082*** [3.78]	0.029*** [4.32]	0.015*** [6.09]	0.030*** [5.83]	0.013*** [4.51]	0.033*** [6.06]
$Crisis_{w,t}$	0.020*** [3.01]	-0.047** [-2.60]	0.019*** [2.77]	-0.051*** [-3.44]	0.015* [1.94]	-0.047*** [-5.08]	0.017** [2.11]	-0.046*** [-5.30]
$RV_{w,t}$	0.21*** [4.72]	0.50*** [3.07]	0.20*** [4.71]	0.62*** [3.38]	0.22*** [4.46]	0.55*** [4.27]	0.22*** [4.38]	0.51*** [4.29]
time trend	-0.0093*** [-5.75]	0.0026 [0.41]	-0.0091*** [-5.48]	0.0021 [0.42]	-0.015*** [-4.67]	0.022*** [7.33]	-0.011*** [-3.54]	0.015*** [3.84]
$CS(TI_{i,t}^{QT})$	0.023 [1.14]	-0.028 [-1.63]						
$\overline{TI}_{i,t}^{QT}$			0.0058 [0.074]	0.053 [1.41]				
$CS(TI_{i,t}^{df})$					0.029*** [7.71]	0.041*** [6.91]		
$\overline{TI}_{i,t}^{df}$							0.066*** [9.96]	0.11*** [9.47]
Observations	206	206	206	206	206	206	206	206
Adjusted R-squared	0.644	0.526	0.643	0.560	0.644	0.478	0.646	0.483
Region	DM	EM	DM	EM	DM	EM	DM	EM

Table 1.15: Cross-Sectional Dispersion in Exchange Rate Risk Premiums

This table reports regressions for the cross-sectional dispersion of the exchange rate risk premium. Expected returns are calculated based on Table 1.8, with global expected returns estimated using the following predictive regression:

$$r_{w,t+1}^{fx} = \alpha + \beta_1 r_{w,t}^{fx} + \beta_2 i_{us,t}^S + \beta_3 term_{us,t} + \varepsilon_{w,t}$$

where $i_{us,t}^S$ is the U.S. short rate and $term_{us,t}$ is the U.S. term premium. Note that expected returns are calculated using a balanced sample and the cross-sectional dispersion of the risk premium is computed in annualized volatility units. We then estimate

$$CS(E_t[r_{i,t+1}^{fx}]) = \alpha + \beta_1 f(Open_{i,t}) + \beta_2 CS(PR_{i,t}) + \beta_3 \overline{PR_{i,t}} + \beta_4 CS(Cycle_{i,t}) + \beta_5 Cycle_{w,t} + \beta_6 CS(Crisis_{i,t}) + \beta_7 Crisis_{w,t} + \beta_8 RV_{w,t} + \beta_9 t + \varepsilon_{i,t}$$

where $f(Open_{i,t})$ is either the cross-sectional dispersion or the mean across countries of the openness variable. We report the complete results for the financial openness variables. In each specification, there are four rows with $TI_{i,t}^{QT}$ and $TI_{i,t}^{df}$. These are the coefficients on the trade openness measures in regressions where financial openness is replaced with trade openness. The remaining coefficients are robust and therefore not reported. Bolded coefficients are also significant at the 10% level or lower and have the same sign in a regression without the trend term. Asterisks (***, **, and *) indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$	$CS(E_t[r_{it+1}^{fx}])$
$CS(FI_{i,t}^{Smm})$	-0.023*** [-4.49]	0.023*** [3.12]						
$\overline{FI_{i,t}^{Smm}}$			0.10*** [3.86]	0.057*** [3.67]				
$CS(FI_{i,t}^{df})$					0.0035*** [4.13]	0.0098*** [3.02]		
$\overline{FI_{i,t}^{df}}$							0.0082*** [4.49]	0.077*** [5.40]
$CS(PR_{i,t})$	0.053*** [2.74]	0.032 [1.57]	0.033* [1.85]	0.017 [0.84]	0.026* [1.84]	-0.0053 [-0.18]	0.023 [1.56]	0.0048 [0.17]
$\overline{PR_{i,t}}$	-0.11*** [-3.54]	0.047 [0.56]	-0.14*** [-4.60]	0.041 [0.52]	-0.20*** [-8.50]	-0.0057 [-0.078]	-0.19*** [-8.19]	0.018 [0.28]
$CS(Cycle_{i,t})$	-0.051*** [-2.87]	-0.015 [-1.13]	-0.055*** [-2.81]	-0.024** [-1.98]	-0.047*** [-3.55]	0.018 [1.00]	-0.056*** [-4.00]	0.014 [0.83]
$Cycle_{w,t}$	0.00023 [0.94]	-0.00092*** [-3.42]	-0.000025 [-0.11]	-0.00073*** [-2.77]	0.00031* [1.94]	-0.0022*** [-6.95]	0.00031* [1.86]	-0.0022*** [-7.00]
$CS(Crisis_{i,t})$	-0.011** [-2.43]	-0.0045 [-1.03]	-0.010** [-2.51]	-0.0080* [-1.68]	0.044*** [10.2]	0.0077 [1.50]	0.040*** [10.7]	0.00093 [0.18]
$Crisis_{w,t}$	0.060*** [3.54]	-0.019* [-1.97]	0.047*** [3.00]	-0.039*** [-3.91]	0.0029 [0.21]	-0.033*** [-2.68]	0.0098 [0.69]	-0.028** [-2.54]
$RV_{w,t}$	0.17** [2.17]	-0.18** [-2.48]	0.20** [2.59]	-0.14** [-2.16]	0.21*** [2.98]	0.047 [0.56]	0.21*** [3.02]	0.10 [1.40]
time trend	-0.022*** [-5.93]	-0.025*** [-6.83]	-0.019*** [-6.15]	-0.022*** [-6.66]	-0.010*** [-7.01]	-0.017*** [-4.15]	-0.016*** [-7.60]	-0.0099*** [-2.62]
$CS(TI_{i,t}^{QT})$	0.099*** [5.46]	0.051*** [3.08]						
$\overline{TI_{i,t}^{QT}}$			-0.19*** [-5.51]	-0.068* [-1.97]				
$CS(TI_{i,t}^{df})$					0.010*** [6.44]	0.0054 [1.22]		
$\overline{TI_{i,t}^{df}}$							0.052*** [7.00]	0.024*** [3.31]
Observations	189	189	189	189	189	189	189	189
Adjusted R-squared	0.480	0.787	0.474	0.787	0.717	0.567	0.714	0.592
Region	DM	EM	DM	EM	DM	EM	DM	EM

Figure 1.1: Openness Measures

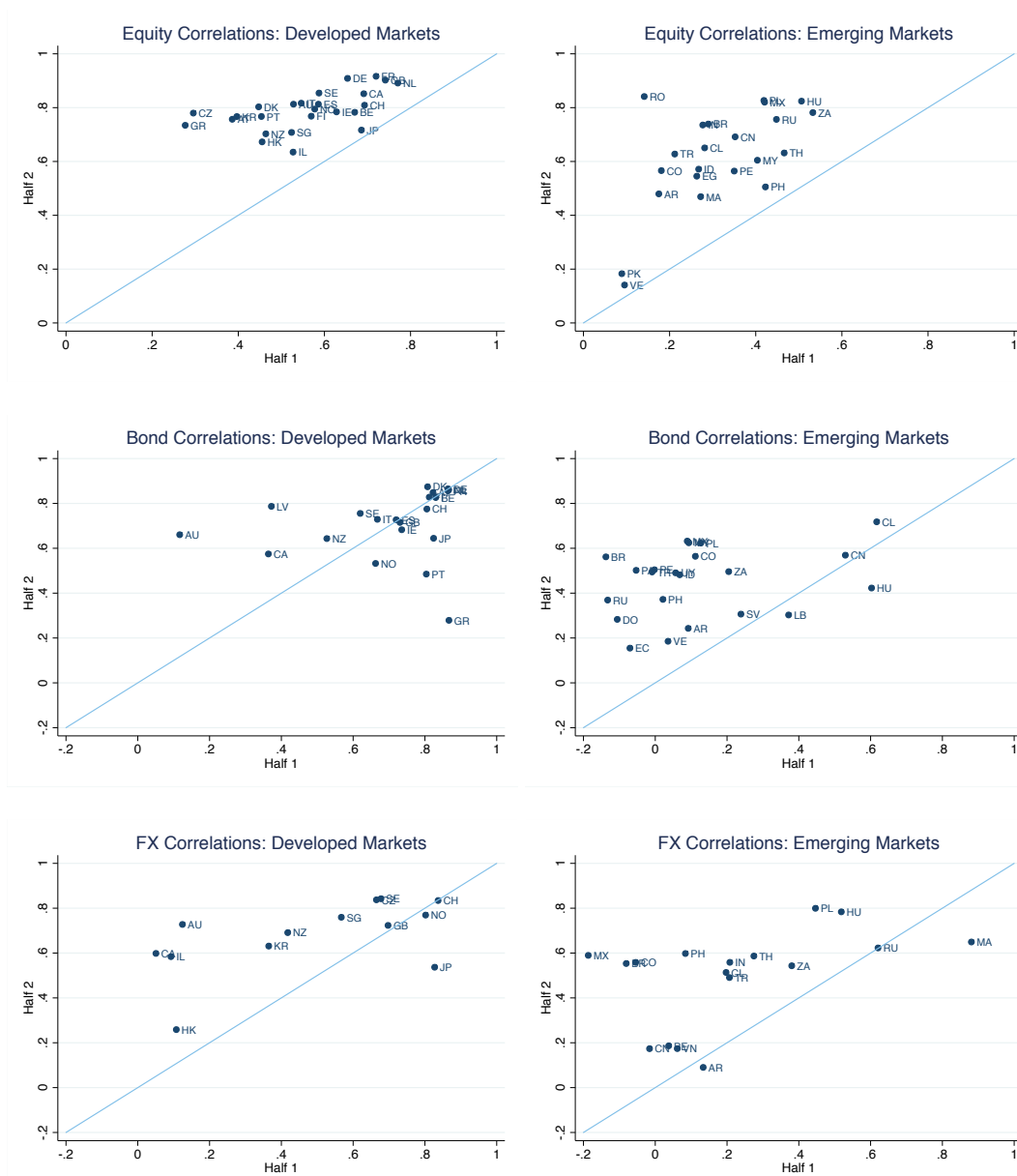
This figure shows *de jure* and *de facto* openness measures for developed and emerging markets. The averages are equally weighted across countries and are calculated as $open_{cg,t}^x = \sum_{i=1}^N w_{i,t} x_{i,t}$, where *cg* is the country group (emerging or developed), *x* is the openness measure, $w_{i,t}$ is the country weight *i* and *N* is the number of countries. For a description of all the openness measures, see Table A.1. Countries are classified as developed or emerging markets according to IMF classifications (for details, see Table A.2).



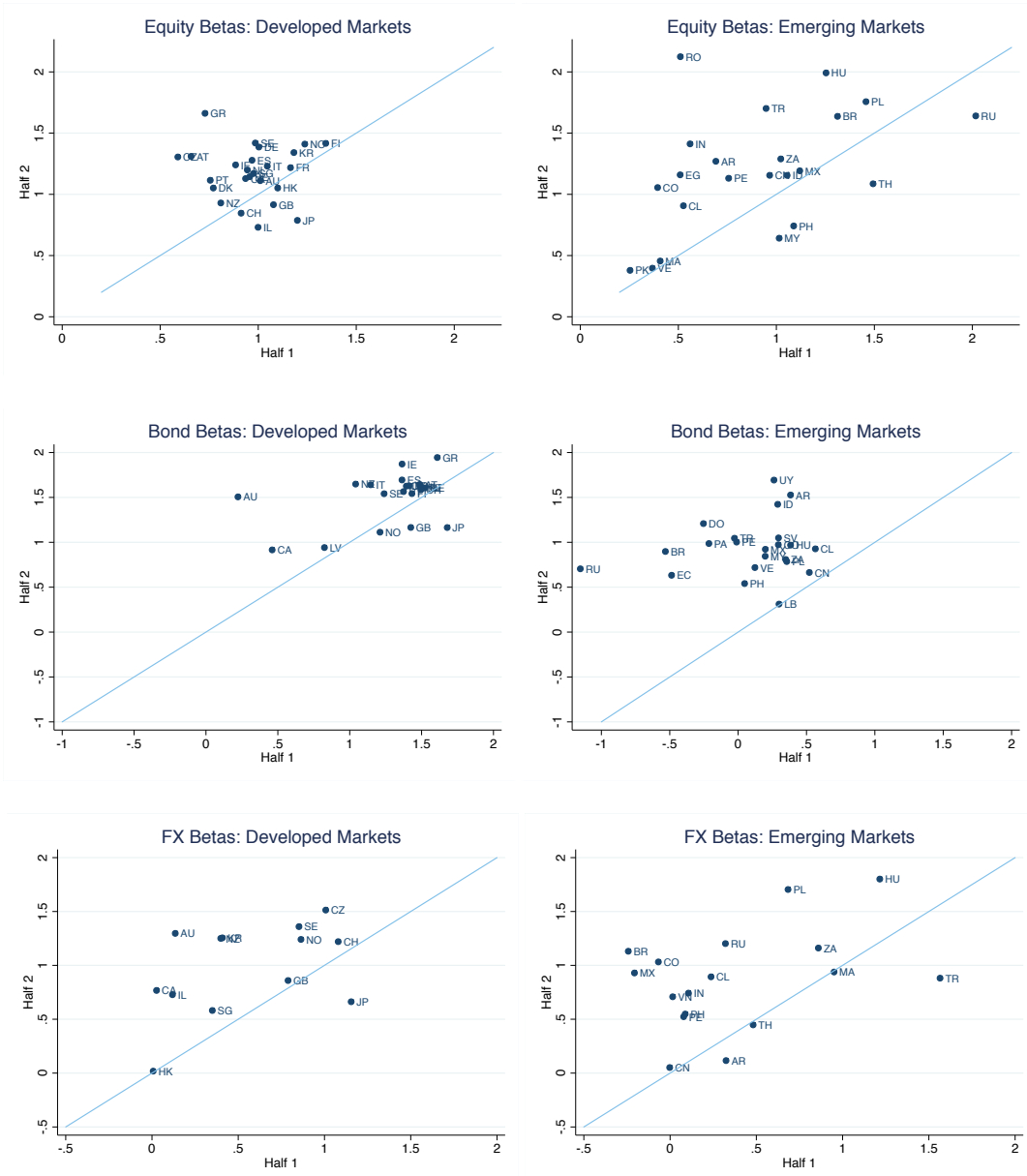
Figure 1.2: Correlations, Betas and Idiosyncratic Risk: First Half versus Second Half

Correlations, betas and idiosyncratic risk: first half versus second half of sample. This figure shows various statistics based on equity, bond, and exchange rate returns in the first versus second half of the sample. Given the unbalanced nature of the panel data, the midpoint is country-specific. Start dates for each country can be found in Table A.2. (a) Correlations between country returns and world returns for each asset class. (b) Betas with world returns and (c) annualized idiosyncratic risk, calculated from the following country-specific regressions for each half: $r_{i,t} = \alpha_i + \beta_i r_{w,t} + \varepsilon_{i,t}$. We report scatter plots for developed and emerging markets, which are grouped according to International Monetary Fund classifications (for details, see Table A.2). The solid line in each graph is a 45° line.

(a) Correlations with World Returns



(b) Betas with World Returns



(c) Idiosyncratic Risk

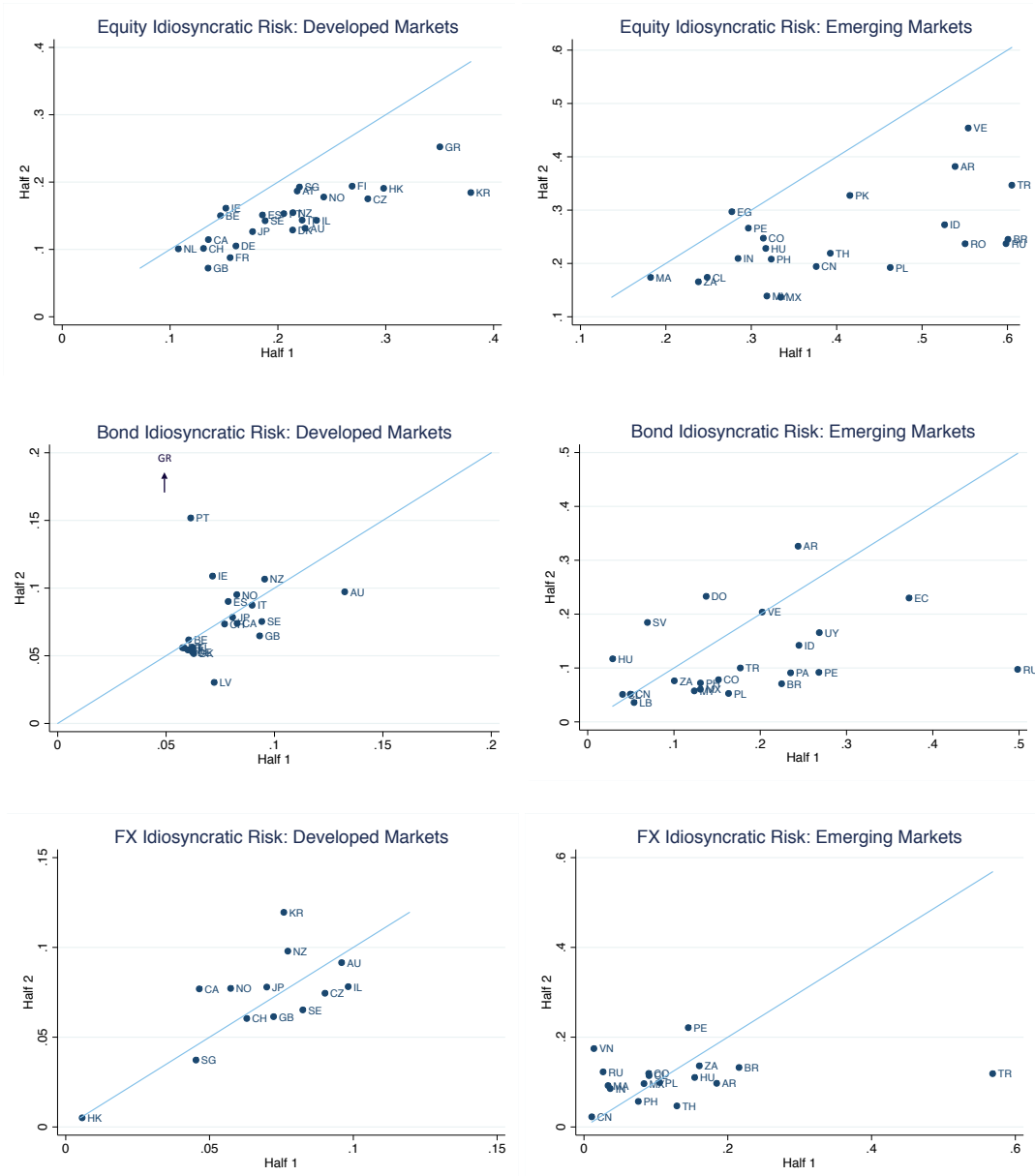
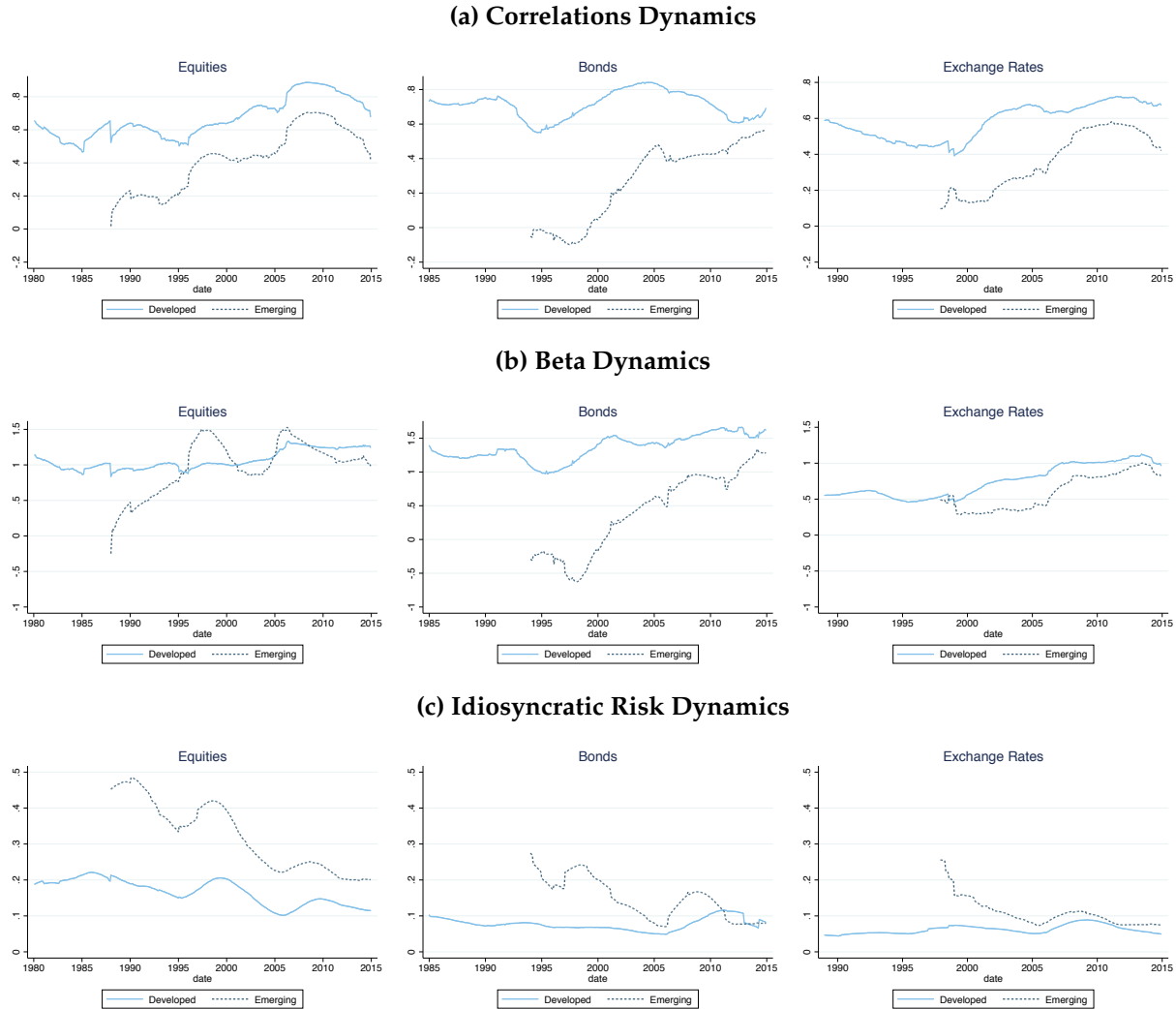


Figure 1.3: Time-Varying Correlations, Betas and Idiosyncratic Risk

This figure plots regional time-varying correlations, betas, and idiosyncratic risk for equity, bond, and exchange rate returns using a kernel method. For each country, given any date t_0 , we split the sample into five-year subsamples and use the 30 data points before and after this point. Within these subsamples, we use a normal kernel to assign weights to the individual observations according to how close they are to t_0 . We then compute kernel-weighted (a) correlations, (b) betas, and (c) idiosyncratic risk at the country level. Finally, we construct regional measures as the equally weighted average across countries.



Chapter 2

Variance Risk in Global Markets

2.1 INTRODUCTION

The conditional volatility of the market return changes over time as the economy goes through periods of tranquility and periods of turbulence. It has long been known that these changes in the volatility of asset returns are priced in option markets. [Jurek and Stafford \(2015\)](#), [Dew-Becker, Giglio, Le, and Rodriguez \(2017\)](#), and [Ait-Sahalia, Karaman, and Mancini \(2019\)](#) provide recent evidence. In theory, the price of this volatility risk is negative as increases in volatility are viewed by investors as a deterioration in the investment opportunity set. Hence, assets like variance swaps that pay off positively when the economy unexpectedly becomes more turbulent should have negative expected returns, and they do have negative average returns. Said differently, selling volatility in option markets makes money on average because losses on such strategies occur in bad states of the world. [Ang, Hodrick, Xing, and Zhang \(2006\)](#) argue that aggregate market return volatility should be a priced risk factor in the cross-section of U.S. stock returns, and they find that stocks with a higher sensitivity to volatility risk earn lower average returns consistent with the idea that volatility risk is negatively priced.¹

It is also well known that a global capital asset pricing model (CAPM), in which the world market return is the only priced risk, yields low discount rates for emerging market assets. While it could be that emerging markets provide valuable diversification benefits to international investors, most people find low discount rates for emerging market companies to be counter-intuitive. Consequently, investors often employ various ad hoc adjustments to discount rates such as adding political risk premiums associated with the default risk of emerging market government bonds to the required return on emerging market equities implied by the CAPM.² Because emerging market equities also perform poorly during turbulent, high-variance regimes, variance risk may be a risk factor across various emerging market asset classes that has the potential to increase their required rates of return. While increases in equity volatility and poor equity market returns often occur together, it is important to recognize that the correlation between the return on equity and the return to the variance swap is only -58%, which is far from perfect. Thus, our postulated

¹Other recent papers that argue for a negative price of variance risk in the cross-section of stocks include [Cremers, Halling, and Weinbaum \(2015\)](#) and [Campbell, Giglio, Polk, and Turley \(2018\)](#)

²See [Bekaert, Harvey, Lundblad, and Siegel \(2014\)](#) for a discussion of political risk in international valuations.

variance risk factor has the potential to affect expected returns on various assets in addition to the influence from equity market risk premiums.

In summary, we seek to explain the excess returns on a variety of assets with a simple three-factor model that includes the return on a benchmark equity portfolio and two additional sources of risk. Because we primarily use U.S. dollar (USD) denominated returns, we also include the excess return on a long-term USD bond. The third source of risk is the return on a variance swap that captures a traded measure of unanticipated increases in volatility.

There are two main parts in the paper. First, we examine the exposure of returns to variance risk at the regional level in developed and emerging equity markets, bond markets, and foreign currency markets. This section also explores whether our three-factor model correctly prices the average excess returns on equities, bonds, and foreign currencies. While the equity and bond exposures strongly vary with the different asset classes we consider, we find a nearly uniform and mainly negative exposure to the variance risk factor. Because the average return on buying volatility is negative, such negative exposures should be compensated by positive risk premiums, and we quantify how much of the global risk premiums assigned by the three-factor model is accounted for by variance risk, finding it to be highly statistically significant and often exceeding 50% of the total risk premium.

Given the short sample, though, it is difficult to distinguish different asset pricing models or to evaluate the fit of factor models using average realized returns. We therefore also ask how much of the cross-country correlation structure is explained by the models for each asset class and how much of the cross-asset correlation structure is explained by the models for each region. For this second part, we use the models to calculate implied correlations across regions, but within asset classes, and then across asset classes, but within regions.

There is extensive evidence in the literature (see [Bekaert, Hodrick, and Zhang \(2009b\)](#); [Hou, Karolyi, and Kho \(2011b\)](#)) that local factors improve the fit of factor models for equities. We do not include such regional risk factors, and we therefore do not expect our model to fully explain the sample correlation structure. There is much less evidence on how global factor models fare with respect to international bond markets ([Xu \(2018\)](#) is an exception) whereas the foreign currency

literature mostly focuses on currency-centric models.³ There is no evidence to our knowledge on how global factor models fit correlations across asset classes. We find that the global factor model explains a substantive fraction of the comovements between international assets, but the fit is best for international equity correlations and is worse for currency returns and across asset correlations.

The remainder of the article is organized as follows. Section 2.2 discusses the sources of the data and some summary statistics. Section 2.3 documents the factor exposures for the three asset classes across the world. Section 2.4 focuses on the implications of the factor model for risk premiums, and Section 2.5 analyzes the effects on comovements across assets. Section 2.6 considers the impact of currency of denomination (dollar versus local returns), and Section 2.7 concludes.

2.2 DATA

This section describes the country-specific, regional, and global data used in the empirical analysis, along with some summary statistics. We use MSCI monthly country-level total USD equity returns from January 1995 to November 2018 for a total of 287 observations. The balanced sample consists of 22 developed markets and 25 emerging markets. The developed markets are subdivided into four groups: Developed Commodity countries (denoted DM Comm) contains Canada, Australia, and New Zealand; Developed Asia includes Japan, Hong Kong, and Singapore, whereas the 16 European countries are split up into those countries that use the euro (denoted EU Euro) and those that do not (denoted EU Non-Euro), to which we add Switzerland and Norway who are not members of the EU. The emerging markets are subdivided into three groups: Emerging Asia; Emerging Europe, Middle East, and Africa (EMEA); and Latin America.⁴ Additional information on the regional affiliations of the various developed and emerging markets and

³See for example [Lustig, Roussanov, and Verdelhan \(2014\)](#), [Verdelhan \(2018\)](#), and [Lustig and Richmond \(2017\)](#). [Aloosh and Bekaert \(2019\)](#) provides an exception.

⁴The included emerging market countries and their two-letter ISO codes are the following: Argentina (AR), Brazil (BR), Chile (CL), China (CN), Colombia (CO), Czech Republic (CZ), Egypt (EG), Hungary (HU), India (IN), Israel (IL), Indonesia (ID), Jordan (JO), Korea (KR), Morocco (MA), Mexico (MX), Malaysia (MY), Peru (PE), Pakistan (PK), Philippines (PH), Poland (PL), Russia (RU), Thailand (TH), Turkey (TR), Taiwan (TW), and South Africa (ZA). The included developed countries are the following: Austria (AT), Australia (AU), Belgium (BE), Canada (CA), Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), United Kingdom (GB), Greece (GR), Hong Kong (HK), Ireland (IE), Italy (IT), Japan (JP), Netherlands (NL), Norway (NO), New Zealand (NZ), Portugal (PT), Sweden (SE), and Singapore (SG).

which countries are used for each asset class are described in Table B.1. Excess returns are calculated by subtracting the one-month U.S. Treasury Bill return obtained from Ibboston Associates. As a proxy for global equity market risk, we use the excess return on the S&P 500 Index.

Bond market data are from JPMorgan’s emerging markets bond index (EMBI Global) for emerging countries and from Bloomberg Barclays global indices for developed markets. Exchange rates are from Bloomberg. Foreign currency returns are calculated as the excess return to investing in the short-term money market of a country (short rates come from Global Financial Data). Thus, foreign currency returns reflect the interest rate differential between the foreign currency and the USD and the appreciation of the currency relative to the USD. As a proxy for global fixed income risk, we use the return on the U.S. bond index.

Our main innovation is to consider the global pricing of volatility risk. As a proxy for global equity market volatility, we define the return on a one-month variance swap on the U.S. equity market. This return is calculated as the difference between the realized variance during a month, calculated from squared daily returns over the month, and the implied variance given at the beginning of the month as measured by the squared VIX index. That is,

$$r_{US,t+1}^{vs} = \sum_{d=1}^{Ndays} \left(\ln \frac{P_{t+1,d}}{P_{t+1,d-1}} \right)^2 \left(\frac{252}{Ndays} \right) - VIX_t^2, \quad (2.1)$$

where $Ndays$ represents the number of trading days in a month, $P_{t+1,d}$ is the value of the $S\&P$ 500 index on day d of month $t + 1$, and the VIX measures the implied volatility of $S\&P$ 500 index options over the next thirty day period, as calculated by the Chicago Board Options Exchange (CBOE).⁵ We use the returns to the variance swap, as we have measured them, because they are easily calculated and should do a reasonable job capturing the innovation in volatility that should be priced in asset markets.

Figure 2.1 shows the VIX and the variance swap return over its full sample. The spikes in the

⁵See Exchange (2009) for how the VIX is constructed using a weighted average of put and call option prices with different strike prices. In using the squared VIX as the risk-neutral expectation of the summation of future squared returns, we follow Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011). See Martin (2013) and Martin (2017) for a discussion of why the squared VIX is not the risk-neutral conditional variance of future returns when prices can jump and for an alternative calculation that weights option prices differently resulting in a simple variance, $SVIX$, that is appropriate. Ait-Sahalia, Karaman, and Mancini (2019) use data on OTC traded variance swaps to characterize the term structure of variance risk. These data are not publicly available.

variance swap are certainly influential data points, and we therefore acknowledge that in 24 years of monthly data it may be difficult to accurately measure the statistics underlying our analysis. Nevertheless, we think it is useful to explore the data keeping this caveat in mind.

Table 2.1 presents summary statistics for the asset returns of all regions as well as the global risk factor returns (the regional indices are simply the equally weighted averages across countries). The sample means of the annualized excess equity returns range from 1.35% for Emerging Asia to 6.20% for the EU Non-Euro countries. Mean annualized excess bond returns range from -0.07% in Developed Asia to 7.34% in Latin America. The sample means for the currency returns range from -0.95% for Developed Asia to 2.36% for Emerging Asia.

The fact that the sample means of bond excess returns exceed the sample means of equity excess returns in Emerging Asia, Latin America, and the EU Euro countries is suggestive that using slightly less than 24 years of monthly data may not provide a long enough sample to allow sample mean returns to accurately reflect true unconditional expected returns. Correlations, on the other hand, may be far better measured.

Table 2.2 presents summary statistics on the risk factors. The annualized mean returns of the risk factors are 5.20% for equities, 2.61% for long term bonds, and -1.14% for the variance swap. The negative price of variance risk indicates that negative correlation of individual country or regional indexes with the return on the variance swap has the potential to increase required rates of return as a negative exposure to this risk factor combined with a negative price of risk implies a positive increment in expected return. The unconditional correlations between the risk factors are both negative and positive. Excess returns on equities and bonds are somewhat negatively correlated at -0.22, while the excess equity return and the variance swap return are strongly negatively correlated at -0.53. Bond returns and the variance swap return are positively correlated at 0.15.

2.3 MEASURING GLOBAL VOLATILITY RISK IN EQUITY, BOND, AND CURRENCY MARKETS

We begin our analysis of equity, bond, and currency market excess return exposures to equity market volatility with a graphical analysis. To demonstrate the sensitivity of returns to the vari-

ance swap return, we first divide the sample into quartiles depending on the realized returns to the variance swap. The first quartile contains the months with the lowest realizations of the variance risk factor, while the fourth quartile contains the months with the highest realizations. We then calculate average excess returns for these sub-samples at the regional level. The four regions are simply the equally weighted averages of country excess returns in Developed Markets; Emerging Asia; Emerging Europe, the Middle East, and Africa; and Latin America.

The bars in Figure 2.2 show the annualized mean excess equity returns for these four portfolios across the different quartiles of realized variance. We see that, across all regions, average excess returns are high, approaching 40% per annum (p.a.), when volatility innovations are low, and average excess returns are negative, also approaching -40% p.a., when volatility innovations are high. The Figure also shows that average excess returns decrease monotonically in Developed Markets, the Emerging EMEA, and Latin America; and they almost monotonically decline for the Emerging Asia sample.

Figures 2.3 and 2.4 repeat this exercise for the excess returns in the bond and foreign currency markets. Once again we see that when volatility is high, emerging market bonds perform poorly and emerging market currencies depreciate versus the dollar. Conversely, in low volatility states, emerging market bonds do well, and their currencies appreciate relative to the dollar. Latin American bond markets and currencies are particularly notable with USD denominated gains of around 15% p.a. in low volatility environments and losses of about 15% in high volatility environments. The broadly monotonic pattern of emerging market bond and fully monotonic pattern of currency returns rather dramatically decreasing with increased U.S. variance swap returns shows that variance risk presents a global risk that affects the major asset classes. The pattern is not entirely monotonic for developed markets, however, as developed market bond and foreign currency average returns in the fourth quartile are higher than they are in the third quartile. It is conceivable that these results are due to the safe haven role of certain foreign bonds and currencies (such as the Swiss franc and the Japanese yen).⁶

Variance risk may be correlated with equity risk. Therefore, Figures 2.5, 2.6, and 2.7 repeat the exercise of plotting regional average excess returns across the quartiles of realized returns to the

⁶See Christiansen, Rinaldo, and Söderlind (2011) and Xu (2018) for a discussion of these issues as they relate to currency returns and international bond returns, respectively.

variance swap, but now, these Figures also condition first on whether the equity market return is up or down. The top panel of each Figure contains the down market results, and the bottom panel contains the up market results.

It is clear from the top part of Figure 2.5 that the four regions all perform much more poorly in high variance down equity markets than in low variance down equity markets. The bottom part of the Figure indicates that average returns are lower in high variance up markets than in low variance up markets. Because variance swap returns and equity returns are correlated (recall Table 2.2), we mostly lose full monotonicity, but the returns in high variance return markets (4th quartile) are invariably and substantially lower than in the low variance return markets (1st quartile).

In global bond markets, the effect of variance risk is starker in that it changes the sign of returns in the down equity markets. Across all regions, bond market returns are positive in low variance return states, but they turn negative in high variance return states. For up equity markets, all bond markets have positive returns, but it is still the case that they are higher in low variance swap return states than they are in high variance swap return states. The patterns are not always monotonic across the regions, but for up equity markets, the pattern is monotonic for Latin America. Figure 2.6 indicates that Latin American bonds do particularly poorly in volatile down equity markets and do particularly well in quiescent up markets, with the return spread a staggering 70%.

The conditional foreign currency returns in Figure 2.7 show patterns similar to the equity returns in Figure 2.5. They are mostly negative in bad equity return states and positive in good equity states. Presumably, the dollar's movements are somewhat correlated with the performance of the equity market. Conditional on the up or down equity states, it remains the case that foreign currency returns are higher in low variance return states than they are in high variance return states, and mostly considerably so. Yet again, we do not observe full monotonicity across the 4 bins. Figure 2.7 also indicates that part of the extreme bond market performance in Latin America emanates from the currency return.

These Figures are suggestive that volatility risk, as proxied by the return on a variance swap, is systematic and not simply reflective of overall equity risk. If volatility risk is systematic, it has the ability to affect the expected returns on a wide variety of asset classes worldwide, including in

emerging markets. The following subsections examine this conjecture more rigorously.

To hold constant other sources of risks, we specify a three-factor model. The first risk factor is the return on the S&P 500 Index, which is our proxy for the global equity market excess return. The second risk factor is the excess return on the the U.S. bond market, and the third risk factor is the return on a variance swap, our volatility risk factor. Since each risk factor is either an excess return or a zero-investment derivative contract, we can assess whether the exposures of an asset to the risk factors correctly price the asset by simply regressing the excess return on an asset class in region i , $r_{i,t}$, on the risk factors, $(r_{US,t}^e, r_{US,t}^b, r_{US,t}^{vs})$, as in

$$r_{i,t} = \alpha_i + \beta_{i,1}r_{US,t}^e + \beta_{i,2}r_{US,t}^b + \beta_{i,3}r_{US,t}^{vs} + \varepsilon_{i,t}, \quad (2.2)$$

where the estimated α_i , the "alpha" of the model, measures the average performance of the asset class not explained by exposures to the risk factors. In presenting the results of equation (2.2), we will superscript the asset classes with an e for equity, a b for bond, and an fx for foreign currency.

2.3.1 Empirical Results for Equities

This section examines whether volatility risk is important in the pricing of equities in global asset markets. The results for the equity markets are presented in Table 2.3, which contains two panels. Panel A reports regression results for our seven regions of the world.

In each case the slope coefficients on the U.S. equity excess return are highly significant. The estimated slope coefficients also are relatively similar, ranging from 0.80 for Latin America to 0.95 for the EU Euro region. The U.S. bond return is only marginally significant in one region, the EU Non-Euro region, and the coefficient is negative. The exposures to the variance risk factor are also highly significant in all cases with coefficients ranging from -2.99 for Developed Asia to -5.19 for Latin America. The three-factor model overestimates the average returns realized in the sample as all of the alphas are negative. The alphas for the Developed Asia and Emerging Asia regions and for the EU Euro region are significantly different from zero; and the model overstates these annualized average excess returns by about 6% p.a. This should not be surprising as Table 2.1 shows that these regions happened to have quite low average returns during this particular sample period. The factor model likely provides more plausible estimates of equity risk premiums

for these regions than do the sample averages.

The results in Panel A use data on regional equity indexes that are equally weighted averages of the countries in those regions. Because there are too many countries in the regions to present all the individual country-level results in the paper, Panel B of Table 2.3 provides additional diagnostic statistics associated with the individual country-level regressions.⁷ The means of the slope coefficients across countries for a given region are presented in the first row, and the percent of those coefficients that are significant at the 10% level are presented in the second row. The third row presents the 10-th and 90-th percentiles of the estimated slope coefficients in a region.

Unsurprisingly, most of the individual countries show significant exposures to the global equity return as only in Emerging EMEA do we see less than 100% significant coefficients. Yet, there is still cross-country dispersion in the country exposures, especially in the emerging market regions. Whereas for developed markets the 80% range for the coefficients is [0.73,1.11], it increases to [0.49, 1.20] for Latin American and to [0.08,1.44] for the Emerging EMEA region.

Similarly, given the aggregate results, it is unsurprising that the percentage of countries with significant equity market exposures to the bond market risk factor range between 0% for Latin America and 23% for the Developed countries. The bond exposures of the various equity markets are very dispersed, with large negative and positive exposures, but the average exposure is negative for all four groups. This is consistent with the portfolio results.

Finally, the exposures to the volatility factors are mostly negative and statistically significant, with the percent of significant coefficients above 90%, except for the Emerging Asia region where it is 78%. We also observe considerable dispersion in the individual coefficient estimates. These range from -7.80 for the 10-th percentile of Latin America to 0.98 for the 90-th percentile of Emerging Asia. In the other three regions, the 10%-90% range for the coefficients is uniformly negative.

At the country level, there are few significant alphas in the regressions (36% in the developed markets; 11% in Emerging Asia and none elsewhere). Note that the factor model understandably produces lower R^2 's for the individual countries than for the regional portfolios, with larger R^2 's occurring for the developed markets. This finding is largely due to the higher country-specific risks in emerging markets.

⁷Individual country results are provided in the Online Appendix.

2.3.2 Empirical Results for Bonds

Table 2.4 contains two panels as in Table 2.3, but the dependent variables are now USD denominated excess bond returns. Panel A reports regression results for the same seven regions of the world. As one might expect, the U.S. bond return is highly significant in all regions, with slope coefficients ranging from 0.51 for the Emerging EMEA region to 0.99 for the EU Euro region. The slope coefficients on the U.S. excess equity return and the variance swap are significant in six of these seven portfolios, with the exception being Developed Asia. The exposures to the variance risk factor once again show the largest range of coefficients from 1.23 for Developed Asia to -4.98 for Latin America. Yet, the remaining exposures vary in a tight range between -1.33 (EU Euro) and -2.10 (DM Commodities). The alphas are all insignificant with the largest mispricing estimated at -2.2% for the DM Commodities region.

Panel B of Table 2.4 reports the means of the coefficients of the individual country regressions, as well as the percent significant and the 10-th and 90-th percentiles of the estimated coefficients. Between 73% (Emerging EMEA) and 92% (Latin America) of bond returns for the individual countries have significant exposure to the equity risk factor, while between 55% (Emerging EMEA) and 100% (Developed) of the bond returns for the individual countries have significant exposures to the bond risk factor. Exposure of the individual bond market returns to the variance risk factor shows comparable significance with between 55% (Emerging EMEA) and 100% (Emerging Asia) of the countries having significant exposures.

Once again, the magnitude and the spread of the coefficients associated with the variance risk factor are larger than the magnitudes of the estimated coefficients and the spreads for the other two risk factors. However, the 10-th to 90-th percentile ranges show only one positive coefficient namely for Emerging EMEA at 0.29. The alphas are statistically significant in less than 10% of the countries.

2.3.3 Empirical Results for Currencies

Table 2.5 is similar to the previous two Tables, but the dependent variables are now USD-denominated excess currency returns. Panel A reports regression results for the same seven areas of the world.

The slope coefficients on the U.S. excess equity return are now mostly much smaller than for bond returns, but they are all at least marginally significant. Coefficients on the U.S. bond return are significant in five of the regions, and the exposures are invariably positive. The coefficients on the variance swap are significant in six of the seven markets with the exception being Developed Asia. The exposures to the variance risk factor once again show the largest range of coefficients across the regions ranging from 0.37 for Developed Asia to -2.04 for DM Commodities. Again, similar to the bond return analysis, the range is tighter outside these extremes, varying between -0.57 and -1.64. Finally, three of the alphas are marginally significant with the largest mispricing estimated at -3.9% for the EU Euro region.

Examining the summary statistics of the individual country regressions in Panel B indicates that most of the currencies show significant exposure to the equity market with the percent significant across the regions ranging from 80% for Emerging EMEA to 88% for Emerging Asia.

The importance of the bond market risk ranges from 0% significant for Emerging Asia and Latin America to 82% significant for Developed. The bond risk exposures of currency returns are quite dispersed, with the 10-th to 90-th percentile range for bond market exposures switching signs for all three emerging market groups.

The variance risk factor is significant for 91% of the Developed market currency returns, 86% of the Latin American currencies, 60% of the Emerging EMEA currencies, but only in 38% of the Emerging Asia currencies. The coefficients on the variance swap risk factor once again show the largest range across the countries of the different regions, with the 90-th percentile values positive for the Emerging Asia and Emerging EMEA regions. Not surprisingly, given the regional portfolio results, the alphas are only significant in a small fraction of the emerging markets (less than 20%), but the proportion of statistically significant alphas rises to 73% for developed markets.

2.4 THE ECONOMIC IMPORTANCE OF GLOBAL VOLATILITY RISK

This section explores the economic importance of volatility risk in more detail. We calculate implied returns for two models calculated as exposures to risk factors times the average returns of the risk factors. Model 1 includes only the excess returns on the equity and bond markets as risk factors whereas Model 2 includes the return on the variance swap as an additional risk factor.

Table 2.6 repeats the average returns across the different regions and for the three asset classes in the second column and presents the implied expected returns from the two models in the third and fourth columns. In most cases, the average returns are closer to the implied expected returns of Model 1. In 19 of the 21 portfolios, the implied expected return from Model 2 is larger than the implied expected return from Model 1. The exceptions are bonds and currencies for Developed Asia. Although the average return to the variance risk factor is only -1.2% p.a., because the exposures are large, the implied expected returns from Model 2 are sometimes increased quite substantially compared to those of Model 1.

To highlight the economic importance of the variance risk premium as a determinant of the overall expected return in Model 2, we examine the proportions of the risk premiums that are accounted for by variance risk. That is, we examine the ratio of the part of the expected return due to variance risk relative to the total expected return implied by the model:

$$\frac{\beta_{i,3}\mu_3}{\beta_{i,1}\mu_1 + \beta_{i,2}\mu_2 + \beta_{i,3}\mu_3}, \quad (2.3)$$

where the β_i 's are the regression coefficients in equation (2.2), and μ_1 , μ_2 , and μ_3 are the sample means of the U.S. equity excess return, the U.S. bond excess return, and the variance swap return, respectively.⁸

The results are summarized in column five of Table 2.6 with the standard errors of the ratio given in column six. For the equity markets, the proportions of the implied expected returns of Model 2 that are due to the inclusion of the variance swap return range from 47% with a standard error of 5% to 67% with a standard error of 18%.

For the bond and foreign currency markets, the results are similar except for the Developed Asia region, which has a large negative contribution due to the positive beta on the variance swap return documented above. The proportions of the implied expected returns of Model 2 due to the variance swap range from 31% to 59% for the bond markets and from 43% to 67% for the foreign currency markets. Most of these proportions appear statistically significantly different from zero, and they are clearly economically large. In sum, exposure to variance risk almost invariably

⁸Appendix A.2 formally describes the GMM system of orthogonality conditions used to conduct inference about the ratio in equation (2.3).

increases required risk premiums, across all regions and the three major asset classes.

There remains the issue that the two-factor model appears to fit the historical average returns better than the three-factor model, at least for a number of regions. To verify this formally, we conduct standard [Gibbons, Ross, and Shanken \(1989\)](#) tests for the joint significance of the alphas. This test assumes conditional homoskedasticity of innovations in returns, which is generally counterfactual, so we also report an analogous GMM test that corrects for heteroskedasticity and possible autocorrelation.

Table 2.7 reports the chi-square test statistics and the p-values for three sets of test assets. The column indicated by "regional" uses the seven regional portfolios, the EM columns use all emerging markets separately, and the DM columns use all of the developed markets. The tests largely confirm our main point that historical average returns have little information that can be used to distinguish models. For the regional portfolios, we only reject the null of zero alphas for Model 2 for equities, at the 5% level for the GMM test and at the 10% level for the GRS test. Other than that, the performance of both models is similar, but of course, it is likely the tests lack power. For emerging markets, we again fail to reject the null of the zero alphas at the 5% level for both bonds and equities, whatever the test considered, but we strongly reject the null under either test for foreign currency returns. The tests fail to distinguish Models 1 and 2. For developed markets, the evidence depends on which test is used. There is no evidence against zero alphas for bonds returns under either test. For foreign currency returns, the GRS tests rejects zero alphas for both Model 1 and Model 2; the GMM tests fails to reject both models. For equities, the GMM test rejects both models at the 5% level, but the GRS test only rejects Model 2. Clearly, the tests weakly confirm that Model 1 fits the historical averages slightly better than Model 2, but only for equities. However, recall that the period we consider is relatively short and includes a major global financial crisis, making it unlikely that historical returns are representative of long-run risk premiums. It is therefore important to get independent validation on the factor model. We do so now by examining the fit of the models with return correlations.

2.5 COMOVEMENTS OF RETURNS

In this section we ask how much of the sample correlation structure of returns is explained by our factor model. Given the statistical noise in average returns, the ability of the factor model to explain comovements of returns provides an alternative, potentially more powerful, test of its usefulness. We investigate comovements of returns from two perspectives. First, we investigate the correlations of returns across regions or countries within an asset class. Here, we build on a large literature that examines international stock return comovements, often focusing on how globalization has increased correlations over time (see e.g. [Bekaert, Hodrick, and Zhang \(2009b\)](#), [Christoffersen, Errunza, Jacobs, and Langlois \(2012\)](#); and [Pukthuanthong and Roll \(2009\)](#)). [Xu \(2018\)](#) examines both bond and stock return correlations across countries, showing that bond return correlations are mostly lower than stock return correlations. [Bekaert, Ehrmann, Fratzscher, and Mehl \(2014b\)](#) suggest that local factors are necessary to fully explain comovements across worldwide industry equity portfolios. We therefore cast our investigation as determining how much of the cross-region return correlations over the 1995-2018 period can be explained by our very parsimonious global factor model.

Second, we also investigate the correlations across asset classes within each region. While clearly useful from an asset management perspective, there is, in fact, fairly little research on cross-asset correlations, with the exception of research focusing on stock-bond return correlations (see e.g. [Baele and Soriano \(2010\)](#)).

The model-implied correlation of two returns, $r_{i,t}$ and $r_{j,t}$, is calculated as in [Bekaert, Hodrick, and Zhang \(2009b\)](#) by dividing the model-implied covariance of the two returns by the product of their sample standard deviations:

$$\text{Model Correlation} = \frac{\beta_i' \text{var}(f_t) \beta_j}{\sqrt{\text{var}(r_{i,t}) \text{var}(r_{j,t})}}, \quad (2.4)$$

where $\text{var}(f_t)$ is the covariance matrix of the three risk factors and the β_i and β_j are the vectors of factor exposures of the two assets. We first report the ratio of model implied correlations to sample correlations interpreting this ratio as the percentage of the cross-region correlation that is explained by the model. [Table 2.8](#) presents the results for the equity, bond, and currency markets

in three panels.

2.5.1 Proportion of Correlations Explained

In equity markets, we find that the three-factor model explains a substantive fraction of the cross-country correlations (on average, 73%). The proportion of explained correlation ranges from 57% for the correlation between the Developed Asia and Emerging Asia regions to 88% for the correlation between the EU Euro and Developed Asia regions. It is perhaps telling that the model does not fit as well for nearby regions, indicating that it may be missing a regional factor. The explained proportion is on average 60% for the three Emerging market regions, 80% for the four developed market groups, and 74% when considering emerging markets relative to the four developed market portfolios. We report the underlying sample correlations that we would like the model to fit in Table 2.9. Over our sample period, these correlations are quite high, varying between 61% for Emerging Asia and the EU Euro countries, and 92% for the EU Euro and EU Non-Euro countries. On average, the correlations are 75%.

These sample correlations reveal that bond returns indeed show smaller correlations than equity markets, in some cases quite considerably smaller. The average correlation between bond markets is 40%, although there is considerable dispersion with the pairwise correlations as low as 1%. The correlation between the Latin-American and Developed Asian bond markets is very low correlation (3%), and the factor model estimates the correlation to be negative. So, even though the fit is actually good in an absolute sense, when expressed as a fraction of the sample correlation, we obtain a large negative number for the explained proportion. The model also over-fits several correlations, leading to ratios greater than 1. We circumvent this problem below by examining root mean squared error statistics for the difference between the sample and model correlations.

Finally, in the foreign currency markets, the three-factor model explains about 30% of the correlations across regions, with the fractions being the highest for the correlations between Developed Commodity region with the Emerging Market regions and the Latin America region with other the regions. Within the emerging market regions, the average proportion is 42%, but it is only 18% within the developed market regions. The proportion for the cross-correlation between developed and emerging market regions is on average 30%. As indicated above, the Developed Commodity countries play a large role here. Actual correlations for currency returns are mostly

in-between those for bond and equity markets, varying between 22% for Latin-American and Developed Asia, to 94% for the two European country groups. While the high correlation within Europe is not surprising given the efforts there to reduce currency variation, the fact that they are generally relatively high may be due to a common dollar factor. However, commodity factors may also play a role, as the currency returns of the Developed Commodity countries appear highly correlated with emerging market currencies.⁹

Next, we study the comovements of equity, bond, and foreign currency returns within regions in Table 2.10. The bottom panel of the table reports the actual correlations between the various asset classes for the seven regional portfolios. On average the correlations of returns are highest between bonds and foreign currency, followed by the correlations between equities and foreign currency, with the correlations between equities and bonds being the lowest. However, these averages hide large cross-regional dispersion. The equity-bond return correlation varies from 0.11 in Developed Asia to 0.78 for the Developed Commodity countries. The lowest and highest correlations of equity returns with foreign currency returns occur for the three same regions. The correlation in Developed Asia is 0.36 and in Developed Commodity countries it is 0.83. The correlations of bond returns and foreign currency returns are as low as 0.32 for the Emerging EMEA region, but they are as high as 0.93 for the Developed Commodity countries.

The upper panel of the Table 2.10 reports the proportion of the correlations explained by the three-factor model. In emerging markets, the three-factor model explains, on average, 53%, 43% and 55% of the correlations between equities and bonds, equities and exchange rates, and bonds and exchange rates, respectively. Meanwhile, in developed markets, the model is less successful; it explains, on average, only 39% and 19% of the correlations between equities and foreign currency, and bonds and foreign currency, respectively. For bonds and equities, the Developed Asia correlation (which is low at 0.11) is predicted with the wrong sign, explaining the negative ratio. The fit for the other three regions is 41% on average. When the model correlation overshoots, or the sign is wrong, the ratio we report is not very informative.

⁹Aloosh and Bekaert (2019) show that a dollar currency factor (including the USD, the CAD, the AUD, and the NZD) and a commodity factor describe currency market correlations rather well.

2.5.2 Root Mean Squared Error Correlation Analysis

Table 2.11 provides an alternative, overall perspective on the fit of the model-implied correlations. We provide the root mean squared error of the difference between the model-implied correlations and the sample correlations for both within-asset and across-asset correlations. That is, for N asset returns, we calculate

$$RMSE = \sqrt{\frac{1}{N(N-1)/2} \sum_{i=1}^N \sum_{j>i}^N [corr_s(r_{i,t}, r_{j,t}) - corr_m(r_{i,t}, r_{j,t})]^2}. \quad (2.5)$$

We use the regional portfolios as underlying assets (in this case N is seven). We also perform the same analysis for individual countries within emerging or developed markets (the EM and DM columns). Starting with the correlations across countries but within one asset class in Panel A, the RMSE for equities for our regional portfolios is only 0.046. This is a remarkable fit for correlations which average 75%. The fit worsens only slightly when considering individual developed market countries (0.05) or emerging market countries (0.076). The RMSE is 0.070 for the regional bond returns and 0.080 for emerging market bond returns, but worsens considerably for developed market bonds, increasing to 0.273. Given an average correlation among developed market bonds of 48%, this is a poor fit.

The three-factor model has the most difficult time matching the correlations among foreign currency returns, where the RMSE is a respectable 0.100 for emerging markets but increases to 0.443 for developed markets. Because the exposures of foreign currency returns to our global factors are relatively modest, we miss a currency-centric factor that can fully capture the international correlations here.

In Panel B, we report the RMSE for the correlations across asset classes. Here the RMSE statistics vary between 0.114 for emerging market countries and 0.240 for developed markets. This number must be judged relative to an average correlation across asset classes of 43%, for emerging markets, 60% for developed markets.

Finally, Table 2.11 also reports the same RMSE statistics for Model 1, which does not contain the variance swap return as a risk factor. It is invariably the case that the RMSE produced by the three-factor model, Model 2, is lower than the RMSE produced by the two-factor model, Model

1. However, we must concede that the improvement is marginal and unlikely to be statistically significant.

2.6 VARIANCE BETAS: DOLLAR VERSUS LOCAL CURRENCY

One potential issue with analysis thus far is that all returns have been measured in dollars. This raises two issues. First, it is conceivable that the bond and equity results are really driven by exposures of the dollar exchange rates to volatility risk. Second, there is considerable interest in hedged investment strategies that mitigate currency exposures. For example, ETFs that are hedged against currency risk have become available in the U.S. offering U.S. investors exposure to international bond and equity markets essentially denominated in foreign currency. Such hedged returns would not be subject to a "currency factor" due to exposure of currencies to variance risk.

In this section, we decompose country-level equity returns into local currency and dollar components. We summarize the results in Figure 2.8, with more detailed results relegated to the Online Appendix. We run multiple regressions of equity returns on the three risk factors as in equation (2.2). The bars represent the betas on the variance swap return from these regressions with equity returns denominated in dollars, while the diamonds are the betas from these regressions with equity returns denominated in local currency. The beta from the foreign currency regression is approximately the difference between the height of the bar and the diamond. Diamonds that are filled indicate statistical significance at the 10% marginal level of significance. Bars are shaded according to denote the country's region within emerging and developed markets. We find that most of variance risk betas in emerging market equities arise from the covariances of the variance swap return with the local currency equity returns. The local currency variance risk beta is statistically significant in 18 out of 24 countries.¹⁰ In developed markets the currency component plays a greater role. Here the local currency equity return betas with respect to variance risk are not significant for 8 out of 22 countries, and the currency component adds 50% or more of the variance risk for about 10 countries. The local currency equity return variance risk beta is positive for Switzerland and Finland. Note that the difference between the bar and the diamond measures the exposure of the currency to variance risk. This exposure remains predominately negative for

¹⁰In Turkey and Pakistan, the beta is positive, but it is solidly negative in all other countries.

all of the countries. One prominent exception is Japan where the currency exposure is positive, as the exposure of the local currency return is more negative than the exposure of the dollar equity return, reflecting the well-known safe haven property of the yen.

2.7 CONCLUSIONS

This article proposes variance risk as a new risk factor in international finance. We proxy variance risk by the tradable return on a variance swap on the S&P500. We then consider the exposures of three asset classes, country-level equities, bonds, and currencies to this new risk factor, while controlling for equity risk, proxied by the return on the U.S. equity market, and bond risk, proxied by the return on a U.S. bond index. We cast a wide net geographically investigating returns worldwide, including in emerging markets. To keep the analysis manageable, our results focus primarily on regional returns, decomposing emerging markets in three regions (Emerging Asia, Latin-America, and Emerging EMEA), whereas we consider the developed (Non-U.S.) markets mostly as one group, or split them up into four groups (DM Commodities, Developed Asia, EU Euro, EU Non-Euro).

We find almost uniformly negative exposures of returns to variance risk across all asset classes and all regions, including emerging markets. Whereas the equity and bond exposures are logically quite different across the three asset classes, the variance risk betas are rather similar across asset classes. It consequently appears difficult to escape variance risk exposure. Economically, the variance risk factor contributes significantly to global risk premiums, with its contribution hovering in the 40-60% range of the total premium for most portfolios we consider. Because our sample is relatively small, average realized returns are not very informative about differential risks across different assets. Accounting for variance risk matters substantially, and a two-factor model that ignores variance risk would typically assign lower risk premiums to most of the assets we consider. Statistical tests on alphas, though, cannot distinguish the two models over a sample period this short.

We also investigate how much of the comovement of international returns can be captured by our three-factor model, both within an asset class and across asset classes. The global factor model also accounts for a substantive fraction of international and cross-asset comovements

in returns. The model is more successful in fitting equity return comovements than it is in fitting bond and foreign currency return comovements. Interestingly, for the latter, it is especially the comovements among developed market countries that is sub-par, whereas the fit for regional portfolios is still satisfactory, especially for bond returns. The extant literature has documented that local and regional factors may still matter, but here we demonstrate that a very simple model captures a non-negligible fraction of international asset return comovements. We also examine cross-asset return comovements, and here, the three-factor model does best for the correlations between equity returns and bond returns, capturing on average 47% of the positive correlations, while capturing only 41% of the equity return-foreign currency return correlations and 34% of the bond return-foreign currency return correlations. Yet, overall, our three-factor model always fits comovements of returns better than the two-factor model that ignores variance risk exposure. Uncovering additional risk factors that can improve the fit in this regard is an important challenge for future research.

TABLES AND FIGURES

Figure 2.1: The *VIX* and the Variance Swap Return

This figure shows time-series plots of the *VIX* and the variance swap return, which measures global variance innovations. The sample period is monthly date from January 1995 to November 2018.

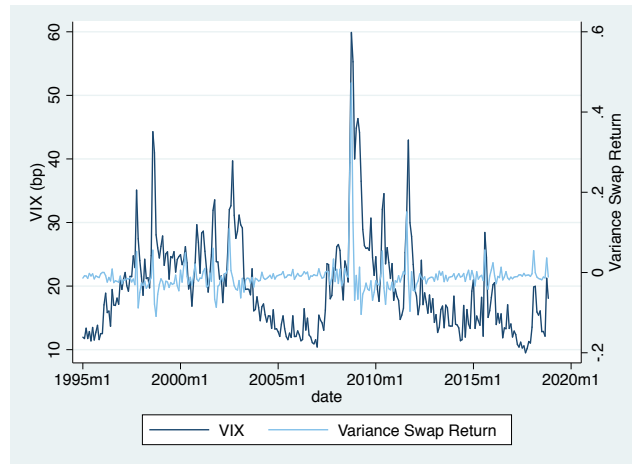


Figure 2.2: Excess equity returns and global variance by region

The bars show the sample means of annualized excess equity returns for regional portfolios conditional on contemporaneous global variance innovations being within the lowest quartile (No. 1) to the highest quartile (No. 4) of their sample distributions. The regional portfolio returns are an equally weighted averages across countries. The sample period is monthly data from January 1995 to November 2018.

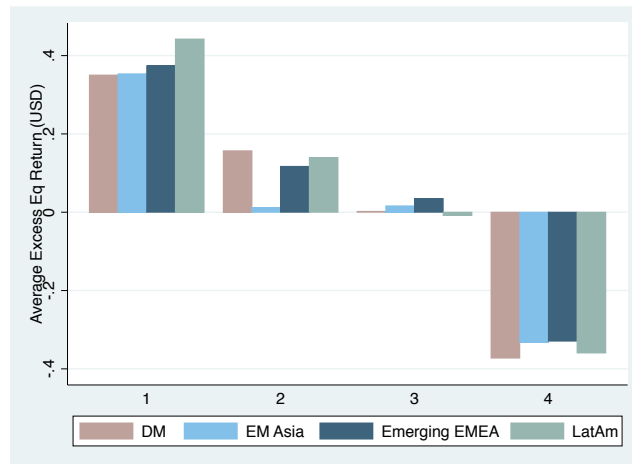


Figure 2.3: Excess bond returns and global variance by region

The bars show sample mean excess bond returns for regional portfolios conditional on contemporaneous global variance innovations being within the lowest quartile (No. 1) to the highest quartile (No. 4) of their sample distributions. The regional portfolio returns are an equally weighted averages across countries. The sample period is monthly data from January 1995 to November 2018.

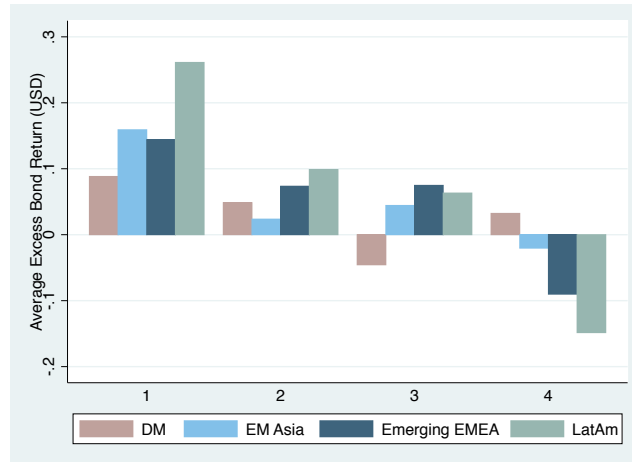


Figure 2.4: Excess foreign currency returns and global variance by region

The bars show sample mean excess foreign currency returns for regional portfolios conditional on contemporaneous global variance innovations being within the lowest quartile (No. 1) to the highest quartile (No. 4) of their sample distributions. The regional portfolio returns are an equally weighted averages across countries. The sample period is monthly data from January 1995 to November 2018.

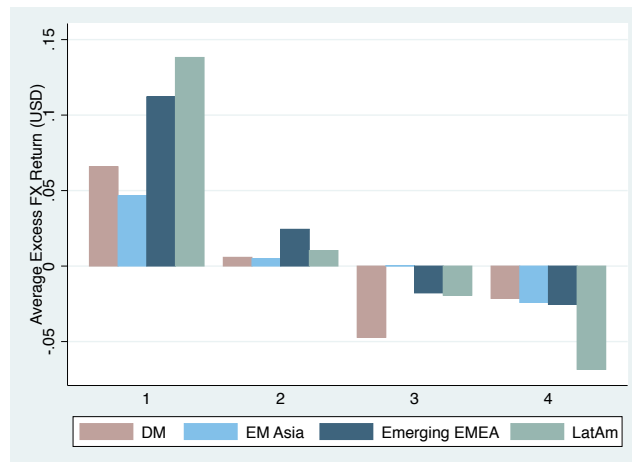


Figure 2.5: Excess equity returns and global variance by region and global equity market state

The bars show sample mean excess equity returns for regional portfolios conditional on contemporaneous global variance innovations being within the lowest quartile (No. 1) to the highest quartile (No. 4) of their sample distributions after having sorted on down (first panel) versus up (second panel) global equity market returns. The regional portfolio returns are an equally weighted averages across countries. The sample period is monthly data from January 1995 to November 2018.

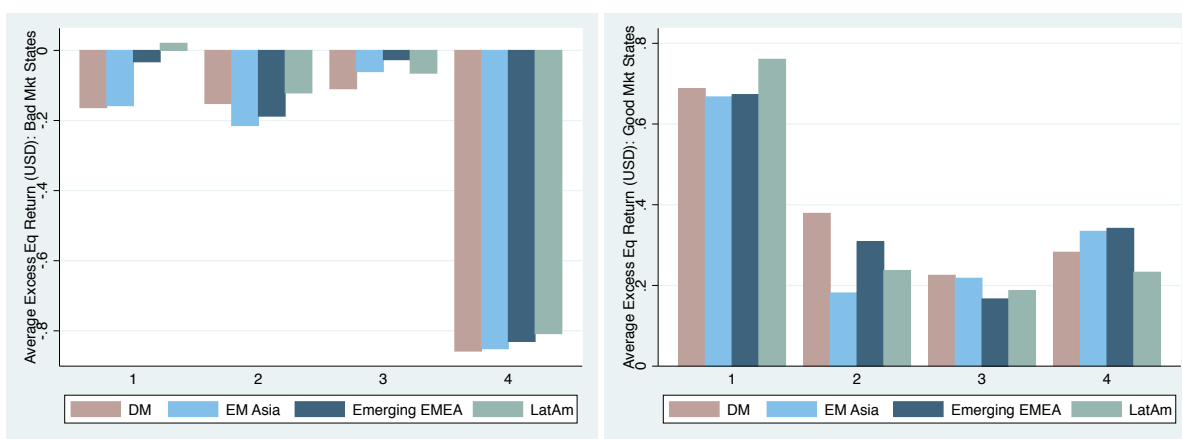


Figure 2.6: Excess bond returns and global variance by region and global equity market state

The bars show sample mean excess bond returns for regional portfolios conditional on contemporaneous global variance innovations being within the lowest quartile (No. 1) to the highest quartile (No. 4) of their sample distributions after having sorted on down (first panel) versus up (second panel) global equity market returns. The regional portfolio returns are an equally weighted average across countries. The sample period is monthly data from January 1995 to November 2018.

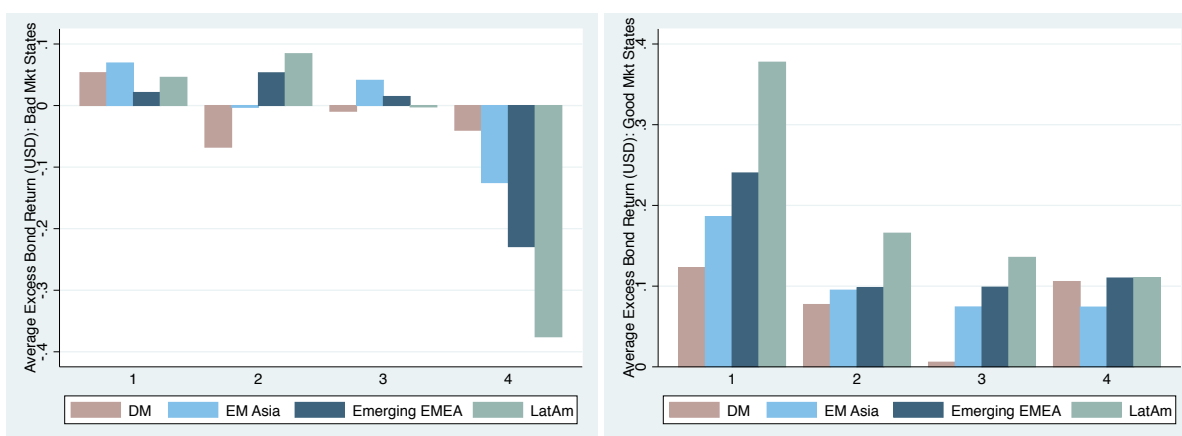


Figure 2.7: Excess foreign currency returns and global variance by region and global equity market state

The bars show sample mean excess foreign currency returns for regional portfolios conditional on contemporaneous global variance innovations being within the lowest quartile (No. 1) to the highest quartile (No. 4) of their sample distributions after having sorted on down (first panel) versus up (second panel) global equity market returns. The regional portfolio returns are an equally weighted average across countries. The sample period is monthly data from January 1995 to November 2018.

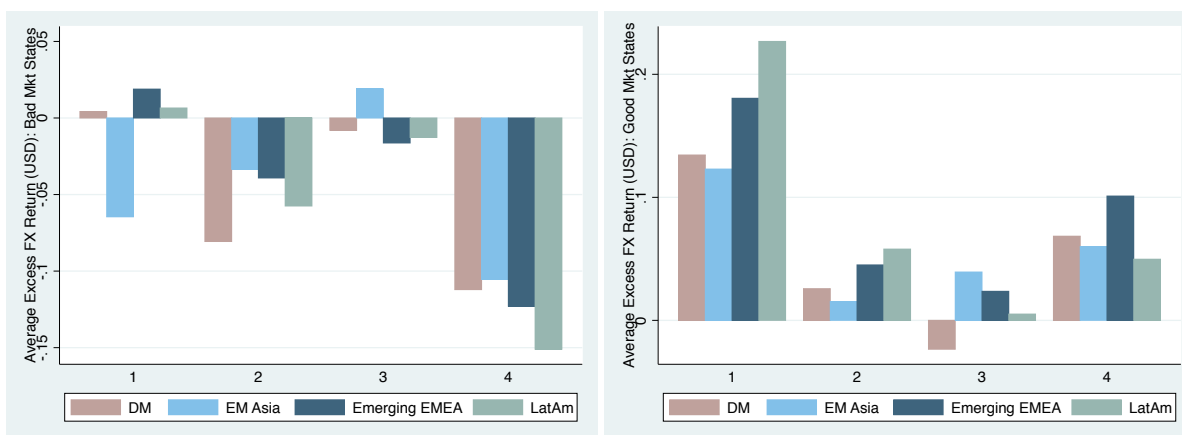


Figure 2.8: Variance Betas: Dollar versus Local Currency

The bars represent betas from regressions with equity returns in dollars, while the diamonds are the betas from regressions with equity returns in local currency. The beta from exchange rate regressions is, approximately, the difference between the diamond and the bar. Diamonds that are filled in are significant at the 10% level. Bars are shaded to denote the country's region within developed and emerging markets.

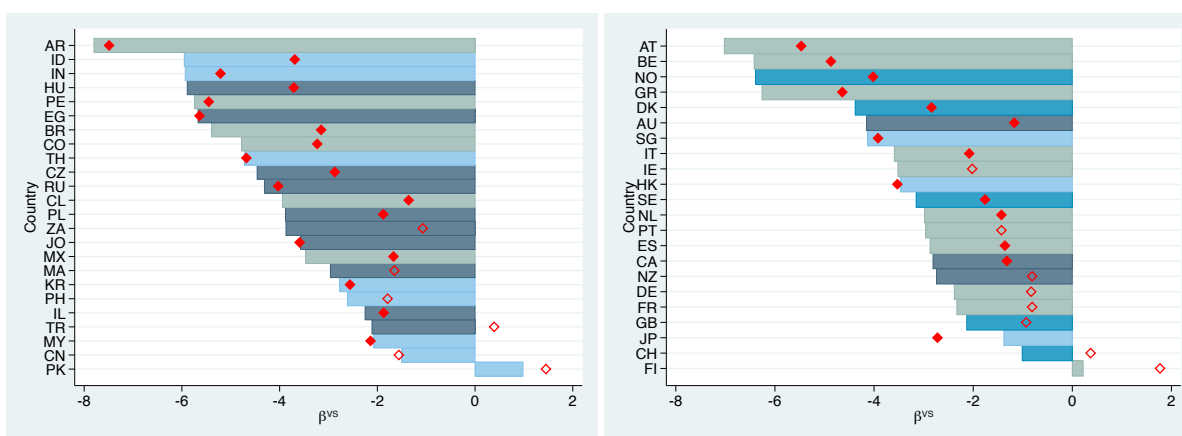


Table 2.1: Summary Statistics - Regional Index Returns

The summary statistics are the mean, median, and standard deviation (SD) of the excess returns on regional portfolios that are equally weighted country returns. The sample period is monthly data from January 1995 to November 2018.

	N	Mean	Median	SD
Panel A: Excess Equity Returns				
Developed Comm	287	5.54	8.77	18.51
Developed Asia	287	2.02	7.09	19.21
EU, Euro	287	2.23	7.76	20.73
EU, Non-Euro	287	6.20	12.77	18.20
Emerging Asia	287	1.35	7.89	22.74
Emerging EMEA	287	5.05	11.76	21.56
Latin America	287	5.48	13.35	24.67
Panel B: Excess Bond Returns				
DM Comm	287	4.06	5.76	9.94
Developed Asia	287	-0.07	1.63	11.49
EU, Euro	287	3.08	4.76	10.34
EU, Non-Euro	287	2.63	1.25	8.87
Emerging Asia	265	4.84	5.87	7.01
Emerging EMEA	266	3.52	7.43	14.1
Latin America	287	7.34	11.31	15.42
Panel C: Excess Foreign Currency Returns				
DM Comm	287	1.89		
Developed Asia	287	-0.95		
EU, Euro	287	-0.61		
EU, Non-Euro	287	-0.23		
Emerging Asia	287	0.50		
Emerging EMEA	287	2.36		
Latin America	287	1.55		

Table 2.2: Summary Statistics for Risk Factors

The table presents the summary statistics for the three risk factors: the excess return on the S&P 500 equity index, the excess return on the U.S. bond index, and the return on the variance swap. Panel A presents the mean, median, and standard deviation, Panel B presents the correlations. The sample period is January 1995 to November 2018.

Panel A: Excess Returns				
	N	Mean	Median	SD
r_{US}^e	287	5.20	10.49	14.61
r_{US}^b	287	2.61	2.39	4.24
r_{US}^{vs}	287	-1.14	-1.27	4.24

Panel B: Correlations			
	$r_{US,t}^e$	$r_{US,t}^b$	$r_{US,t}^{vs}$
$r_{US,t}^e$	1.00		
$r_{US,t}^b$	-0.22	1.00	
$r_{US,t}^{vs}$	-0.53	0.15	1.00

Table 2.3: Global Equity Market Returns Priced by Their Exposures to U.S. Equity Market, Bond Market, and Variance Risks

The Table reports regressions of excess equity returns denominated in U.S. dollars on the risk factors from the U.S. equity, bond, and variance markets:

$$r_{i,t}^e = \alpha_i + \beta_{i,1}r_{US,t}^e + \beta_{i,2}r_{US,t}^b + \beta_{i,3}r_{US,t}^{vs} + \varepsilon_{i,t}$$

Panel A presents results for equally weighted regional portfolios in which the N column lists the number of months. Panel B lists summary statistics of the individual country-level regressions: the mean, the percent significant at the 10% level (% signif.), and the 10-th percentile and the 90-th percentile (p10 / p90) of the coefficient estimates. The N column presents the number of countries. The sample period is January 1995 to November 2018.

Region		$r_{US,t}^e$	$r_{US,t}^b$	$r_{US,t}^{vs}$	Constant	N	Adj R2
Panel A: Regional Regressions							
DM Commodities	coef	0.85***	0.18	-3.23***	-0.031	287	0.637
	t-stat	[14.1]	[1.16]	[-6.41]	[-1.36]		
Developed Asia	coef	0.80***	0.011	-2.99***	-0.056**	287	0.527
	t-stat	[13.4]	[0.061]	[-4.35]	[-2.10]		
EU Euro	coef	0.95***	-0.27	-3.65***	-0.062***	287	0.662
	t-stat	[14.5]	[-1.52]	[-6.10]	[-2.66]		
EU Non-Euro	coef	0.84***	-0.28*	-3.41***	-0.013	287	0.692
	t-stat	[16.2]	[-1.80]	[-5.31]	[-0.63]		
Emerging Asia	coef	0.83***	-0.078	-3.16***	-0.064*	287	0.409
	t-stat	[9.03]	[-0.36]	[-3.79]	[-1.87]		
Emerging EMEA	coef	0.84***	-0.14	-3.90***	-0.034	287	0.508
	t-stat	[8.97]	[-0.62]	[-5.38]	[-1.11]		
Latin America	coef	0.80***	-0.20	-5.19***	-0.041	287	0.425
	t-stat	[7.22]	[-0.71]	[-5.41]	[-1.03]		
Panel B: Summary Statistics for Country-Level Regressions							
Developed	mean	0.89	-0.17	-3.45	-0.05	22	0.50
	% signif.	1.00	0.23	0.91	0.36		
	p10 / p90	0.73 / 1.11	-0.59 / 0.29	-6.39 / -1.38	-0.08 / -0.00		
Emerging Asia	mean	0.83	-0.08	-3.16	-0.06	9	0.22
	% signif.	1.00	0.22	0.78	0.11		
	p10 / p90	0.41 / 1.12	-0.64 / 0.82	-5.95 / 0.98	-0.13 / 0.01		
Emerging EMEA	mean	0.84	-0.14	-3.90	-0.03	10	0.24
	% signif.	0.80	0.10	0.90	0.00		
	p10 / p90	0.08 / 1.44	-0.97 / 0.55	-5.78 / -2.18	-0.07 / 0.00		
Latin America	mean	0.80	-0.20	-5.19	-0.04	6	0.28
	% signif.	1.00	0.00	1.00	0.00		
	p10 / p90	0.49 / 1.20	-0.71 / 0.58	-7.80 / -3.47	-0.10 / -0.01		

Table 2.4: Global Bond Market Returns Priced by Their Exposures to U.S. Equity Market, Bond Market, and Variance Risks

The Table reports regressions of excess bond market returns denominated in U.S. dollars on the risk factors from the U.S. equity, bond, and variance markets:

$$r_{i,t}^b = \alpha_i + \beta_{i,1}r_{US,t}^e + \beta_{i,2}r_{US,t}^b + \beta_{i,3}r_{US,t}^{vs} + \varepsilon_{i,t}$$

Panel A presents results for equally weighted regional portfolios in which the N column lists the number of months. Panel B lists summary statistics of the individual country-level regressions: the mean, the percent significant at the 10% level (% signif.), and the 10-th percentile and the 90-th percentile (p10 / p90) of the coefficient estimates. The N column presents the number of countries. The sample period is January 1995 to November 2018.

Region		$r_{US,t}^e$	$r_{US,t}^b$	$r_{US,t}^{vs}$	Constant	N	Adj R2
Panel A: Regional Regressions							
DM Commodities	coef	0.29***	0.91***	-2.10***	-0.022	287	0.403
	t-stat	[7.03]	[8.13]	[-5.68]	[-1.41]		
Developed Asia	coef	0.068	0.92***	1.23	-0.014	287	0.120
	t-stat	[1.22]	[5.93]	[1.48]	[-0.62]		
EU Euro	coef	0.13**	0.99***	-1.33***	-0.017	287	0.192
	t-stat	[2.40]	[6.58]	[-2.87]	[-0.91]		
EU Non-Euro	coef	0.11***	0.91***	-1.56***	-0.021	287	0.241
	t-stat	[2.71]	[7.87]	[-4.78]	[-1.38]		
Emerging Asia	coef	0.13**	0.82***	-1.78***	0.0027	265	0.402
	t-stat	[2.36]	[7.70]	[-4.13]	[0.21]		
Emerging EMEA	coef	0.32**	0.51***	-1.52***	-0.0083	266	0.164
	t-stat	[2.29]	[3.29]	[-2.66]	[-0.30]		
Latin America	coef	0.40***	0.74***	-4.98***	-0.024	287	0.442
	t-stat	[4.02]	[3.56]	[-6.81]	[-0.93]		
Panel B: Summary Statistics for Country-Level Regressions							
Developed	mean	0.16	0.93	-1.34	-0.02	22	0.23
	% signif.	0.86	1.00	0.77	0.05		
	p10 / p90	0.07 / 0.31	0.76 / 1.05	-2.09 / -0.50	-0.03 / 0.00		
Emerging Asia	mean	0.15	0.84	-2.61	-0.00	4	0.32
	% signif.	0.75	0.75	1.00	0.00		
	p10 / p90	0.06 / 0.21	0.61 / 0.98	-5.14 / -1.24	-0.02 / 0.02		
Emerging EMEA	mean	0.29	0.54	-1.76	0.01	11	0.17
	% signif.	0.73	0.55	0.55	0.09		
	p10 / p90	0.10 / 0.74	0.18 / 0.95	-2.88 / 0.29	-0.01 / 0.03		
Latin America	mean	0.32	0.84	-4.79	-0.02	12	0.35
	% signif.	0.92	0.67	0.92	0.08		
	p10 / p90	0.09 / 0.53	0.43 / 1.13	-9.06 / -1.60	-0.10 / 0.02		

Table 2.5: Global Foreign Exchange Market Returns Priced by Their Exposures to U.S. Equity Market, Bond Market, and Variance Risks

The Table reports regressions of excess foreign exchange market returns denominated in U.S. dollars on the risk factors from the U.S. equity, bond, and variance markets:

$$r^f x_{i,t} = \alpha_i + \beta_{i,1} r_{US,t}^e + \beta_{i,2} r_{US,t}^b + \beta_{i,3} r_{US,t}^{vs} + \varepsilon_{i,t}$$

Panel A presents results for equally weighted regional portfolios in which the N column lists the number of months. Panel B lists summary statistics of the individual country-level regressions: the mean, the percent significant at the 10% level (% signif.), and the 10-th percentile and the 90-th percentile (p10 / p90) of the coefficient estimates. The N column presents the number of countries. The sample period is January 1995 to November 2018.

Region		$r_{US,t}^e$	$r_{US,t}^b$	$r_{US,t}^{vs}$	Constant	N	Adj R2
Panel A: Regional Regressions							
DM Commodities	coef	0.29***	0.27**	-2.04***	-0.026	287	0.335
	t-stat	[6.57]	[2.20]	[-4.98]	[-1.60]		
Developed Asia	coef	0.078***	0.33***	0.37	-0.018*	287	0.092
	t-stat	[3.28]	[4.77]	[1.13]	[-1.93]		
EU Euro	coef	0.098*	0.43***	-1.50***	-0.039**	286	0.085
	t-stat	[1.81]	[2.76]	[-3.28]	[-2.11]		
EU Non-Euro	coef	0.11**	0.31***	-1.56***	-0.034**	287	0.113
	t-stat	[2.37]	[2.62]	[-4.34]	[-2.09]		
Emerging Asia	coef	0.16***	0.065	-0.57*	-0.011	287	0.128
	t-stat	[4.62]	[0.73]	[-1.72]	[-0.95]		
Emerging EMEA	coef	0.19***	0.23*	-1.19***	-0.0056	287	0.231
	t-stat	[4.61]	[1.86]	[-3.98]	[-0.39]		
Latin America	coef	0.18***	0.054	-1.64***	-0.014	287	0.238
	t-stat	[5.39]	[0.59]	[-5.74]	[-0.98]		
Panel B: Country-Level Regressions							
Developed	mean	0.13	0.37	-1.33	-0.03	22	0.12
	% signif.	0.82	0.82	0.86	0.73		
	p10 / p90	0.07 / 0.25	0.06 / 0.45	-2.01 / -0.21	-0.04 / -0.02		0.06 / 0.23
Emerging Asia	mean	0.15	0.06	-0.53	-0.01	8	0.06
	% signif.	0.88	0.00	0.38	0.12		
	p10 / p90	0.03 / 0.37	-0.03 / 0.23	-2.29 / 0.11	-0.03 / 0.02		0.01 / 0.15
Emerging EMEA	mean	0.19	0.23	-1.19	-0.01	10	0.10
	% signif.	0.80	0.40	0.60	0.10		
	p10 / p90	0.02 / 0.32	-0.19 / 0.48	-2.58 / 0.28	-0.03 / 0.02		0.00 / 0.19
Latin America	mean	0.18	0.05	-1.64	-0.01	6	0.13
	% signif.	0.83	0.00	0.83	0.17		
	p10 / p90	0.01 / 0.31	-0.16 / 0.19	-2.60 / -0.54	-0.06 / 0.03		-0.01 / 0.25

Table 2.6: Regional Risk Premiums: Does Global Volatility Matter?

The sample mean excess return is \bar{r}_i . The implied expected excess return from the two factor model with excess returns on the U.S. equity and bond markets as risk factors is $E(r_{Model1})$. The implied expected excess return from the three factor model that adds the return on the variance swap as an additional risk factor is $E(r_{Model2})$. The implied expected excess returns are calculated using the long-run means for the excess returns on U.S. equities, bonds, and the variance swap, which are 5.20%, 2.61%, and -1.14%, respectively. The proportion of the implied expected return from Model 2 that is due to the variance swap return is $\beta_3 VSP / E(r_{Model2})$. Standard errors (SE) for the proportions are in the last column. The sample period is January 1995 to November 2018.

Asset Class	Region	\bar{r}_i	$E(r_{Model1})$	$E(r_{Model2})$	$\frac{\beta_3 VSP}{E(r_{Model2})}$	SE
Equities	DM Commodities	5.54	5.05	8.41	46.56	4.64
	Developed Asia	2.02	4.23	7.34	49.38	5.26
	EU Euro	2.23	4.13	7.92	55.71	8.79
	EU Non-Euro	6.20	3.56	7.10	58.16	9.62
	Emerging Asia	1.35	4.11	7.39	51.74	6.28
	Emerging EMEA	5.05	4.08	8.12	58.05	7.22
	Latin America	5.48	3.92	9.31	67.42	8.02
Bonds	DM Commodities	4.06	4.50	6.68	38.05	14.31
	Developed Asia	-0.07	2.97	1.69	-88.13	189.10
	EU Euro	3.08	3.89	5.27	30.57	17.49
	EU Non-Euro	2.63	3.61	5.23	36.06	18.97
	Emerging Asia	4.84	3.48	5.31	40.57	22.37
	Emerging EMEA	3.52	3.32	4.88	37.75	12.59
	Latin America	7.34	5.01	10.18	59.19	11.23
Exchange Rates	DM Commodities	1.89	2.52	4.63	53.23	7.85
	Developed Asia	-0.95	1.31	0.92	-48.08	51.21
	EU Euro	-0.61	2.04	3.59	50.39	17.34
	EU Non-Euro	-0.23	1.73	3.34	56.35	14.23
	Emerging Asia	0.50	1.02	1.61	42.66	4.96
	Emerging EMEA	2.36	1.77	3.00	47.90	9.13
	Latin America	1.55	1.28	2.98	66.58	4.53

Table 2.7: Pricing Errors

The Table reports the [Gibbons, Ross, and Shanken \(1989\)](#) (GRS) joint test of the significance of the pricing errors for Model 1, the two-factor risk model, and Model 2, the three-factor risk model, as well as an asymptotic GMM test that allows for conditional heteroskedasticity. The GRS test is

$$T \left(1 + E(f)' \hat{\Omega}^{-1} E(f) \right)^{-1} \hat{\alpha}' \hat{\Sigma}^{-1} \hat{\alpha} \sim \chi_N^2$$

The GMM test is

$$\hat{\alpha}' \text{var}(\hat{\alpha})^{-1} \hat{\alpha} \sim \chi_N^2$$

		Regional		EM		DM	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
GRS	Equities	11.6 [0.11]	13.74 [0.06]	9.11 [1.00]	12.23 [0.98]	23.79 [0.36]	35.32 [0.04]
	Bonds	5.46 [0.60]	6.9 [0.44]	23.39 [0.22]	21.4 [0.32]	8.32 [0.98]	11.32 [0.91]
	FX	10.16 [0.18]	9.23 [0.24]	165.04 [0.00]	170.67 [0.00]	56.78 [0.00]	51.04 [0.00]
GMM	Equities	11.21 [0.13]	14.68 [0.04]	15.13 [0.94]	17.75 [0.85]	35.05 [0.04]	40.74 [0.01]
	Bonds	5.65 [0.58]	7.44 [0.38]	24.5 [0.18]	28 [0.08]	10.24 [0.95]	15.05 [0.72]
	FX	10.29 [0.17]	11.93 [0.10]	130.83 [0.00]	128.49 [0.00]	21.96 [0.46]	19.93 [0.59]

Table 2.8: Model-Implied Relative to Realized Regional Correlations for Equity, Bond and Foreign Currency Markets

The Table reports the ratio of model implied correlations to sample correlations for excess returns on regional equities, bonds and exchange rates. The implied excess returns are the fitted values from the regression of regional excess returns on the excess returns on U.S. equity, bond, and variance swap markets. The sample period is January 1995 to November 2018.

Asset Class	Region	DM Comm.	Dev. Asia	Euro	Non-Euro	Em. Asia	EMEA
Equities	Developed Asia	0.72					
	EU Euro	0.81	0.88				
	EU Non-Euro	0.79	0.83	0.74			
	Emerging Asia	0.69	0.57	0.87	0.83		
	Emerging EMEA	0.72	0.74	0.75	0.75	0.63	
	Latin America	0.69	0.67	0.79	0.77	0.59	0.58
Bonds	Developed Asia	0.29					
	EU Euro	0.39	0.41				
	EU Non-Euro	0.41	0.36	0.26			
	Emerging Asia	0.73	1.17	0.97	0.90		
	Emerging EMEA	0.69	1.20	1.02	0.96	0.34	
	Latin America	0.74	-0.43	0.89	0.88	0.54	0.43
FX	Developed Asia	0.19					
	EU Euro	0.25	0.13				
	EU Non-Euro	0.28	0.12	0.11			
	Emerging Asia	0.42	0.10	0.25	0.28		
	Emerging EMEA	0.38	0.19	0.18	0.22	0.41	
	Latin America	0.51	0.21	0.39	0.42	0.46	0.40

Table 2.9: Correlations of Regional Equity, Bond and Foreign Exchange Markets

The Table reports the sample correlations for excess returns across regional equity, bond, and foreign currency markets. The sample period is January 1995 to November 2018.

Asset Class	Region	DM Comm.	Dev. Asia	Euro	Non-Euro	Em. Asia	EMEA
Equities	Developed Asia	0.80					
	EU Euro	0.80	0.68				
	EU Non-Euro	0.84	0.73	0.92			
	Emerging Asia	0.75	0.83	0.61	0.65		
	Emerging EMEA	0.80	0.71	0.78	0.80	0.73	
	Latin America	0.76	0.71	0.68	0.70	0.72	0.80
Bonds	Developed Asia	0.29					
	EU Euro	0.69	0.30				
	EU Non-Euro	0.76	0.36	0.91			
	Emerging Asia	0.55	0.10	0.30	0.36		
	Emerging EMEA	0.37	0.01	0.14	0.17	0.67	
	Latin America	0.57	0.03	0.25	0.30	0.70	0.66
FX	Developed Asia	0.42					
	EU Euro	0.64	0.48				
	EU Non-Euro	0.70	0.49	0.94			
	Emerging Asia	0.51	0.46	0.37	0.42		
	Emerging EMEA	0.75	0.40	0.75	0.76	0.43	
	Latin America	0.56	0.22	0.32	0.38	0.39	0.59

Table 2.10: Correlations for Equities, Bonds, and Foreign Exchange within Regions

The Table reports the ratio of model-implied correlations to sample correlations and the sample correlations for excess returns within regions for equity returns and bond returns, equity returns and foreign exchange returns, and bond returns and foreign exchange returns. The implied excess returns are the fitted values from the regression of regional excess returns on the excess returns on U.S. equity, bond, and variance swap markets. The sample period is January 1995 to November 2018.

	Region	Corr(Eq,Bond)	Corr(Eq,FX)	Corr(Bond,FX)
Model-Implied/Realized	DM Commodities	0.55	0.56	0.36
	Developed Asia	-0.54	0.20	0.11
	EU Euro	0.30	0.35	0.13
	EU Non-Euro	0.39	0.44	0.16
	Emerging Asia	0.50	0.36	0.48
	Emerging EMEA	0.56	0.49	0.61
	Latin America	0.53	0.45	0.55
Sample Correlations	DM Commodities	0.78	0.83	0.93
	Developed Asia	0.11	0.36	0.89
	EU Euro	0.45	0.50	0.92
	EU Non-Euro	0.44	0.54	0.92
	Emerging Asia	0.50	0.66	0.34
	Emerging EMEA	0.51	0.69	0.32
	Latin America	0.77	0.70	0.58

Table 2.11: Model Fit: Root Mean Square Error

This table reports the RMSE for two models. Model 1 refers to a two factor model with excess returns on the U.S. equity and bond market as risk factors, while Model 2 refers to a three factor model that adds the return on the variance swap as an additional risk factor. The RMSE measure is the square root of the mean square error defined as

$$RMSE = \sqrt{\frac{1}{N(N-1)/2} \sum_{i=1}^N \sum_{j>i}^N [corr_s(r_{i,t}, r_{j,t}) - corr_m(r_{i,t}, r_{j,t})]^2} \quad (2.6)$$

where $corr_s$ is the sample correlation, $corr_m$ is the model-implied correlation and N is the number of portfolios. Panel A shows the results for the correlations across countries (within asset class), and Panel B shows the results for the correlations within countries (across asset classes).

	Regional		EM		DM	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Panel A: Across countries, within asset class						
Equities	0.061	0.046	0.084	0.076	0.060	0.050
Bonds	0.083	0.070	0.108	0.080	0.292	0.273
Exchange Rates	0.184	0.170	0.105	0.100	0.468	0.443
Panel B: Within countries, across asset classes						
All asset classes	0.202	0.179	0.127	0.114	0.261	0.240

Chapter 3

Time-Varying Integration and Valuation in Emerging Markets

3.1 INTRODUCTION

The cost of capital is notoriously difficult to measure, and can be even more complicated in emerging markets, where the cost of capital changes as markets integrate with the world. The link between changes in market integration and expected returns has been extensively studied to explain why different countries command different risk premiums. As markets integrate, the dependence on the world factor should presumably increase. Meanwhile expected returns in completely segmented markets should have little to no covariance with global market returns, with different (idiosyncratic) sources of risk.

A large body of literature assumes that countries face a one-time permanent integration shock, such that countries can become more integrated to the world and do not go back to segmentation. [Bekaert and Harvey \(2000\)](#), [Han Kim and Singal \(2000\)](#), [Martell and Stulz \(2003\)](#), and [Bekaert, Harvey, and Lumsdaine \(2002\)](#) use equity market liberalizations and the removal of capital controls in emerging markets (mostly in the late 1980s and the beginning of the 1990s) to back out the effects of integration on asset prices, mostly relying on event-study type methodologies. They find that liberalizations tend to increase correlations with global market returns. While the integration we saw over this period could be seen as a structural change, it is not necessarily the case that integration is a permanent one-way street. [Bekaert, Harvey, Kiguel, and Wang \(2016\)](#) show that correlations and betas across countries in equity market returns effectively increased throughout the 1990s and early 2000s, but have since then stabilized and even fell in the period following the Global Financial Crisis. We have also recently seen that even developed markets can become more segmented, with Greece getting demoted from a developed market to an emerging market and Trump's and other developed market's policies shifting towards more protectionist policies. Furthermore, in emerging markets it is common to have constant shocks to integration, especially as political regimes change. Thus, integration is time-varying and, while regimes can be sticky, markets do not always shift smoothly and permanently from segmentation to integration.

Using average returns to measure the cost of capital can be difficult, and thus dividend yields may be a more powerful tool, as these tend to be less variable in short time series (e.g. [Bekaert and Harvey \(2000\)](#), [Bekaert, Harvey, Lundblad, and Siegel \(2011\)](#)). While the literature which parameterizes betas as a function of various integration indicators in the returns space is large (e.g.

Harvey (1995), Bekaert and Harvey (1997), Fratzscher (2002), Bekaert, Harvey, and Ng (2005), Baele and Inghelbrecht (2010)), little has been done with dividend yields. Constant discount rates and cash flow growth are not reasonable assumptions in emerging markets. As the degree of integration varies over time, agents should anticipate such variation and it should be reflected in valuations. Integration can be incorporated into valuation models in a linear fashion, such that the degree of integration directly impacts discount rates and growth opportunities. However, theory and evidence suggest that the dependence on global factors should increase as markets integrate. This gives rise to a quadratic term in the pricing equation, and thus changes in integration with dynamic effects are difficult to accommodate in valuation models.

In this paper, we develop a novel present value model to value cash flows with time-varying expected returns building on the model developed by Ang and Liu (2004), but in our case market integration affect the cost of capital in a time-varying fashion. Integration has a direct impact on valuations, along with an indirect impact through the time-varying nature of the betas with, for example, global discount rates. These two effects lead to an interaction term between the model's state variables (e.g. financial integration with a global risk factor), generating a quadratic Gaussian structure in the pricing equation. This framework prices expectations about future integration, with integration modeled as a mean-reverting process which goes back to the unconditional mean. We use the model to attempt to quantify price effects of changes in *de jure* integration and predict future integration dynamics. We use Argentina as a case study, and calibrate the model to fit a segmentation shock in 2011. We find that the model is able to capture part of the increase in dividend yields as markets became more segmented; however, it falls short of modeling the full impact. To model the full extent of the change in dividends, we need to assume that investors perceive the shock as permanent and thus price lower mean integration following the segmentation shock.

The remainder of this paper is organized as follows. Section 3.2 presents the model for valuing cash flows with time-varying expected returns. We also show some special cases of the model to better understand the financial integration dynamics. Section 3.3 outlines the data we use for the calibration exercise. Section 3.4 describes our Argentina case study, showing how integration has varied over time and describing the 2011 segmentation shock in detail, while Section 3.5 shows the calibration parameters and results. We conclude in Section 3.6.

3.2 DIVIDEND YIELDS AND INTEGRATION

In this section, we develop a novel analytical methodology to price an emerging market security. This framework considers a present value model to value cash flows with time-varying expected returns, where market integration affects the cost of capital in a time-varying fashion. We develop a model based on the closed-form methodology developed by [Ang and Liu \(2004\)](#). The price $P_{i,t}$ of a security in country i can be written as

$$P_{i,t} = E_t \left[\sum_{n=1}^{\infty} \exp \left(\sum_{j=0}^{n-1} -\mu_{i,t+j} \right) D_{i,t+n} \right], \quad (3.1)$$

where $D_{i,t}$ are the dividends of country i , $\mu_{i,t}$ is the log expected return of country i , and assuming that rational expectations and the transversality condition hold. A standard Gordon model assumes that both expected returns and expected cash flow growth are constant (i.e. $\mu_t = \bar{\mu}$ and $E_t(D_{t+n}) = (1 + \bar{g})E_t(D_{t+n-1})$), and the pricing formula reduces to:

$$\frac{P_{i,t}}{D_{i,t}} = \frac{1}{\exp(\bar{\mu} - \bar{g}) - 1}. \quad (3.2)$$

However, empirical studies in emerging markets suggest that local expected returns and cash flow growth rates vary over time; therefore, the Gordon model is not a realistic model and a process must be specified for each variable in order to directly evaluate equation 3.1.

We define the discount rate in country i in the spirit of [Bekaert and Harvey \(1995\)](#), who develop a framework with time-varying integration which allows conditionally expected returns in any country to be affected by their covariance with a world benchmark portfolio and by the variance of country returns. In their specification, as economies become more financially integrated, the global component becomes more relevant; while under complete segmentation, the variance term is the only source of market risk. The idea behind this is that, as countries integrate, their asset prices should converge (as projects of similar risk command a similar price per unit of cash flow in integrated countries) and there should be higher comovement of returns across countries. In contrast to their specification, where the time-varying integration measure is inferred from the

data, we use an explicit measure of financial integration.¹

Consider a conditional log expected return, $\mu_{i,t}$, specified by an international conditional CAPM:

$$\mu_{i,t} = r_{f,t} + \theta_{i,t} + \beta_{i,t}\mu_{w,t} + \lambda_{i,t}E_t(RV_{i,t+1}). \quad (3.3)$$

Discount rates are affected by the global discount rate, $\mu_{w,t}$, and by the conditional variance of country returns, $E_t(RV_{i,t+1})$. We take the perspective of a global investor and thus $r_{f,t}$ is a global risk-free rate, which arises because discount rates are total, not excess, rates. Furthermore, we assume that the constant term, $\theta_{i,t}$, and the sensitivities of discount rates in country i to global discount rates and local variance, measured by $\beta_{i,t}$ and $\delta_{i,t}$, are modeled as

$$z_{i,t} = z_0 + z_1FI_{i,t}, \quad (3.4)$$

where $z = \{\theta_{i,t}, \beta_{i,t}, \lambda_{i,t}\}$ and $FI_{i,t}$ is a measure of financial integration. This model nests the nulls of full integration and full segmentation. In completely segmented markets (β_0 and β_1 are equal to zero), then the CAPM holds. In this case, the $\lambda_{i,t}$ is the local price of risk and measures the representative investor's relative risk aversion (Merton (1980)). Meanwhile, in completely integrated markets (λ_0 and λ_1 are equal to zero), the conditionally expected return in country i is determined by the the country's world risk exposure (as in Harvey (1991)), where $\beta_{i,t}$ is the world price of risk.

Log dividend growth in country i , $\Delta d_{i,t+1}$, is affected by global dividend growth, $\Delta d_{w,t+1}$ and a local component, $LF_{i,t}$:

$$\Delta d_{i,t+1} = \kappa_{i,t} + \gamma_{i,t}\Delta d_{w,t+1} + \varphi_{i,t}LF_{i,t} + \varepsilon_{i,t+1}^d. \quad (3.5)$$

Global dividend growth is defined as

$$\Delta d_{w,t+1} = g_{w,t} + \varepsilon_{w,t+1}^d, \quad (3.6)$$

where $g_{w,t}$ is the expected cash flow growth at time t and $\varepsilon_{w,t+1}^d \sim N(0, \sigma_{w,d}^2)$. That is, like expected

¹In addition to financial integration, it is easy to add political risk as a second segmenting factor in the setup.

returns, cash flow growth varies over time with a global and local factor, but with respect to economic integration. As economies become more economically integrated, local cash flows are expected to vary more with global cash flows; while under complete segmentation, the local factor is the only source of risk. I assume that the constant term, $\kappa_{i,t}$, and the global dividend growth and local factor coefficients, $\gamma_{i,t}$ and $\phi_{i,t}$, vary over time with measures of economic openness and political risk:

$$z_{i,t} = z_0 + z_1 T I_{i,t}, \quad (3.7)$$

where $z = \{\kappa_{i,t}, \gamma_{i,t}, \phi_{i,t}\}$, and $T I_{i,t}$ is a measure of trade integration.

To take the expectation of the pricing equation, I also need to know the evolution of the state variables defined in the previous systems. Assume $X_{w,t} = (g_{w,t} \mu_{w,t} r_{f,t})'$ and $X_{i,t} = (T I_{i,t} F I_{i,t} V R_{i,t} L F_{i,t})'$, where $X_t = (X'_{w,t} X'_{i,t})'$ follows a VAR(1):

$$X_{t+1} = c + \Phi X_t + \epsilon_{t+1} \quad (3.8)$$

with $\epsilon_t \sim iid N(0, \Sigma)$. For simplicity, I assume that global variables only predict global variables and local variables only predict local variables (this can be easily extended for global variables to help predict local variables). That is,

$$\begin{bmatrix} X_{w,t} \\ X_{i,t} \end{bmatrix} = \begin{bmatrix} c_w \\ c_i \end{bmatrix} + \begin{bmatrix} \Phi_w & 0 \\ 0 & \Phi_i \end{bmatrix} \begin{bmatrix} X_{w,t-1} \\ X_{i,t-1} \end{bmatrix} + \begin{bmatrix} \eta_{w,t} \\ \eta_{i,t} \end{bmatrix} \quad (3.9)$$

Assume also that idiosyncratic shocks of the United States and country i are uncorrelated.

The following proposition shows how to calculate the valuation of country i under the model specified above.

Proposition 1: Let $X_t = (X'_{w,t} X'_{i,t})'$, with dimensions $K \times 1$, follow the process in equation (3.8). Suppose cash flow growth, $\Delta d_{i,t+1}$, and expected log returns, $\mu_{i,t}$, each follow a quadratic Gaussian structure given by

$$\Delta d_{i,t+1} = \alpha_1 + \xi'_1 X_t + X'_t \Omega_1 X_t + \Gamma'_1 \nu_{t+1} + X'_t \Lambda_1 \nu_{t+1} \quad (3.10)$$

and

$$\mu_{i,t} = \alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t \quad (3.11)$$

where α_1 and α_2 are constants, ξ_1 and ξ_2 are $K \times 1$ vectors, Ω_1 and Ω_2 are symmetric $K \times K$ matrices, Γ_1' is a 2×1 vector, Λ_1 is a $K \times 2$ matrix, and ν_{t+1} is an error vector, $(\varepsilon_{w,t+1}^d \ \varepsilon_{i,t+1}^d)'$, with $\nu_{i,t+1} \sim N(0, \Sigma_\nu)$. The vectors ξ and the matrices Ω map cash flows and expected returns to X_t , while Γ and Λ map the noise terms in the cash flows equation to ν_{t+1} (see Appendix C1 for details). Then, assuming existence, starting from:

$$\frac{P_{i,t}}{D_{i,t}} = E_t \left[\sum_{n=1}^{\infty} \exp \left(\sum_{j=0}^{n-1} -\mu_{i,t+j} + \Delta d_{i,t+j+1} \right) \right], \quad (3.12)$$

Appendix C2 shows that, by induction,

$$\frac{P_{i,t}}{D_{i,t}} = \sum_{n=1}^{\infty} \exp \left(a(n) + b(n)' X_t + X_t' H(n) X_t \right) \quad (3.13)$$

where $a(n)$ is a scalar, $b(n)$ is a $K \times 1$ vector, and $H(n)$ is a $K \times K$ symmetric matrix. The coefficients $a(n)$, $b(n)$ and $H(n)$ are given by the following recursions:

$$\begin{aligned} a(n+1) &= a(n) + \alpha_1 - \alpha_2 + \frac{1}{2} \Gamma_1' \Sigma_\nu \Gamma_1 + b(n)' c + c' H(n) c - \frac{1}{2} \ln \det \left(I - 2 \Sigma H(n) \right) \\ &\quad + \frac{1}{2} \left(b(n) + 2 H(n)' c \right)' \left(\Sigma^{-1} - 2 H(n) \right)^{-1} \left(b(n) + 2 H(n)' c \right) \end{aligned} \quad (3.14)$$

$$\begin{aligned} b(n+1) &= (\xi_1 - \xi_2) + \Lambda_1 \Sigma_\nu \Gamma_1 + \Phi' b(n) + 2 \Phi' H(n)' c \\ &\quad + 2 \Phi' H(n) \left(\Sigma^{-1} - 2 H(n) \right)^{-1} \left(b(n) + 2 H(n)' c \right) \end{aligned} \quad (3.15)$$

$$H(n+1) = (\Omega_1 - \Omega_2) + \frac{1}{2} \Lambda_1 \Sigma_\nu \Lambda_1' + \Phi' H(n) \Phi + 2 \Phi' H(n)' \left(\Sigma^{-1} - 2 H(n) \right)^{-1} H(n) \Phi, \quad (3.16)$$

where the initial conditions are given by:

$$\begin{aligned} a(1) &= \alpha_1 - \alpha_2 + \frac{1}{2} \Gamma_1' \Sigma_\nu \Gamma_1 \\ b(1) &= \xi_1 - \xi_2 + \Lambda_1 \Sigma_\nu \Gamma_1 \\ H(1) &= \Omega_1 - \Omega_2 + \frac{1}{2} \Lambda_1 \Sigma_\nu \Lambda_1'. \end{aligned} \quad (3.17)$$

Note that the quadratic Gaussian structure in this model comes from modeling the interaction of the integration variables with the global and local factors. The pricing formula in equation 3.13

is analytic, given that the coefficients $a(n)$, $b(n)$ and $H(n)$ are known functions and stay constant over time.

3.2.1 The role of financial integration

To better understand the role of the different parameters in the model, we consider a few special cases. First, it is worth noting that the framework can be reduced to a standard Gordon growth model. That is, we can assume that the discount rate and expected cash flows are constant over time by setting $\xi_1 = \xi_2 = \Omega_1 = \Omega_2 = \Gamma_1 = \Lambda_1 = 0$ such that $\Delta d_{i,t+1} = \alpha_1$ and $\mu_{i,t} = \alpha_2$ with $\alpha_1 > \alpha_2 > 0$. While this case is fairly trivial, it shows that the α 's in the model represent the unconditional means of the discount rate and expected cash flows.

Second, to gain intuition on the model, we assume that cash flows follow an autoregressive process (and thus are another state variable in the model) and focus on the discount rate effect. In these specifications, prices move either because of changes in cash flow growth or because state variables affecting expected returns change in X_t . This narrows the state variables down to $X_t = (\mu_{w,t} \ r_{f,t} \ g_{i,t} \ FI_{i,t} \ E_t(VR_{i,t+1}))$, and we further assume that each state variable follows an AR(1) process rather than the VAR(1) specified above. Under these assumptions, we study three cases: (i) betas are constant over time, but factors are time-varying, (ii) betas vary over time with financial integration, but factor risk premia are constant, and (iii) both betas and factors vary over time.

We start by considering the case where betas are constant over time, but global discount rates and local expected variance risk are time-varying. Financial integration still is included as a factor which explains expected returns, but there are no interaction terms. Thus, equation 3.3 reduces to:

$$\mu_{i,t} = r_{f,t} + \theta_0 + \theta_1 FI_{i,t} + \beta_0 \mu_{w,t} + \lambda_0 E_t(RV_{i,t+1}), \quad (3.18)$$

where $\alpha_2 = \theta_0$, $\xi_2 = (e_2 + \theta_1 e_4 + \beta_0 e_1 + \lambda_0 e_5)$, and e_i is a vector of zeros with a one in row i . Equation 3.13 no longer includes a quadratic term, such that the pricing equation in Proposition 1 simplifies to:

$$\frac{P_{i,t}}{D_{i,t}} = \sum_{n=1}^{\infty} \exp\left(a(n) + b(n)' X_t\right), \quad (3.19)$$

where $X_t = (\mu_{w,t} \ r_{f,t} \ g_{i,t} \ FI_{i,t} \ E_t(VR_{i,t+1}))$, $a(n)$ is a scalar, $b(n)$ is a $K \times 1$ vector, and these are given by the following recursions and initial conditions:

$$\begin{aligned}
a(n+1) &= a(n) - \alpha_2 + (e_3 + b(n))'c + \frac{1}{2} \left(e_3 + b(n) \right)' \Sigma^{-1} \left(e_3 + b(n) \right) \\
b(n+1) &= -\xi_2 + \Phi'(e_3 + b(n)) \\
a(1) &= -\alpha_2 + e_3'c + \frac{1}{2} e_3' \Sigma^{-1} e_3 \\
b(1) &= -\xi_2 + \Phi' e_3.
\end{aligned} \tag{3.20}$$

In this case, it is relatively straightforward to evaluate the impact of financial integration on valuations. Assume financial integration increases to 1 at time t (reflected in X_t). The level of financial integration does not affect the constant term, $a(n+1)$, which depends on this variable through its mean and variance terms (i.e. the terms $e_4' b(n) c_{FI}$ and $0.5 b(n)' e_4 \sigma_{FI}^2 e_4' b(n)$). Thus, the direct effect will be reflected in $b(n)$. Iterating over n at time t , it is easy to show that this change directly impacts valuations by $-\theta_1 FI_{i,t}$ in the first period, and that this effect fades as we iterate forward, as we would expect from the mean reverting nature of the AR(1) process (i.e. $-\theta_1(1 + \phi_{FI}) FI_{i,t}$ in the second iteration, $-\theta_1(1 + \phi_{FI} + \phi_{FI}^2) FI_{i,t}$ in the third iteration, and so on). Thus, we can see that higher levels of financial integration leads to lower discount rates, and thus higher price-dividend ratios/lower dividend yields (assuming $\theta_1 < 0$, as theory suggests, and $\phi_{FI} > 0$).

Alternatively, we could assume that betas vary over time with financial integration, but global expected returns and local expected variance risk are constant (we allow the risk-free rate to vary in this scenario). In this case, equation 3.3 reduces to:

$$\mu_{i,t} = r_{f,t} + \theta_0 + \theta_1 FI_{i,t} + (\beta_0 + \beta_1 FI_{i,t}) \overline{\mu_w} + (\lambda_0 + \lambda_1 FI_{i,t}) \overline{E_t(RV_i)}, \tag{3.21}$$

where $\overline{\mu_w}$ and $\overline{E_t(RV_i)}$ are mean global discount rates and local expected returns, respectively, $\alpha_2 = \theta_0 + \beta_0 \overline{\mu_w} + \lambda_0 \overline{E_t(RV_i)}$, $\xi_2 = (e_2 + [\theta_1 + \beta_1 \overline{\mu_w} + \lambda_1 \overline{E_t(RV_i)}] e_4)$ and e_i is a vector of zeros with a one in row i . Again, this eliminates the quadratic term in equation 3.13 and Proposition 1 simplifies as in equations 3.19 and 3.20, with $X_t = (r_{f,t} \ g_{i,t} \ FI_{i,t})$. We repeat the exercise above and assume financial integration increases to 1 at time t . Here, in addition to the direct impact on local discount rates, financial integration also indirectly impacts these by changing the betas on global

discount rates and expected variance risk, reflected in the term $b(n)$. Iterating this term over n at time t , we again find that the change in financial directly impacts valuations by $-\theta_1 FI_{i,t}$ in the first period. However, this time there is also an indirect effect via $(-\beta_1 \overline{\mu_w} - \lambda_1 \overline{E_t(RV_i)}) FI_{i,t}$; the idea being that greater financial increases the loading on the global factor (we would expect β_1 to be greater than zero) and decreases the loading on the local factor ($\lambda_1 < 0$). Both the direct and indirect effects fade in line with ϕ_{FI} as we iterate forward (i.e. $-\theta_1 + \beta_1 \overline{\mu_w} + \lambda_1 \overline{E_t(RV_i)}(1 + \phi_{FI}) FI_{i,t}$ in the second iteration, $-\theta_1 + \beta_1 \overline{\mu_w} + \lambda_1 \overline{E_t(RV_i)}(1 + \phi_{FI} + \phi_{FI}^2) FI_{i,t}$ in the third iteration, and so on). Thus, the impact on the discount rate, and thus dividend yields, depends on the combined effect. If the direct effect dominates the combined indirect effects, then discount rates should fall when financial integration rises, leading to higher price-dividend rates/lower dividend yields. Also, as in the case of constant betas, note that the level of financial integration does not affect the constant term $a(n + 1)$, which depends only on the mean and variance terms (although here the coefficients on these terms depend on the loadings on global discount rates and local variance risk, in addition to impact through the theta's). Furthermore, note that the same conclusions for these two cases can be extracted by working with expected cash flows, as in equation 3.10, rather than assuming they follow an autoregressive process.

Finally, we study the case where betas vary over time with financial integration and factors are time-varying as well. We add two simplifying assumptions to reduce the number of parameters in the calibration and focus on the roles of financial integration and the quadratic effects on valuations:

1. We assume each state variable follows an AR(1) and that the variables are demeaned, such that:

$$\tilde{X}_t = \Phi \tilde{X}_{t-1} + \epsilon_{t+1}, \quad (3.22)$$

where $\tilde{X}_t = X_t - \bar{X}$ are the demeaned state variables, $\tilde{X}_t = (\tilde{\mu}_{w,t} \tilde{r}_{f,t} \tilde{g}_{i,t} \tilde{F}I_{i,t} E_t(\tilde{V}R_{i,t+1}))$, Φ is a $K \times K$ matrix with the AR(1) coefficients on the diagonal and zeros on the off-diagonal elements, and $\epsilon_t \sim N(0, \Sigma)$ with Σ a $K \times K$ matrix with the individual regression σ 's on the diagonal and zeros on the off-diagonal.

2. Expected log returns, $\mu_{i,t}$, follow a quadratic Gaussian structure given by

$$\mu_{i,t} = \alpha_2 + \xi_2' \tilde{X}_t + \tilde{X}_t' \Omega_2 \tilde{X}_t, \quad (3.23)$$

such that α_2 captures the mean local discount rate.

The following proposition shows how to calculate the valuation of country i under the model specified above.

Proposition 2: Let \tilde{X}_t , with dimensions $K \times 1$, follow the process in equation 3.22. Suppose expected log returns, $\mu_{i,t}$, follow a quadratic Gaussian structure given by equation 3.23, where α_2 is a constant, ξ_2 is a $K \times 1$ vector and Ω_2 is a symmetric $K \times K$ matrix. The vectors ξ and the matrices Ω map expected returns to \tilde{X}_t (see Appendix C1 for details). Then, assuming existence, starting from:

$$\frac{P_{i,t}}{D_{i,t}} = E_t \left[\sum_{n=1}^{\infty} \exp \left(\sum_{j=0}^{n-1} -\mu_{i,t+j} + \Delta d_{i,t+j+1} \right) \right], \quad (3.24)$$

Appendix C3 shows that, by induction,

$$\frac{P_{i,t}}{D_{i,t}} = \sum_{n=1}^{\infty} \exp \left(a(n) + b(n)' \tilde{X}_t + \tilde{X}_t' H(n) \tilde{X}_t \right) \quad (3.25)$$

where $a(n)$ is a scalar, $b(n)$ is a $K \times 1$ vector, and $H(n)$ is a $K \times K$ symmetric matrix. The coefficients $a(n)$, $b(n)$ and $H(n)$ are given by the following recursions:

$$\begin{aligned} a(n+1) &= a(n) + \alpha_1 - \alpha_2 - \frac{1}{2} \ln \det \left(I - 2\Sigma H(n) \right) \\ &\quad + \frac{1}{2} \left(e_3 + b(n) + 2H(n)' \Phi \right)' \left(\Sigma^{-1} - 2H(n) \right)^{-1} \left(e_3 + b(n) + 2H(n)' \Phi \right) \\ b(n+1) &= -\xi_2 + \Phi' (e_3 + b(n)) + 2\Phi' H(n) \left(\Sigma^{-1} - 2H(n) \right)^{-1} \left(e_3 + b(n) \right) \\ H(n+1) &= -\Omega_2 + \Phi' H(n) \Phi + 2\Phi' H(n)' \left(\Sigma^{-1} - 2H(n) \right)^{-1} H(n) \Phi, \end{aligned} \quad (3.26)$$

where the initial conditions are given by:

$$\begin{aligned}
a(1) &= \alpha_1 - \alpha_2 + \frac{1}{2} e_3' \Sigma e_3 \\
b(1) &= -\xi_2 + \Phi' e_3 \\
H(1) &= -\Omega_2.
\end{aligned} \tag{3.27}$$

This model essentially combines the two cases we just studied, where we have a direct impact of financial integration on valuations and an indirect impact through the time-varying nature of the betas. However, having both effects together leads to an interaction between the model's state variables (i.e. financial integration with global discount rates and with local expected variance risk), generating a quadratic Gaussian structure in the local discount rate, $\mu_{i,t}$, and by extension the pricing equation. Tracing out the effects of financial integration on valuations analytically is much more involved here, as the quadratic term, $H(n)$, feeds into the constant and linear terms, $a(n)$ and $b(n)$, respectively. We leave this analysis for our case study in the following sections.

For the remainder of the paper, we will focus on this simplified model which only captures the discount rate effect. The full model turns out to be very difficult to apply to gain intuition, given the large amount of parameters in the estimate and the many effects which interact.

3.3 DATA

This section describes the country-level returns and financial data, as well as the global components and the openness variables. All variables are nominal and denominated in dollars.

To construct annualized monthly equity returns, I start with the country-level MSCI total returns index and calculate the total return of the stock market index, $1 + R_{i,t+1}^m$, where $R_{i,t+1}^m$ is the return obtained in country i from month t to month $t + 1$. I then compute monthly log rates of return on the index from month t to month $t + 1$, $r_{i,t+1}^m = \ln(1 + R_{i,t+1}^m)$, and aggregate over 12 months to form annual log returns, $r_{i,t+12} = \sum_{j=1}^{12} r_{i,t+j}^m$.

For each month, I also construct annualized monthly risk-free returns in order to calculate excess returns. I consider the perspective of a representative global investor and consequently use the monthly return on the one-month Treasury bill from Ibboston Associates as the risk-free rate,

$r_{f,t+1}^m$. Returns are then continuously compounded such that $r_{f,t+12} = \prod_{j=1}^{12} (1 + r_{t+j}^m)$. Finally, annualized monthly excess returns are calculated as $r_{i,t}^e = r_{i,t} - r_{f,t}$.

Dividend yields (DY) come from MSCI for the Argentina example, which calculates the country ratio as the average of the individual yields weighted by the market value. Market capitalization and cash flow growth (based on dividends, $\Delta d_{i,t}$) all refer to the MSCI Country Index. Note that, following the literature, we use the 12-month moving average of dividends to calculate cash flow growth and dividend yields, to smooth out jumps. The data limits the starting point of our sample to June 2004.

With respect to global variables, global expected discount rates ($\mu_{w,t}$) and expected cash flow growth ($g_{w,t}$) are empirically estimated following the sum-of-the-parts (SOP) approach outlined in [Ferreira and Santa-Clara \(2011\)](#). The SOP method proposes decomposing log stock market returns into three components: growth in the price-dividends ratio (Δpd_w), growth in dividends (Δd_w) and the dividend-price ratio (dp_w).² Each of these components can then be forecast separately to predict the conditional expected return $\mu_{w,s} = E_s(r_{w,s+1})$; that is

$$\hat{\mu}_{w,s} = \hat{\mu}_{w,s}^{\Delta pd} + \hat{g}_{w,s} + \hat{\mu}_{w,s}^{dp} \quad (3.28)$$

In line with Ferreira and Santa Clara, the global components are estimated as follows: (i) expected dividends growth, $\hat{g}_{w,s}$, is estimated using a 20-year moving average of growth in dividends up to time s ; (ii) the expected dividend-price ratio $\hat{\mu}_{w,s}^{dp}$ is estimated by the current dividend-price ratio, dp_s (the logarithm of one plus the current dividend-price ratio), and (iii) expected growth of the price dividend ratio $\hat{\mu}_{w,s}^{\Delta pd}$ is assumed to be zero.

Global components are proxied by US data extending from January 1966 to December 2014. The world market return is proxied by the Standard & Poor's (S&P) 500 index return including dividends, with dividend growth and the dividend-price ratio also referring to the S&P 500 In-

²The total return on the stock market index can be decomposed as:

$$1 + R_{t+1} = \frac{P_{t+1}}{P_t} + \frac{D_{t+1}}{P_t} = \frac{P_{t+1}/D_{t+1}}{P_t/D_t} \frac{D_{t+1}}{D_t} + \frac{D_{t+1}}{P_{t+1}} \frac{P_{t+1}}{P_t} = \frac{P_{t+1}/D_{t+1}}{P_t/D_t} \frac{D_{t+1}}{D_t} \left(1 + \frac{D_{t+1}}{P_{t+1}}\right)$$

Taking logs, $r_{t+1} = \ln(1 + R_{t+1}) = \Delta pd_{t+1} + \Delta d_{t+1} + dp_{t+1}$, where $\Delta pd_{t+1} = \ln\left(\frac{P_{t+1}/D_{t+1}}{P_t/D_t}\right)$, $\Delta d_{t+1} = \ln\left(\frac{D_{t+1}}{D_t}\right)$, and $dp_{t+1} = \ln\left(1 + \frac{D_{t+1}}{P_{t+1}}\right)$.

dex. Note that the forecast period starts in January 1987 because expected dividends growth is estimated using a 20-year moving average.

We need a forward looking measure of variance risk, and thus estimate expected country variance risk by forecasting the annual realized variance in country i in the spirit of Bekaert and Hoerova (2014) as follows:

$$RV_{i,t}^a = c + \beta_1 RV_{i,t-1}^a + \beta_2 RV_{i,t-1}^m + \beta_3 r_{i,t-1} + \beta_4 r_{us,t-1} + \epsilon_{i,t} \quad (3.29)$$

where $RV_{i,t-1}^a$ and $RV_{i,t-1}^m$ are local lagged annual and monthly realized variance and $r_{i,t-1}$ and $r_{us,t-1}$ represent lagged local and foreign equity returns. Realized variances are constructed based on daily data, and calculated from squared daily returns over 22 days for the monthly frequency and over 264 days for the annual frequency. For Argentina, we use the MSCI index in dollars, while realized variance in the US is based on the S&P500.

Openness variables fall into two categories: economic and financial integration. In the simplified version of the model, cash flows simply follow an AR(1), so we focus on the financial indicator. To measure financial openness, we use a capital account openness index compiled by [Fernandez, Klein, Rebucci, Schindler, and Uribe \(2016\)](#) based on a coding of the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) narrative description. The categories are broken down such that 1 represents the presence of a restriction and 0 represents no restrictions. The aggregate index, S_ka , considers transaction level regulations for 10 types of investment (among them, equities, bonds, money market instruments, and derivatives). In this paper, we use one minus the index, such that higher scores indicate less restrictions in place/more openness. The dataset's coverage is from 1995 to 2015, but we extend it back to 1980 as in [Bekaert, Harvey, Kiguel, and Wang \(2016\)](#).³

³The Schindler measure starts in 1995, however, it can be extended back to 1980 using other *de jure* measure to predict what the value would have been. We use the *de jure* current and capital account measures compiled by [Quinn and Toyoda \(2008\)](#), QT_Cur100 and QT_Cap100 , and the Chinn and Ito (2008) capital account measure, CI_KA_Open , to predict the Schindler indicators from 1980 to 1994. We estimate the value based on the following panel regressions:

$$S_ka = \alpha + \beta_1 CI_KA_Open + \beta_2 QT_Cur100 + \beta_3 QT_Cap100$$

3.4 CASE STUDY: ARGENTINA 2011

Argentina is a great example of the importance of incorporating time-varying integration into financial models. While long-term average integration is 0.45, this measure has fluctuated considerably over different political regimes. Markets were fairly segmented between 1980 and 1991, with average integration at 0.4; and then, with the adoption of the Convertibility Plan under President Menem, along with other market-friendly measures such as massive privatizations and deregulation of labor laws, financial integration increased to an average of 0.80 between 1992 and 2001. Later, following the default and the beginning of populist governments under the Kirchners, integration fell to an average of 0.26 between 2002 and 2015. In December 2015, market-friendly candidate Mauricio Macri was elected president, and worked hard to re-integrate Argentina to the world.

We use Argentina to illustrate a practical application of the framework outlined above by working with an example of market segmentation in 2011. As capital outflows increased significantly in 2011, Cristina Kirchner's government implemented the *Cepo Cambiario*, a set of capital controls in the exchange rate market intended to stem the capital flight. In October 2011, right after Kirchner was re-elected as president, the federal tax agency, Administración Federal de Ingresos Públicos (AFIP), unexpectedly announced that it would begin to regulate who could purchase foreign currency and how many dollars they could buy (both at the individual and corporate level). The measures gradually became tighter over time as dollars became scarcer and international reserves continued to fall, and lasted until Macri took office in December 2015. Figure 3.1a shows the monthly net foreign asset formation by the non-financial private sector, where negative (positive) numbers indicate foreign asset purchases (sales). Here we can see that official foreign asset purchases increased greatly throughout 2011, and then suddenly halted with the implementation of the restrictions. Foreign asset purchases remained low until Macri announced the end of the *cepo* five days after starting his presidency (December 15, 2015), seen in the sudden spike down in December 2015. It is worth noting that, in this period, most dollar purchases took place in the parallel exchange rate market, where the gap between the official exchange rate and the parallel rate averaged 46%, peaking at 100% in 2013. This gap closed as soon as the end of the *cepo* was announced (Figure 3.1b). We focus on this example for the remainder of the paper.

While *de facto* financial integration measures are able to capture trends in financial integration over time, these measures are annual and miss the exact timing of the changes in integration when studying data at a monthly level. This is especially relevant here, since we focus on a segmentation shock in October 2011 and follow this one-year out in our case study. We use a modified version Schindler’s financial integration measure in this analysis (see Data section for details on the original measure). The idea is to use the *cepo* chronology to pinpoint the timing of the deterioration in financial integration more accurately. This way, rather than saying capital controls were imposed in 2011 and linearly interpolating the annual data to obtain a monthly series, we can identify exactly when the initial shock took place and how the restrictions gradually became tighter. For example, in the original restrictions implemented in October 2011, individuals could theoretically convert up to 40% of their salary from pesos to foreign currency, while in May 2012 this number was officially reduced to 25% (although it is true that in practice the limits were more obscure and at the government’s discretion). On the corporate side, when the *cepo* first started, firms were allowed to buy up to USD500mn daily without authorization from the Central Bank (BCRA), and this limit fell to USD50mn over time.

3.5 CALIBRATION

3.5.1 Parameters

Ideally, we would like to estimate the pricing model in one step. However, it turns out that the estimation is too sensitive and the model easily explodes given all the parameters. Thus, to analyze the effects of financial integration, we work with the simplified model specified in Proposition 2 and calibrate our practical application of the framework. We calibrate the parameters to loosely target the coefficients of the following regression: (1) we regress realized returns on global returns and variance risk to estimate the time-varying coefficients that will be used in the discount rate equation, and (2) we run AR(1) regressions for each state variable to estimate their evolution. We then use these parameters to calibrate the pricing equation.

To calibrate the discount rate in equation 3.23, we first estimate the time-varying coefficients that will be used discount rates equation by using realized returns data ($r_{i,t+1}^e$) for Argentina; specifically we run the following regression:

$$r_{i,t+1}^e = \theta_t + \beta_t r_{w,t+1}^e + \lambda_t E_t(VR_{i,t+1}) + \varepsilon_{i,t+1}^r. \quad (3.30)$$

where $r_{w,t+1}^e$ is the U.S. equity market return in excess of the risk-free rate, $E_t(VR_{i,t+1})$ represents expected country variance risk, and the coefficients vary over time with financial integration ($x_t = x_0 + x_1 FI_{i,t}$ for $x_t = \{\theta_{i,t}, \beta_{i,t}, \lambda_{i,t}\}$ and $FI_{i,t}$ financial integration). The right hand side variables are demeaned so that the constant (θ_0) approaches mean returns, in line with α_2 in equation 3.26 in Proposition 2. The sample ranges from January 1995 to December 2014. Note that the constant is not exactly equal to mean returns given that we include quadratic terms in the regression, but it is much closer than with level variables. Theoretically, expected returns should fall as markets become more integrated (thus we would expect $\theta_1 < 0$), local returns should move positively with global returns ($\beta_0 > 0$), and expected variance risk (which can be thought of as a risk aversion indicator) should also vary positively with expected returns ($\lambda_0 > 0$). The regression yields the expected signs for financial integration and global expected returns (with $\theta_0 = -0.35$ and $\beta_0 = 1.46$), but not for expected variance risk, which yields a negative coefficient. For this case, we use a coefficient of 1.1 instead. With respect to the interaction terms, local expected returns should load more on global factors when integration increases (thus $\beta_1 > 0$), but greater integration should decrease the exposure to local risks ($\lambda_1 < 0$). While the regression targets the right sign for variance risk ($\lambda_1 = -1.9$), we find the wrong sign for global expected returns and thus base the calibration on the upper bound of the 95% confidence interval ($\beta_1 = 0.24$). The calibration coefficients are summarized in Panel A of Table 3.2.

Next, we estimate the evolution of the state variables as in equation 3.22, assuming all state variables follow an autoregressive process with homoscedastic innovations (all errors are independent, zero mean, with variance sigma) and are demeaned such that there are no constant terms in the calibration (i.e. $\tilde{X}_t \equiv X_t - \bar{X}$). Note, however, that mean cash flows are captured by α_1 in equation 3.26. We base our calibration coefficients of Φ and Σ on these regressions (Table 3.2, Panel B). We tone down the persistence of cash flow growth (to 0.02 from 0.2, in line with the coefficient we would get if we extend the sample through December 2018), and financial integration (to 0.75 from 0.86, within the confidence interval) to improve the fit the data at the time of the shock. Also recall that σ_{gd} is modified, such that the variance is a weighted average of GDP growth and cash

flow growth (to 0.005).

Finally, in the third stage, we calibrate the dividend yields using Proposition 2, along with the parameters estimated in the first two steps. To complete this exercise, we still need to specify the mean parameters, α_1 and α_2 . It is worth noting that when mean expected cash flows are greater than mean expected returns, the system will not converge. In emerging economies, it is often the case the cash flow growth is very high and volatile. Thus, we adjust mean cash flow growth (α_1 in the calibration) such that it mean reverts to GDP growth in cases where historical dividend growth is very high, as dividends cannot grow so much faster than GDP indefinitely.⁴ In the Argentina example, we proxy long term GDP growth with average GDP between 1990 and 2018, which reached 2.9%. The weighted average of this and the mean cash flow growth of 12% in our sample result in $\alpha_1 = 3.5\%$. Meanwhile, we assume that the long term discount rate can be proxied by the sum of the expected global discount rate (6.6%) and the expected long-term country risk (we assume this is around 500bp based on the average EMBI, excluding the default period).

3.5.2 Results

We start by measuring how sensitive the dividend yield in the model is to different values of financial integration, leaving all else equal. For illustrative purposes, we calibrate the dividend yield at the time of the shock (October 2011), using the parameters specified above. At this point in time (which we will refer to as t_0), the financial integration measure was at 0.18, suggesting markets were already fairly segmented, even relative to the country's own history. Table 3.3 shows we are to match the dividend yields quite well (6.79 actual, 6.74 calibrated). We then study what happens to the dividend yield if we use the long-term mean of financial integration (0.45), the 5th

⁴We run the following regression to estimate the weight that should be used on mean GDP:

$$(\Delta d_{i,t+1} - cycle_{i,t+1}) = \phi(\Delta d_{i,t} - cycle_{i,t}) + \epsilon_{i,t+1},$$

and thus,

$$E[\Delta d_{i,t+1}] = (1 - \phi)\overline{cycle}_{i,t} + \phi\overline{\Delta d}_{i,t}.$$

We estimate this for a panel of Latin American countries, to have a sense of potential long-term dividend growth. The empirical results yield $\phi = 0.06$, which tells us to put 94% weight on GDP growth and 6% weight on dividend growth. The weighted average of these time series gives us a proxy for long-term dividend growth in the region. I make this same adjustment to σ_{gd} :

$$var[\Delta d_{i,t+1}] = (1 - \phi)^2 var(cycle_{i,t}) + \phi^2 var(\Delta d_{i,t}) + 2\phi(1 - \phi)cov(cycle_{i,t}, \Delta d_{i,t}),$$

This value replaces the variance of cash flow growth in the calibration.

percentile (0.01) and the 95th percentile (0.91). We find that dividend yields decrease to 4.98 from 6.78 when financial integration increases to 0.45 from 0.18. The more extreme values of financial integration bring dividend yields to 8.10 and 2.93 in the 5th and 95th percentiles, respectively. While these ranges are wide and the model is able to generate meaningful changes in dividend yields, we acknowledge that it is not capable of replicating the full range of dividend yields we see in the data, suggesting that changes in the level financial integration are not the only factor behind changes in dividend yields.

Next, we study symmetric changes in financial integration with respect to the sample mean (0.2). Here, we consider increases and decreases in financial integration of 0.1 and 0.2 versus the mean. We run this analysis for two cases: (i) the full model with the quadratic Gaussian structure, and (ii) a model where betas are constant over time, as described in Section 3.1 (i.e. there is no quadratic). The bottom panel of Table 3.3 shows these results. Here we can see that dividend yields evaluated at mean financial integration increase by 1.12bp when the quadratic term is included in the model. We can also see that including the quadratic term drags dividend yields in the wrong direction; that is, including a quadratic term leads to higher dividend yields with respect to an affine model as integration increases, and decreases the ratio when integration decreases. With respect to the magnitudes, we actually find that segmentation shocks decrease discount rates more than integration shocks increase them. This can be seen as dividend yields increase by 4.14bp and 7.00bp as deviations in financial integration from the mean increase from 0 to 0.1 and 0.2, respectively, but decrease by 3.57bp and 8.00bp as integration increases by 0.1 and 0.2, respectively. This is likely associated with the relative importance of the interaction terms in our calibration. That said, these results show that the quadratic effects are second order, with the majority of the change in dividend yields coming from the linear terms.

We next focus on our most relevant calibration exercise. We use the calibration at the time the *cepo* started, look through the integration shock and calibrate the dividend yields a year later. Essentially, we want to see how the change in financial integration affects pricing, i.e. is the reaction more consistent with a permanent or temporary shock to financial integration? If investors expect financial integration to increase in the future, as Cristina Kirchner is unlikely to govern forever, then the shock should be temporary in nature and this would be captured by the mean-reverting nature of our model. This should also give us a sense of whether magnitudes of the changes in

Table 3.3 are meaningful enough. However, if investors perceive the shock as permanent, then it will not be captured by the model as they are essentially pricing a change in the mean.

In this analysis, we first run the model with the initial t_0 calibration parameters to see how well the system fits a temporary shock, assuming only a decrease in financial integration. If the model specified above (which assumes stationarity) is correct, then we should see the variables mean revert to the unconditional mean (i.e. the shock is temporary) and this should be enough to, at least partially, fit the dividend yields. The columns "Temporary - FI" and "Permanent - FI" of Table 3.4 show how dividend yield change when financial integration falls to 0.07 from 0.18 over one year, all else equal. The model alone is able to capture an 86bp increase in dividend yields to 7.60 from 6.74; however, it is true that this falls quite a bit short of the actual 7.1pp rise in dividend yields (to 13.9 from 6.79). Thus, we consider a scenario where investors expect a more permanent change in financial integration, i.e. a change in the mean (or a time-varying drift), which is not captured by the model, to improve the dividend yield fit. Note that as we are working with demeaned variables, this requires adjusting α_2 by $\theta_0 + \theta_1 \overline{FI}_i + \lambda_1 E(\overline{RV}_i)$, in addition to changing the mean which is subtracted from the variable at time t . By assuming that mean financial integration falls from 0.22 to 0.12 after the shock, we are able to generate a change in the discount rate large enough to match the increase in dividend yields (13.8 model, 13.9 actual). This suggests that investors consider this change in financial integration as permanent. It is true that the discount rate associated with this move is quite large (it increases from 11.5% to 18%); however, we note it is an upper bound to the rate, as all other variables remain constant.

Next, we allow cash flow growth to change as well to see if that helps us get closer to actual dividend yields. Including this change only helps us explain another 14bp of the change in dividend yields (the calibrated value increases to 7.74 from 7.60 with only financial integration, column five). That said, if we also allow expected variance risk to change, then we do get a more meaningful change in dividend yields, which increase another 75bp to 8.51. In this case, we are able to match the actual dividend yields (13.9) by assuming that financial integration falls from 0.22 to 0.141 (discount rates increase to 16.7%). This still suggests that investors consider the segmentation shock to be relatively permanent, as financial integration reverts to a much lower level. That said, there are likely other factors which help capture the change in dividend yields, which are not included in the simplified version of this model (e.g. political risk and variables which

capture the economic cycle).

3.6 CONCLUSION

Most would agree that the degree of financial market integration changes over time, especially in emerging economies which are faced with shocks. However, nearly all previous research has either assumed that markets only go from segmentation to integration, or has analyzed time-varying betas in the returns space. In this paper, we provide a framework which allows for time-varying integration in a present value model. Argentina is a great example where integration follows a mean-reverting process, justifying modeling it as an AR(1) process rather than a jump process. In this article, we focus on the discount rate channel to study the relative importance of the direct effect of an integration shock versus the indirect effects through the interaction terms of integration with risk factors. Using a case study based on a segmentation shock in Argentina in 2011, we find that the model is able to generate meaningful changes in dividend yields, and the direct effect of the shock is dominant in valuations while the quadratic terms play a smaller role.

It is true that with these factors, we are not able to fully capture the change in dividend yields. However, the model could be extended to incorporate other factors in order to improve the results. For example, in addition to financial integration, political risk likely has a significant roll in explaining the time-variation in the coefficients and the two variables complement one another. It could be incorporated into the model by adding a second interaction term, where local discount rates load more on global discount rates and less on local expected variance risk when political risk is perceived to fall, and would thus be another state variable in the system. We could also incorporate the analysis of time-varying integration on cash flows. Through this channel, factors related to the economic cycle would impact the pricing equation. We leave this for future research.

Another interesting issue which stems from this analysis is related to valuation measures. Traditionally it has been argued that price-dividend ratios may be a better measure of valuations in short samples, as they tend to be more stable than returns. However, this may not necessarily be the case in emerging markets. We have found that cash flow growth is actually fairly noisy. In fact, in developed markets, most analysis is based on dividends yields which are smoothed over many years. Given the shorter samples we have to work with in emerging economies, we would lose

many observations if we were to take this approach. Thus, while it is true that returns are very noisy, it is not clear that dividend yields are the best metric for valuing emerging market assets.

Table 3.1: Argentina 2011-2105 Capital Controls Timeline

The table presents a timeline of the exchange rate controls imposed in Argentina between 2011 and 2015, known as the *cepo cambiario*. The controls gradually became tighter over time as dollars became scarcer, thus we build a measure based on the number of restrictions imposed each month. The dates below correspond to the implementation date of a measure; if the control is implemented on a date different from the announcement date, then announcement date is in parenthesis. [La Nación \(2015\)](#), [Cronista \(2015\)](#), [Infobae \(2015\)](#)

Date	Description
Oct 31, 2011 (Oct 28)	The Central Bank of the Republic of Argentina (BCRA) announced the <i>Program for Exchange Rate Operation Consultations</i> (Communication A5329), i.e. the beginning of the <i>cepo cambiario</i> . Under this program, the federal tax agency (Administración Federal de Ingresos Públicos, AFIP) must authorize individuals and corporates to buy foreign exchange (Resolution 3210/11). In theory, individuals could convert up to 40% of their salary to foreign currency, but in practice the limits were more obscure and at the government's discretion.
Dec 13, 2011	The BCRA announced that banks must give 10 days notice to buy dollars for clients.
Feb 1, 2012 (Jan 5)	The AFIP created the <i>Declaración Juridica Anticipada de Importación</i> (DJAI) with Resolution 3252, meaning that importers must now declare what goods they import, along with quantities and prices.
Feb 9, 2012	Corporates need the BCRA's approval to transfer dollars abroad, either to pay for imports or transfer profits. The main novelty here was in dividend payments, which especially affected multilateral corporations.
Apr 3, 2012 (Mar 9)	The BCRA established that cash withdrawals made with local debit cards from ATMs abroad could only be done from hard currency accounts going forward (Communication A5294). No limits were imposed on how much could be taken out. Individuals could no longer travel abroad and draw USD from ARS accounts.
May 9, 2012	The AFIP reduced the limit on foreign currency purchases by individuals to 25% of their salary from 40%.
May 28, 2012 (May 23)	<ul style="list-style-type: none"> - The BCRA eliminated exceptions from Communication A5249 and extends restrictions to mortgages (Communication A5309). Those with access to financing to buy properties now need permission from the AFIP to buy USD with the ARS provided by the bank. - The AFIP implemented restrictions on dollars for tourism (Resolution 3333). This was aimed at closing loopholes from individuals buying tourist packages from travel agents, who had unlimited access to the official exchange rate.

Jun 13, 2012	The AFIP eliminated invoices in foreign currency, which especially affected big agricultural companies and importers
Jun 15, 2012	<ul style="list-style-type: none"> - The AFIP eliminated the possibility of buying USD for savings purposes (this was implemented by the AFIP in June, but the BCRA officially banned it on July 5 in Communication A5318). Authorities limited the purchase of USD to: travel abroad, real estate/some mortgages/some types of rent, to pay for merchandise purchased abroad with a credit card, some services, companies authorized to transfer profits and dividends, and donations to organizations and the government. - The BCRA prohibits banks from buying USD bonds locally and paying them out offshore (since 2005, they were allowed to transfer 1% of their equity)
Jul 2012	Authorities limit foreign exchange transaction to money in bank accounts.
Aug 8, 2012	Foreign currency may only be purchased up to 7 days before travel and only in the currency of the destination country (e.g. when traveling to Uruguay, only Uruguayan pesos can be purchased; you can no longer buy USD).
Aug 21, 2012	Banks and credit cards can no longer accept pre-payment in USD.
Sep 1, 2012 (Aug 31)	The AFIP announced that all purchases abroad made with credit or debit cards, including online shopping and tourist packages, would now be subject to a 15% surcharge (Resolution 3378).
Sep 7, 2012	The BCRA bans banks and exchange houses from selling dollars at airports and ports. Only public banks can operate in these places going forward.
Oct 31, 2012 (Nov 1)	The BCRA bans the possibility of using ARS mortgages to buy USD.
Mar 15, 2013	Can no longer use local credit cards to buy casino chips abroad.
Mar 18, 2013	The AFIP announced that all purchases abroad made with credit or debit cards, including online shopping and tourist packages, would now be subject to a 20% surcharge
Dec 3, 2013	The AFIP increased the credit and debit card surcharges on purchases abroad to 35% from 20%.
Jan 22, 2014	Locals may only purchase goods two times a year online, up to USD25 per year. Purchases greater than USD25 will be subject to a 50% tax.
Jan 27, 2014	The limit on individual USD purchases decreased to 20% of the salary, up to a maximum of USD2000 monthly.
Oct 27, 2015	<ul style="list-style-type: none"> - The BCRA increased restrictions for companies: USD which they could purchase "semi-automatically" according to the DJAI fell USD75mn from USD150mn. - Authorities force insurance companies to sell USD bonds. - The <i>cepo</i> is tightened for travel agencies.

Table 3.2: Calibration parameters

Panel A of this table presents the calibration coefficients based on the country return regressions on US returns and expected local variance, with the following specification:

$$r_{i,t+1}^e = \theta_0 + \theta_1 FI_{i,t} + \beta_0 r_{us,t+1}^e + \beta_1 r_{us,t+1}^e FI_{i,t} + \delta_0 E_t(VR_{i,t+1}) + \delta_1 erv_{i,t} FI_{i,t} + \varepsilon_{i,t+1},$$

where $r_{us,t}^e$ is the U.S. equity market return in excess of the risk-free rate, $E_t(VR_{i,t+1})$ represents expected country variance risk, $FI_{i,t}$ is financial integration. The sample ranges from January 1995 to December 2014. Panel b of this table presents the calibration parameters based on the first order autoregressive coefficients and the variances for the state variables during our sample period.

$$X_{t+1} = \phi X_t + \sigma_x \varepsilon_{t+1},$$

where X is each demeaned state variables: μ_{us} , expected U.S. discount rates; r_{us}^f , the risk-free rate; g_i local cash flow growth; FI_i , financial integration in country i ; and $E_t(VR_{i,t+1})$ represents expected country variance risk. The sample ranges from June 2005 to December 2014. Given the overlapping observations, we correct the standard errors with [Newey and West \(1986\)](#).

Panel A: Discount Rate parameters			
θ_0	0.115	θ_1	-0.35
β_0	1.46	β_1	0.24
λ_0	1.1	θ_1	-1.9
Panel B: Autoregressive parameters			
ϕ_μ	0.47	σ_μ^2	0.0001
ϕ_{rf}	0.77	σ_{rf}^2	0.0002
ϕ_d	0.02	σ_d^2	0.005
ϕ_{fi}	0.75	σ_{fi}^2	0.009
ϕ_{evr}	-0.17	σ_{evr}^2	0.003

Table 3.3: Dividend yields under different values of financial integration

This table presents the calibrated dividend yields under different values of financial integration (actual dividend yields were 6.79 in October 2011). We look at financial integration at the time of the segmentation shock, at the long term average, and the 5th and 95th percentiles. We also study deviations from the sample mean by looking at 0.1 and 0.2 increases and decreases in financial integration to understand the implications of symmetric shocks. The column labeled "with quad" refers to the full model with quadratic Gaussian terms, while the column labeled "no quad" assumes the betas are constant over time, as described in Section 2.1. Dividend yields are presented in percentage points, while changes in dividends yields (quadratic - no quadratic) are reported in basis points.

	FI	DY (with quad)	DY (no quad)	change (bp)
$FI_{t=0}$	0.18	6.74	6.75	
FI_{LTmean}	0.45	4.98	4.91	
FI_{p5}	0.01	8.10	8.19	
FI_{p95}	0.91	2.93	2.81	
$FI_{mean} + 0.2$	0.42	5.15	5.07	7.00
$FI_{mean} + 0.1$	0.32	5.75	5.71	4.14
FI_{mean}	0.22	6.43	6.42	1.12
$FI_{mean} - 0.1$	0.12	7.18	7.22	-3.57
$FI_{mean} - 0.2$	0.02	8.02	8.10	-9.12

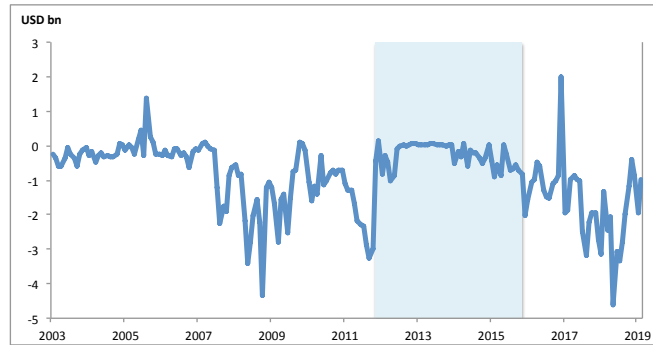
Table 3.4: The Cepo Shock: Permanent versus Temporary Changes in Financial Integration

This table presents the calibrated dividend yields at the time of the shock (October 2011), and then one year after the shock. The "temporary" columns assumes that that the change in financial integration is temporary and fades over time with the Φ parameters specified above. Meanwhile, the "permanent" columns refer to the case where the shock is perceived as permanent, leading to a change in mean financial integration. The columns labeled FI assume that only financial integration changes from the t_0 value to the t_1 value, those labeled FI, CF assume that both financial integration and cash flows change between periods, and FI, CF, ERV assume financial integration, cash flows and expected variance risk all change between periods.. Dividend yields are presented in percentage points.

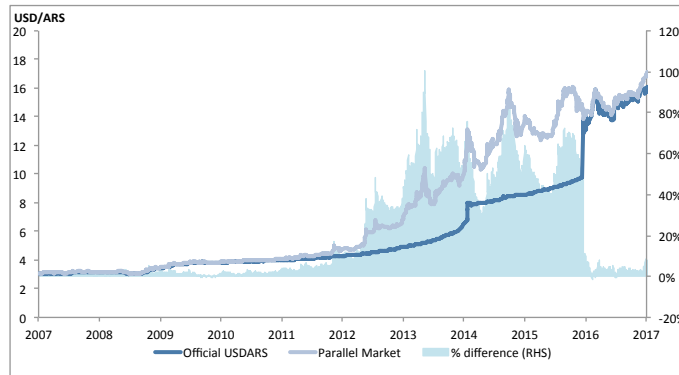
	Initial Shock	in 1 year					
		FI	Temporary FI, CF	Temporary FI, CF, ERV	FI	Permanent FI, CF	Permanent FI, CF, ERV
DY actual	6.79	13.9	13.9	13.9	13.9	13.9	13.9
DY fit	6.74	7.60	7.74	8.51	13.8	13.7	13.9
$FI_{i,t}$	0.18	0.07	0.07	0.07	0.07	0.07	0.07
\overline{FI}_i	0.22	0.22	0.22	0.22	0.12	0.125	0.141
α_1	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%	3.3%
α_2	11.5%	11.5%	11.5%	11.5%	18.1%	17.7%	16.7%

Figure 3.1: Capital Controls 2011

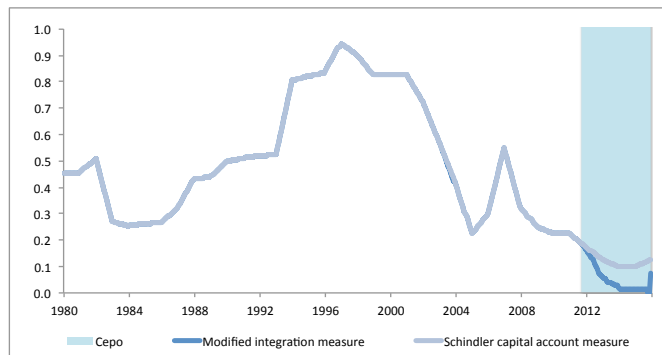
(a) Net foreign asset formation (non-financial private sector)



(b) Official versus parallel exchange rate



(c) Integration Measure



Bibliography

- Ait-Sahalia, Y., Karaman, M., and Mancini, L. (2019). The term structure of variance swaps and risk premia. *Journal of Econometrics*.
- Aizenman, J., Jinjark, Y., and Park, D. (2013). Capital flows and economic growth in the era of financial integration and crisis, 1990–2010. *Open Economies Review*, 24(3), 371–396.
- Aizenman, J., and Noy, I. (2009). Endogenous financial and trade openness. *Review of Development Economics*, 13(2), 175–189.
- Aloosh, A., and Bekaert, G. (2019). *Currency factors*. (NBER Working Paper No. 25449)
- Amiti, M., and Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. *The American Economic Review*, 97(5), 1611–1638.
- Ammer, J., and Mei, J. (1996). Measuring international economic linkages with stock market data. *The Journal of Finance*, 51(5), 1743–1763.
- Ang, A., and Bekaert, G. (2002). International asset allocation with regime shifts. *Review of Financial studies*, 15(4), 1137–1187.
- Ang, A., and Bekaert, G. (2007). Stock return predictability: Is it there? *Review of Financial studies*, 20(3), 651–707.
- Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance*, 61(1), 259–299.
- Ang, A., and Liu, J. (2004). How to discount cashflows with time-varying expected returns. *The Journal of Finance*, 59(6), 2745–2783.
- Bae, K.-H., Karolyi, G. A., and Stulz, R. M. (2003). A new approach to measuring financial conta-

- gion. *Review of Financial studies*, 16(3), 717–763.
- Baele, L. (2005). Volatility spillover effects in european equity markets. *Journal of Financial and Quantitative Analysis*, 40(02), 373–401.
- Baele, L., Bekaert, G., Cho, S., Inghelbrecht, K., and Moreno, A. (2015). Macroeconomic regimes. *Journal of Monetary Economics*, 70, 51–71.
- Baele, L., Bekaert, G., and Inghelbrecht, K. (2010). The determinants of stock and bond return comovements. *Review of Financial Studies*, 23(6), 2374–2428.
- Baele, L., Bekaert, G., and Schäfer, L. (2015). An anatomy of central and Eastern European equity markets. Available at SSRN 2636900.
- Baele, L., Ferrando, A., Hördahl, P., Krylova, E., and Monnet, C. (2004). Measuring European financial integration. *Oxford Review of Economic Policy*, 20(4), 509–530.
- Baele, L., and Inghelbrecht, K. (2009). Time-varying integration and international diversification strategies. *Journal of Empirical Finance*, 16(3), 368–387.
- Baele, L., and Inghelbrecht, K. (2010). Time-varying integration, interdependence and contagion. *Journal of International Money and Finance*, 29(5), 791–818.
- Baele, L., and Soriano, P. (2010). The determinants of increasing equity market comovement: economic or financial integration? *Review of World Economics*, 146(3), 573–589.
- Bansal, R., and Dahlquist, M. (2000). The forward premium puzzle: different tales from developed and emerging economies. *Journal of international Economics*, 51(1), 115–144.
- Baxter, M., and Crucini, M. J. (1995). Business cycles and the asset structure of foreign trade. *International Economic Review*, 36(4), 821–854.
- Beine, M., Cosma, A., and Vermeulen, R. (2010). The dark side of global integration: Increasing tail dependence. *Journal of Banking and Finance*, 34(1), 184–192.
- Bekaert, G. (1995). Market integration and investment barriers in emerging equity markets. *The World Bank Economic Review*, 9(1), 75–107.
- Bekaert, G., Ehrmann, M., Fratzscher, M., and Mehl, A. (2014a). The global crisis and equity market contagion. *The Journal of Finance*, 69(6), 2597–2649.
- Bekaert, G., Ehrmann, M., Fratzscher, M., and Mehl, A. (2014b). The global crisis and equity market contagion. *Journal of Finance*, 69(6), 2597–2649.
- Bekaert, G., and Harvey, C. R. (1995). Time-varying world market integration. *The Journal of*

- Finance*, 50(2), 403–444.
- Bekaert, G., and Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics*, 43(1), 29–77.
- Bekaert, G., and Harvey, C. R. (2000). Foreign speculators and emerging equity markets. *The Journal of Finance*, 55(2), 565–613.
- Bekaert, G., and Harvey, C. R. (2003). Emerging markets finance. *Journal of Empirical Finance*, 10(1), 3–55.
- Bekaert, G., Harvey, C. R., Kiguel, A., and Wang, X. (2016). Globalization and asset returns. *Annual Review of Financial Economics*, 8, 221–288.
- Bekaert, G., Harvey, C. R., and Lumsdaine, R. L. (2002). Dating the integration of world equity markets. *Journal of Financial Economics*, 65(2), 203–247.
- Bekaert, G., Harvey, C. R., and Lundblad, C. (2005). Does financial liberalization spur growth? *Journal of Financial Economics*, 77(1), 3–55.
- Bekaert, G., Harvey, C. R., and Lundblad, C. (2006). Growth volatility and financial liberalization. *Journal of International Money and Finance*, 25(3), 370–403.
- Bekaert, G., Harvey, C. R., and Lundblad, C. (2011). Financial openness and productivity. *World Development*, 39(1), 1–19.
- Bekaert, G., Harvey, C. R., Lundblad, C., and Siegel, S. (2007). Global growth opportunities and market integration. *The Journal of Finance*, 62(3), 1081–1137.
- Bekaert, G., Harvey, C. R., Lundblad, C. T., and Siegel, S. (2011). What segments equity markets? *Review of Financial Studies*, 24(12), 3841–3890.
- Bekaert, G., Harvey, C. R., Lundblad, C. T., and Siegel, S. (2013). The European Union, the Euro, and equity market integration. *Journal of Financial Economics*, 109(3), 583–603.
- Bekaert, G., Harvey, C. R., Lundblad, C. T., and Siegel, S. (2014). Political risk spreads. *Journal of International Business Studies*, 45(4), 471–493.
- Bekaert, G., Harvey, C. R., Lundblad, C. T., and Siegel, S. (2016). Political risk and international valuation. *Journal of Corporate Finance*, 37, 1–23.
- Bekaert, G., Harvey, C. R., and Ng, A. (2005). Market integration and contagion. *Journal of Business*, 78(1), 39–69.
- Bekaert, G., and Hodrick, R. J. (1992). Characterizing predictable components in excess returns on

- equity and foreign exchange markets. *The Journal of Finance*, 47(2), 467–509.
- Bekaert, G., Hodrick, R. J., and Zhang, X. (2009a). International stock return comovements. *The Journal of Finance*, 64(6), 2591–2626.
- Bekaert, G., Hodrick, R. J., and Zhang, X. (2009b). International stock return comovements. *The Journal of Finance*, 64(6), 2591–2626.
- Bekaert, G., Hodrick, R. J., and Zhang, X. (2012). Aggregate idiosyncratic volatility. *Journal of Financial and Quantitative Analysis*, 47(06), 1155–1185.
- Bekaert, G., and Liu, J. (2004). Conditioning information and variance bounds on pricing kernels. *Review of Financial Studies*, 17(2), 339–378.
- Bekaert, G., and Popov, A. A. (2016). Consumption volatility and trade openness. *Working Paper*.
- Bekaert, G., and Wang, X. S. (2009). Globalization and asset prices. *Available at SSRN 1480463*.
- Bollerslev, T., Tauchen, G., and Zhou, H. (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies*, 22(11), 4463–4492.
- Bonfiglioli, A. (2008). Financial integration, productivity and capital accumulation. *Journal of International Economics*, 76(2), 337–355.
- Borio, C. E., and Filardo, A. J. (2007). Globalisation and inflation: New cross-country evidence on the global determinants of domestic inflation. *BIS working paper*.
- Boyer, B. H., Gibson, M. S., and Loretan, M. (1999). Pitfalls in tests for changes in correlations. *Federal Reserve Board IFS Discussion Paper*, 597(1).
- Breedon, F., Henry, B., and Williams, G. (1999). Long-term real interest rates: evidence on the global capital market. *Oxford Review of Economic Policy*, 128–142.
- Brooks, R., and Del Negro, M. (2004). The rise in comovement across national stock markets: Market integration or IT bubble? *Journal of Empirical Finance*, 11(5), 659–680.
- Bruno, V., and Shin, H. S. (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, 71, 119–132.
- Bunzel, H., and Vogelsang, T. J. (2005). Powerful trend function tests that are robust to strong serial correlation, with an application to the prebisch–singer hypothesis. *Journal of Business and Economic Statistics*, 23(4), 381–394.
- Campa, J. M., and Fernandes, N. (2006). Sources of gains from international portfolio diversification. *Journal of Empirical Finance*, 13(4), 417–443.

- Campbell, J. Y., Giglio, S., Polk, C., and Turley, R. (2018). An intertemporal capm with stochastic volatility. *Journal of Financial Economics*, 128(2), 207–233.
- Campbell, J. Y., and Hamao, Y. (1992). Predictable stock returns in the United States and Japan: A study of long-term capital market integration. *The Journal of Finance*, 47(1), 43–69.
- Carrieri, F., Chaieb, I., and Errunza, V. (2013). Do implicit barriers matter for globalization? *Review of Financial Studies*, 26(7), 1694–1739.
- Carrieri, F., Errunza, V., and Hogan, K. (2007). Characterizing world market integration through time. *Journal of Financial and Quantitative Analysis*, 42(04), 915–940.
- Cavaglia, S., Brightman, C., and Aked, M. (2000). The increasing importance of industry factors. *Financial Analysts Journal*, 56(5), 41–54.
- Chen, N., Imbs, J., and Scott, A. (2009). The dynamics of trade and competition. *Journal of International Economics*, 77(1), 50–62.
- Chen, N., and Zhang, F. (1997). Correlations, trades and stock returns of the pacific-basin markets. *Pacific-Basin Finance Journal*, 5(5), 559–577.
- Chinn, M. D., and Ito, H. (2008). A new measure of financial openness. *Journal of comparative policy analysis*, 10(3), 309–322.
- Christiansen, C., Rinaldo, A., and Söderlind, P. (2011). The time-varying systematic risk of carry trade strategies. *Journal of Financial and Quantitative Analysis*, 46(4), 1107–1125.
- Christoffersen, P., Errunza, V., Jacobs, K., and Langlois, H. (2012). Is the potential for international diversification disappearing? a dynamic copula approach. *Review of Financial Studies*, 25(12), 3711–3751.
- Cox, W. M. (2007). Globalization, aggregate productivity, and inflation. *Staff Papers Federal Reserve Bank of Dallas*, March(1).
- Cremers, M., Halling, M., and Weinbaum, D. (2015). Aggregate jump and volatility risk in the cross-section of stock returns. *Journal of Finance*, 70(2), 577–614.
- Cronista. (2015). *Cronología: los hechos clave que le dieron forma al cepo cambiario*. <https://www.cronista.com/economiapolitica/Cronologia-los-hechos-clave-que-le-dieron-forma-al-cepo-cambiario-20161026-0120.html>.
- De Jong, F., and de Roon, F. A. (2005). Time-varying market integration and expected returns in emerging markets. *Journal of Financial Economics*, 78(3), 583–613.

- Dew-Becker, I., Giglio, S., Le, A., and Rodriguez, M. (2017). The price of variance risk. *Journal of Financial Economics*, 123(2), 225–250.
- Di Giovanni, J., and Levchenko, A. A. (2009). Trade openness and volatility. *The Review of Economics and Statistics*, 91(3), 558–585.
- Drechsler, I., and Yaron, A. (2011). What’s vol got to do with it. *The Review of Financial Studies*, 24(1), 1–45.
- Dumas, B., Harvey, C. R., and Ruiz, P. (2003). Are correlations of stock returns justified by subsequent changes in national outputs? *Journal of International Money and Finance*, 22(6), 777–811.
- Edison, H. J., and Warnock, F. E. (2003). A simple measure of the intensity of capital controls. *Journal of Empirical Finance*, 10(1), 81–103.
- Eichengreen, B. (2001). Capital account liberalization: What do cross-country studies tell us? *The World Bank Economic Review*, 15(3), 341–365.
- Eiling, E., and Gerard, B. (2015). Emerging equity market comovements: trends and macroeconomic fundamentals. *Review of Finance*, 19(4), 1543–1585.
- Eiling, E., Gerard, B., Hillion, P., and de Roon, F. A. (2012). International portfolio diversification: Currency, industry and country effects revisited. *Journal of International Money and Finance*, 31(5), 1249–1278.
- Erb, C. B., Harvey, C. R., and Viskanta, T. E. (1994). Forecasting international equity correlations. *Financial analysts journal*, 50(6), 32–45.
- Eun, C. S., and Lee, J. (2010). Mean–variance convergence around the world. *Journal of Banking and Finance*, 34(4), 856–870.
- Exchange, C. B. O. (2009). The cboe volatility index-vix. *White Paper*, 1–23.
- Fama, E. F., and French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of financial economics*, 105(3), 457–472.
- Fernández, A., Klein, M. W., Rebucci, A., Schindler, M., and Uribe, M. (2015). *Capital control measures: A new dataset* (Tech. Rep.). National Bureau of Economic Research.
- Fernandez, A., Klein, M. W., Rebucci, A., Schindler, M., and Uribe, M. (2016). Capital control measures: A new dataset. *IMF Economic Review*, 64(3), 548–574.
- Ferreira, M. A., and Gama, P. M. (2005). Have world, country, and industry risks changed over time? an investigation of the volatility of developed stock markets. *Journal of Financial and*

Quantitative Analysis, 40(1), 195–222.

- Ferreira, M. A., and Santa-Clara, P. (2011). Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, 100(3), 514–537.
- Foerster, S. R., and Karolyi, G. A. (1999). The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States. *The Journal of Finance*, 54(3), 981–1013.
- Forbes, K. J., and Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, 57(5), 2223–2261.
- Frankel, J. A. (1989). International financial integration, relations among exchange rates and interest rates, and monetary indicators. In C. Pigott (Ed.), *International financial integration and the conduct of U.S. monetary policy* (pp. 17–49). Federal Reserve Bank of New York.
- Fratzscher, M. (2002). Financial market integration in europe: on the effects of emu on stock markets. *International Journal of Finance and Economics*, 7(3), 165–193.
- Gagnon, J. E., and Unferth, M. D. (1995). Is there a world real interest rate? *Journal of international Money and Finance*, 14(6), 845–855.
- Gibbons, M. R., Ross, S. A., and Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121–1152.
- Goldberg, L. G., Lothian, J. R., and Okunev, J. (2003). Has international financial integration increased? *Open Economies Review*, 14(3), 299–317.
- Gourinchas, P.-O., and Jeanne, O. (2006). The elusive gains from international financial integration. *The Review of Economic Studies*, 73(3), 715–741.
- Griffin, J. M. (2002). Are the fama and french factors global or country specific? *Review of Financial Studies*, 15(3), 783–803.
- Gupta, N., and Yuan, K. (2009). On the growth effect of stock market liberalizations. *Review of Financial Studies*, 22(11), 4715–4752.
- Han Kim, E., and Singal, V. (2000). Stock market openings: Experience of emerging economies. *The Journal of Business*, 73(1), 25–66.
- Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4), 1029–1054.
- Hardouvelis, G. A., Malliaropoulos, D., and Priestley, R. (2004). The impact of globalization on

- the equity cost of capital. *CEPR Discussion Paper No. 4346*.
- Harrison, A., and Hanson, G. (1999). Who gains from trade reform? some remaining puzzles. *Journal of development Economics*, 59(1), 125–154.
- Harvey, C. R. (1991). The world price of covariance risk. *The Journal of Finance*, 46(1), 111–157.
- Harvey, C. R. (1995). The risk exposure of emerging equity markets. *The World Bank Economic Review*, 9(1), 19–50.
- Harvey, C. R., Liu, Y., and Zhu, H. (2016). ...and the cross-section of expected returns. *Review of Financial Studies*, 29(1), 5–68.
- Henry, P. B. (2000). Stock market liberalization, economic reform, and emerging market equity prices. *The Journal of Finance*, 55(2), 529–564.
- Heston, S. L., and Rouwenhorst, K. G. (1994). Does industrial structure explain the benefits of international diversification? *Journal of Financial Economics*, 36(1), 3–27.
- Hou, K., Karolyi, G. A., and Kho, B.-C. (2011a). What factors drive global stock returns? *Review of Financial Studies*, 24(8), 2527–2574.
- Hou, K., Karolyi, G. A., and Kho, B.-C. (2011b). What factors drive global stock returns? *Review of Financial Studies*, 24(8), 2527–2574.
- Imbs, J. (2004). Trade, finance, specialization, and synchronization. *Review of Economics and Statistics*, 86(3), 723–734.
- Infobae. (2015). *Paso a paso: cómo fueron los cuatro años de cepo cambiario*. <https://www.infobae.com/2015/12/16/1776957-paso-paso-como-fueron-los-cuatro-anos-cepo-cambiario/>.
- Jappelli, T., and Pagano, M. (2008). Financial market integration under EMU.
- Jeanne, O., Subramanian, A., and Williamson, J. (2012). *Who needs to open the capital account*. Peterson Institute.
- Jorion, P. (1996). Does real interest parity hold at longer maturities? *Journal of International Economics*, 40(1), 105–126.
- Jurek, J. W., and Stafford, E. (2015). The cost of capital for alternative investments. *Journal of Finance*, 70(5), 2185–2226.
- Kalemli-Ozcan, S., Papaioannou, E., and Peydró, J.-L. (2013). Financial regulation, financial globalization, and the synchronization of economic activity. *The Journal of Finance*, 68(3), 1179–

1228.

- Karolyi, G. A. (2003). Does international financial contagion really exist? *International Finance*, 6(2), 179–199.
- Karolyi, G. A. (2015). *Cracking the emerging markets enigma*. Oxford University Press, USA.
- Karolyi, G. A., and Stulz, R. M. (2003). Are financial assets priced locally or globally? *Handbook of the Economics of Finance*, 1, 975–1020.
- Kim, E. H., and Singal, V. (2000). Stock market openings: Experience of emerging economies*. *The Journal of Business*, 73(1), 25–66.
- King, M., Sentana, E., and Wadhvani, S. (1994). Volatility and links between national stock markets. *Econometrica: Journal of the Econometric Society*, 901–933.
- Kose, M. A., Otrok, C., and Prasad, E. S. (2008). Global business cycles: convergence or decoupling? *National Bureau of Economic Research*.
- Kose, M. A., Prasad, E., Rogoff, K., and Wei, S.-J. (2009). Financial globalization: A reappraisal. *IMF Staff Papers*, 8–62.
- Kose, M. A., Prasad, E. S., and Taylor, A. D. (2011). Thresholds in the process of international financial integration. *Journal of International Money and Finance*, 30(1), 147–179.
- Kose, M. A., Prasad, E. S., and Terrones, M. E. (2006). How do trade and financial integration affect the relationship between growth and volatility? *Journal of international Economics*, 69(1), 176–202.
- Kose, M. A., Prasad, E. S., and Terrones, M. E. (2009). Does financial globalization promote risk sharing? *Journal of Development Economics*, 89(2), 258–270.
- La Nación. (2015). *Cepo cambiario: cronología de estos cuatro años de restricciones*. <https://www.lanacion.com.ar/economia/cepo-cambiario-cronologia-de-estos-cuatro-anos-de-restricciones-nid1854739>.
- Lane, P. R. (1997). Inflation in open economies. *Journal of International Economics*, 42(3), 327–347.
- Lane, P. R., and Milesi-Ferretti, G. M. (2007). The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004. *Journal of international Economics*, 73(2), 223–250.
- Levy Yeyati, E., and Williams, T. (2012). Emerging economies in the 2000s: Real decoupling and financial recoupling. *Journal of International Money and Finance*, 31(8), 2102–2126.

- Longin, F., and Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990? *Journal of international money and finance*, 14(1), 3–26.
- Lustig, H., and Richmond, R. J. (2017). *Gravity in fx r-squared: Understanding the factor structure in exchange rates*. (NBER Working Paper No. 23773)
- Lustig, H., Roussanov, N., and Verdelhan, A. (2014). Countercyclical currency risk premia. *Journal of Financial Economics*, 111(3), 527–553.
- Martell, R., and Stulz, R. M. (2003). Equity-market liberalizations as country ipo's. *American Economic Review*, 93(2), 97–101.
- Martin, I. (2013). *Simple variance swaps* (Tech. Rep.). National Bureau of Economic Research.
- Martin, I. (2017). What is the expected return on the market? *The Quarterly Journal of Economics*, 132(1), 367–433.
- McConnell, M. M., and Perez-Quiros, G. (2000). Output fluctuations in the united states: What has changed since the early 1980's? *American Economic Review*, 90(5), 1464–1476.
- Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of financial economics*, 8(4), 323–361.
- Newey, W. K., and West, K. D. (1986). *A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix*. National Bureau of Economic Research Cambridge, Mass., USA.
- Ng, A. (2000). Volatility spillover effects from japan and the us to the pacific-basin. *Journal of International Money and Finance*, 19(2), 207–233.
- Nishiotis, G. P. (2004). Do indirect investment barriers contribute to capital market segmentation? *Journal of Financial and Quantitative Analysis*, 39(03), 613–630.
- Obstfeld, M. (1994). Risk-taking, global diversification, and growth. *American Economic Review*, 84(5), 1310–1329.
- Petzev, I., Schrimpf, A., and Wagner, A. F. (2016). Has the pricing of stocks become more global?
- Phylaktis, K. (1997). Capital market integration in the pacific-basin region: An analysis of real interest rate linkages. *Pacific-Basin Finance Journal*, 5(2), 195–213.
- Phylaktis, K., and Xia, L. (2006). Sources of firms' industry and country effects in emerging markets. *Journal of International Money and Finance*, 25(3), 459–475.
- Pukthuanthong, K., and Roll, R. (2009). Global market integration: An alternative measure and

- its application. *Journal of Financial Economics*, 94(2), 214–232.
- Quinn, D., and Toyoda, A. M. (2008). Does capital account liberalization lead to growth? *Review of Financial Studies*, 21(3), 1403–1449.
- Reinhart, C. M., and Rogoff, K. (2009). *This time is different: Eight centuries of financial folly*. Princeton University Press.
- Rey, H. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence. *National Bureau of Economic Research*.
- Rodriguez, F., and Rodrik, D. (2000). Trade policy and economic growth: a skeptic's guide to the cross-national evidence. *NBER macroeconomics annual*, 15(2000), 261–325.
- Rodrik, D. (1998). Why do more open economies have bigger governments? *Journal of Political Economy*, 106(5), 997–1032.
- Rogoff, K. (2003). Globalization and global disinflation. *Economic Review Federal Reserve Bank of Kansas City*, 88(4), 45.
- Sachs, J. D., and Warner, A. (1995). Economic reform and the process of global integration. *Brookings papers on economic activity*, 1995(1), 1–118.
- Schindler, M. (2009). Measuring financial integration: A new data set. *IMF Staff Papers*, 56(1).
- Stulz, R. M. (1999). Globalization, corporate finance, and the cost of capital. *Journal of applied corporate finance*, 12(3), 8–25.
- Stulz, R. M. (2005). The limits of financial globalization. *The Journal of Finance*, 60(4), 1595–1638.
- Topalova, P., and Khandelwal, A. (2011). Trade liberalization and firm productivity: The case of India. *Review of economics and statistics*, 93(3), 995–1009.
- Verdelhan, A. (2018). The share of systematic variation in bilateral exchange rates. *Journal of Finance*, 73(1), 375–418.
- Wacziarg, R., and Welch, K. H. (2008). Trade liberalization and growth: New evidence. *The World Bank Economic Review*, 22(2), 187–231.
- Xu, N. R. (2018). *Essays on risk appetite and uncertainty*. (Columbia University dissertation)

Appendix

APPENDIX FOR CHAPTER 1

Table A.1: Data Description

The following table describes the variables used in this paper. Note that all variables with a quarterly or annual frequency are turned into monthly variables using the weighted average of the quarterly or annual variable in the current quarter/year and last quarter/year. That is, in cases where there is only annual data, a variable, $X_{i,t}$ is calculated as follows,

$$X_{i,t} = \frac{12 - m}{12} X_{i,s-1,a} + \frac{m}{12} X_{i,s,a},$$

where $X_{i,s,a}$ is the variable in the current year, $X_{i,s-1,a}$ is the variable in the previous year, and m is the current month. Meanwhile, in cases where there is only quarterly data, $X_{i,t}$ is

$$X_{i,t} = \frac{3 - m}{3} X_{i,s-1,q} + \frac{m}{3} X_{i,s,q},$$

where $X_{i,s,q}$ is the variable in the current quarter, $X_{i,s-1,q}$ is the variable in the previous quarter, and m is the current month.

Variable	Description
----------	-------------

Local Financial Data:

continued

Table A.1 – *Continued*

Variable	Description
$r_{i,t}^e$	Local excess log equity returns are constructed using country-level stock market total returns indices in U.S. dollars. Returns are in excess of the one-month U.S. Treasury bill from Ibbotson Associates. Frequency: Monthly. Source: MSCI (and Datastream for Venezuela and Romania).
$r_{i,t}^b$	Local excess log bond returns are constructed using country-level bond market total returns indices in U.S. dollars. Returns are in excess of the one-month U.S. Treasury bill from Ibbotson Associates. In emerging markets, we use external debt indices, while in developed markets we use local currency bond indices. Frequency: Monthly. Source: JPMorgan Emerging Markets Bond Index (EMBI), Barclays Emerging Markets Aggregate Index, Citibank World Global Bond Index (WGBI).
$r_{i,t}^{fx}$	Local log excess currency returns are constructed using country-level spot rates and one-month forward rates (appreciation is positive): $r_{i,t+1}^s = i_{i,t} - i_{us,t} + \Delta s_{i,t+1} \approx s_{i,t+1} - f_{i,t}$. Frequency: Monthly. Source: Bloomberg.
$r_{i,t}^{e,LC}$	Local net log equity returns in local currency are constructed using country-level stock market total returns indices in local currency. Frequency: Monthly. Source: MSCI (and Datastream for Venezuela and Romania).
$r_{i,t}^{b,LC}$	Local net log bond returns in local currency are constructed using country-level bond market total returns indices in dollars and local log currency returns. Frequency: Monthly. Source: JPMorgan Emerging Markets Bond Index (EMBI), Barclays Emerging Markets Aggregate Index, Citibank World Global Bond Index (WGBI), International Financial Statistics, Bloomberg.
$i_{i,t}^S$	Nominal short-term interest rate in local currency (3-month Treasury bill, 3 month interbank rate or money market rate). Rates are annualized. Frequency: Monthly. Source: Global Financial Data, Datastream, International Financial Statistics.
$DY_{i,t}$	Dividend yield for country i . Frequency: Monthly. Source: Datastream.

continued

Table A.1 – *Continued*

Variable	Description
Global Financial Data:	
$r_{w,t}^e$	Global excess log equity returns are constructed as the GDP weighted average of G7 country-level stock market total returns indices in U.S. dollars. Returns are in excess of the one-month U.S. Treasury bill from Ibbotson Associates. Frequency: Monthly. Source: MSCI, International Financial Statistics.
$r_{w,t}^b$	Global excess log bond returns are constructed as the GDP weighted average of G7 country-level bond market total returns indices in U.S. dollars. Returns are in excess of the one-month U.S. Treasury bill from Ibbotson Associates. Frequency: Monthly. Source: Citibank World Global Bond Index (WGBI), International Financial Statistics.
$r_{w,t}^{fx}$	Global log excess currency returns are constructed as the GDP weighted average of G7 country-level excess currency returns (appreciation is positive). Note that for countries that adopted the Euro (Germany, France and Italy), we use the Deutsche Mark total returns before 1999 and subsequently the Euro. All currencies are based against the U.S. dollar so the currency basket has six currencies. Frequency: Monthly. Source: Bloomberg, International Financial Statistics.
$RV_{w,t}$	Global realized variance is constructed as the GDP weighted average of G7 country-level local realized variance. More specifically, we use daily log equity returns in U.S. dollars to calculate the local realized variance as
	$RV_{i,t+1} = \sum_{d=1}^{Ndays} \left(\ln \frac{P_{t+1,d}}{P_{t+1,d-1}} \right)^2 \left(\frac{22}{Ndays} \right),$
	where $Ndays$ represents the number of trading days in a month and $P_{t+1,d}$ is the value of the MSCI index on day d of month $t + 1$. Source: MSCI, International Financial Statistics.
<i>De jure</i> Integration Measures:	

continued

Table A.1 – *Continued*

Variable	Description
$FI_{i,t}^{Seq}$	Measure of equity market openness, compiled originally by Schindler (2009) and then extended by Fernández et al. (2015) , based on a coding of the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) narrative description. This index refers to restrictions on equity shares or other equity securities, excluding those investments for the purpose of acquiring a lasting economic interest. We use one minus the index, which is between zero and one, so that higher scores indicate less restrictions in place and thus more openness. The dataset’s coverage is from 1995 to 2013. We extend the index back to 1980 using other <i>de jure</i> measures to predict the value. ⁵ Frequency: Annual. Source: Fernández et al. (2015) , Quinn and Toyoda (2008) , Chinn and Ito (2008) .
$FI_{i,t}^{Sbo}$	Measure of bond market openness, compiled originally by Schindler (2009) and then extended by Fernández et al. (2015) , based on a coding of the IMF’s AREAER narrative description. Specifically, this index accounts for restrictions on bonds or other debt securities with an original maturity of more than one year. We use one minus the index, which is between zero and one, so that higher scores indicate less restrictions in place and thus more openness. The dataset’s coverage is from 1997 to 2013, therefore, we extend the index back to 1980 using other <i>de jure</i> measures to predict the value. ⁵ Frequency: Annual. Source: Fernández et al. (2015) , Quinn and Toyoda (2008) , Chinn and Ito (2008) .

continued

⁵ The Schindler et al (2015) measure starts in 1995 for equity and money markets and in 1997 for bond markets; therefore, we use the *de jure* measures compiled by Quinn and Toyoda (2008), QT_Cur100 and QT_Cap100, and Chinn and Ito (2008), CI_KA_Open, to predict the Schindler indicators from 1980 to 1994 (1996 for bonds). We predict the value based on the following panel regressions:

$$S_{i,t}^j = \alpha_{i,t} + \beta_1 CI_KA_Open_{i,t} + \beta_2 QT_Cur100_{i,t} + \beta_3 QT_Cap100_{i,t} + \varepsilon_{i,t}$$

for $j = \{eq, bo, mm\}$.

Table A.1 – *Continued*

Variable	Description
$FI_{i,t}^{Smm}$	Measure of money market openness, compiled originally by Schindler (2009) and then extended by Fernández et al. (2015) , based on a coding of the IMF’s AREAER narrative description. Specifically, this category refers to restrictions on money market instruments, which includes securities with an original maturity of one year or less, in addition to short-term instruments such as certificates of deposit, among others. We use one minus the index, which is between zero and one, so that higher scores indicate less restrictions in place and thus more openness. The dataset’s coverage is from 1995 to 2013. We extend the index back to 1980 using other <i>de jure</i> measures to predict the value. ⁵ Frequency: Annual. Source: Fernández et al. (2015) , Quinn and Toyoda (2008) , Chinn and Ito (2008) .
$FI_{i,t}^{QT}$	The Quinn and Toyoda (2008) capital account openness measure is a 0 to 4 indicator, in half integer units, with 4 representing an economy with fully open capital flows. It covers (a) restrictions on capital outflows by residents, and (b) restrictions on capital inflows by non-residents. The measure is rescaled from 0 to 1, with higher scores indicating greater openness. The data series ends in 2011, therefore we predict this data through 2014 using a regression with all ten Schindler capital account subcategories as explanatory variables (see Schindler et al (2015) for details on all ten categories). Frequency: Annual. Source: Quinn and Toyoda (2008) , Fernández et al. (2015) .

continued

Table A.1 – *Continued*

Variable	Description
$TI_{i,t}^{QT}$	The Quinn and Toyoda (2008) current account openness measure is a 0 to 8 indicator, with 8 indicating the government's full compliance with the IMF's Article VIII obligations to free the proceeds from international trade of goods and services from government restriction. It is the sum of two components: trade (exports and imports) and invisibles (payments and receipts for financial and other services)). The measure is rescaled from 0 to 1, with higher scores indicate greater openness. The data ends in 2011, therefore we predict this data through 2014 using a regression with trade openness, measured as exports plus imports over GDP, and the Schindler et al (2015) capital account measure as explanatory variables. Frequency: Annual. Source: Quinn and Toyoda (2008) , Fernández et al. (2015) , International Financial Statistics.
<i>De facto Integration Measures:</i>	
$TI_{i,t}^{df}$	Measure of <i>de facto</i> trade openness defined as exports plus imports divided by GDP. Frequency: Monthly. Source: International Financial Statistics.
$FI_{i,t}^{df,eq}$	This ratio is defined using Lane and Milesi-Ferretti's Net Foreign Assets database: Equity Assets + Liabilities / GDP. In this database, portfolio equities holdings measure ownership of shares of companies and mutual funds below the 10% threshold that distinguishes portfolio from direct investment. Frequency: Annual. Source: Lane and Milesi-Ferretti (2007)
$FI_{i,t}^{df,debt}$	This ratio is defined using Lane and Milesi-Ferretti's Net Foreign Assets database: Debt Assets + Liabilities / GDP. In this database, portfolio debt securities are defined to include both long and short-term debt, including money markets. We use this indicator for both bond and currency markets. Frequency: Annual. Source: Lane and Milesi-Ferretti (2007)
Other Variables:	

continued

Table A.1 – *Continued*

Variable	Description
$PR_{i,t}$	The political risk rating indicator for country i , which ranges between 0 (high risk) and 1 (low risk) Frequency: Monthly. Source: International Country Risk Guide.
$CorpGov_{i,t}$	This measure of quality of institutions is a combination of three subcomponents of the political risk indicator: corruption, bureaucracy, and law and order. This index was rescaled to range between 0 (high risk) and 1 (low risk) Frequency: Monthly. Source: International Country Risk Guide.
$Cycle_{i,t}$	This country-specific business cycle variables is calculated as the difference between current GDP growth and a moving average of past GDP. Year-over-year GDP growth is in real terms. Frequency: Quarterly (annual for countries where quarterly data is not available). Source: International Financial Statistics and OECD.
$Cycle_{w,t}$	This global business cycle variables is calculated as the GDP-weighted average of G7 country-specific business cycles (i.e. $Cycle_{i,t}$). GDP growth is in real terms. Frequency: Quarterly (annual for countries where quarterly data is not available). Source: International Financial Statistics and OECD.
$Crisis_{i,t}$	A measure by Reinhart and Rogoff which combines seven varieties of financial crises: banking crises, currency crashes, currency conversions/debasement, default on external debt, default on domestic debt, stock market crashes (if the country has a stock market), and high inflation. The crisis variable is the average of these seven components and takes values between 0 and 1. Frequency: Annual. Source: Reinhart and Rogoff (2009) .
$Cycle_{w,t}$	This global crisis variables is calculated as the GDP-weighted average of G7 country-specific crises variables (i.e. $Crisis_{i,t}$). GDP growth is in real terms. Frequency: Annual. Source: Reinhart and Rogoff (2009) .

Table A.2: Country Start Dates and Classifications

Country Label	ISO Code	Region	Equities	Bonds	FX
Argentina	AR	Emerging	1988m1	1994m1	1997m12
Austria	AT	Developed	1980m1	1992m11	
Australia	AU	Developed	1980m1	1985m1	1989m1
Belgium	BE	Developed	1980m1	1991m2	
Bulgaria	BG	Emerging		1997m2	
Brazil	BR	Emerging	1988m1	1994m1	1999m3
Canada	CA	Developed	1980m1	1985m1	1989m1
Switzerland	CH	Developed	1981m1	1985m1	1989m1
Chile	CL	Emerging	1988m1	1999m6	1998m5
China: Mainland	CN	Emerging	1993m1	1994m4	1999m1
Colombia	CO	Emerging	1993m1	1997m3	1999m3
Czech Republic	CZ	Developed	1995m2		1997m1
Germany	DE	Developed	1980m1	1985m1	
Denmark	DK	Developed	1980m1	1989m5	
Dominican Republic	DO	Emerging		2001m12	
Ecuador	EC	Emerging		1994m1	
Egypt	EG	Emerging	1995m1	2001m8	2009m3
Spain	ES	Developed	1980m1	1991m2	
Finland	FI	Developed	1988m1	1995m1	
France	FR	Developed	1980m1	1985m1	
United Kingdom	GB	Developed	1980m1	1985m1	1989m1
Greece	GR	Developed	1988m1	2000m5	
Hong Kong	HK	Developed	1980m1		1989m1
Hungary	HU	Emerging	1995m1	1999m2	1998m8
Indonesia	ID	Emerging	1988m1	1997m2	2004m3
Ireland	IE	Developed	1988m1	1992m11	
Israel	IL	Developed	1993m1		1998m8
India	IN	Emerging	1993m1	2004m6	1999m1
Italy	IT	Developed	1980m1	1985m2	
Japan	JP	Developed	1980m1	1985m1	1989m1
Korea, South	KR	Developed	1988m1		1999m1
Lebanon	LB	Emerging		2008m2	
Sri Lanka	LK	Emerging		2008m1	
Latvia	LV	Developed		2011m7	
Morocco	MA	Emerging	2002m2		2002m1
Mexico	MX	Emerging	1988m1	1994m1	1997m12
Malaysia	MY	Emerging	1988m1	1996m11	2005m5
Netherlands	NL	Developed	1981m2	1985m1	
Norway	NO	Developed	1980m1	1995m1	1989m1
New Zealand	NZ	Developed	1988m1	1992m11	1989m1
Panama	PA	Emerging		1994m1	
Peru	PE	Emerging	1993m1	1994m1	2000m8
Philippines	PH	Emerging	1988m1	1994m1	1999m1
Pakistan	PK	Emerging	1993m1	2004m5	
Poland	PL	Emerging	1993m1	1994m1	1998m8
Portugal	PT	Developed	1988m1	1995m1	
Romania	RO	Emerging	1997m1		2005m3
Russian Federation	RU	Emerging	1995m2	1997m2	2001m9
Sweden	SE	Developed	1980m1	1991m1	1989m1
Singapore	SG	Developed	1980m1		1989m1
El Salvador	SV	Emerging		2001m9	
Thailand	TH	Emerging	1988m1		1997m12
Turkey	TR	Emerging	1988m1	1996m7	1997m12
Ukraine	UA	Emerging		2008m2	
Uruguay	UY	Emerging		1997m2	
Venezuela, Republica Bolivariana de	VE	Emerging	1990m2	1994m1	
Vietnam	VN	Emerging		2005m12	2005m11
South Africa	ZA	Emerging	1993m1	1995m1	1997m12

Table A.3: Openness Measures Correlations

This table shows the correlations across correlations measures. Panel A calculates the correlation across variables over the whole panel, while Panel B calculates the correlation for each variable at the country level, and then takes the average across countries. Note that this second calculation excludes countries with no variation in a pair of variables from the average.

	TI^{QT}	FI^{QT}	FI^{Seq}	FI^{Sbo}	FI^{Smm}	PR	$Cycle$	$Crisis$	TI^{df}	$FI^{df,eq}$	$FI^{df,debt}$
<i>Panel A: Whole Sample</i>											
TI^{QT}	1.00										
FI^{QT}	0.84	1.00									
FI^{Seq}	0.68	0.80	1.00								
FI^{Sbo}	0.62	0.75	0.86	1.00							
FI^{Smm}	0.64	0.77	0.84	0.80	1.00						
PR	0.52	0.54	0.55	0.51	0.52	1.00					
$Cycle$	-0.06	-0.06	-0.02	-0.04	-0.04	-0.01	1.00				
$Crisis$	-0.28	-0.25	-0.18	-0.16	-0.10	-0.34	-0.13	1.00			
TI^{df}	0.23	0.21	0.17	0.10	0.14	0.17	-0.01	-0.17	1.00		
$FI^{df,eq}$	0.32	0.38	0.33	0.32	0.32	0.40	-0.00	-0.19	0.55	1.00	
$FI^{df,debt}$	0.37	0.44	0.39	0.36	0.39	0.32	-0.04	-0.10	0.65	0.70	1.00
<i>Panel B: Average Across Countries</i>											
TI^{QT}	1.00										
FI^{QT}	0.67	1.00									
FI^{Seq}	0.36	0.45	1.00								
FI^{Sbo}	0.32	0.42	0.64	1.00							
FI^{Smm}	0.46	0.48	0.63	0.56	1.00						
PR	0.12	0.14	0.13	0.11	0.15	1.00					
$Cycle$	-0.09	-0.11	-0.04	-0.07	-0.05	0.03	1.00				
$Crisis$	-0.16	-0.12	-0.07	-0.05	-0.02	-0.22	-0.22	1.00			
TI^{df}	0.23	0.26	0.12	0.08	0.20	0.10	0.04	-0.06	1.00		
$FI^{df,eq}$	0.40	0.45	0.20	0.25	0.27	0.20	0.00	-0.25	0.54	1.00	
$FI^{df,debt}$	0.09	0.22	0.15	0.19	0.20	-0.08	-0.01	0.23	0.31	0.31	1.00

APPENDIX FOR CHAPTER 2

Table B.1: Countries and Assets

This Appendix lists the regional breakdown for the countries in the sample. For developed markets, the sample includes data for equities, bonds and currencies for all countries. In emerging markets, we do not have data on all asset classes for all countries, and we specify the breakdown.

Region	Developed Country (ISO Code)	Region	Emerging Country (ISO Code)	Equities	Bonds	FX
DM Commodities	Australia (AU)	Emerging Asia	China (CN)	X	X	X
	Canada (CA)		India (IN)	X		X
	New Zealand (NZ)		Indonesia (ID)	X		X
Developed Asia	Hong Kong (HK)		Malaysia (MY)	X	X	X
	Japan (JP)		Philippines (PH)	X	X	X
	Singapore (SG)		Pakistan (PK)	X	X	X
EU Euro	Austria (AT)		South Korea (KR)	X		X
	Belgium (BE)		Taiwan (TW)	X		
	Finland (FI)		Thailand (TH)	X		X
	France (FR)	Emerging EMEA	Bulgaria (BG)		X	
	Germany (DE)		Czech Republic (CZ)	X		X
	Greece (GR)		Cote d'Ivoire (CI)		X	
	Iceland (IE)		Croatia (HR)		X	
	Italy (IT)		Egypt (EG)	X	X	X
	Netherlands (NL)		Hungary (HU)	X	X	X
	Portugal (PT)		Israel (IL)	X		X
	Spain (ES)		Jordan (JO)	X		X
EU Non-Euro	Denmark (DK)		Lebanon (LB)		X	
	Norway (NO)		Morocco (MA)	X	X	X
	Sweden (SE)		Nigeria (NG)		X	
	Switzerland (CH)		Poland (PL)	X	X	X
	United Kingdom (GB)		Russia (RU)	X	X	X
			Turkey (TR)	X	X	X
			South Africa (ZA)	X	X	X
			Ukraine (UA)		X	
		Latin America	Argentina (AR)	X	X	X
			Brazil (BR)	X	X	X
			Chile (CL)	X	X	X
			Colombia (CO)	X	X	X
			Dominican Republic (DO)		X	
			Ecuador (EC)		X	
			El Salvador (SV)		X	
			Mexico (MX)	X	X	X
			Panama (PA)		X	
			Peru (PE)	X	X	X
		Uruguay (UY)		X		
		Venezuela (VE)		X		

A.2 Asymptotic Distribution of the Ratio Statistic

In order to calculate the importance of variance risk in the determination of expected returns, we examined the ratio of the required return from the variance risk factor to the total required return from the three-factor risk model. To examine standard errors for this statistic, we develop a GMM (Hansen (1982)) system of orthogonality conditions used in estimating the underlying parameters of the statistic which implies an asymptotic distribution of the underlying parameters. We then use the delta method to get the standard error of the ratio.

The orthogonality conditions underlying the estimation of the fundamental parameters form a just-identified system. These orthogonality conditions are the OLS orthogonality conditions from each of the regions and the estimation of the unconditional means of the regressors. Analytically, let ε_t be the vector of regression error terms associated with equation (2.2):

$$\varepsilon_t = r_t - \alpha - \beta_1 r_{US,t}^e - \beta_2 r_{US,t}^b - \beta_3 r_{US,t}^{vs},$$

where r_t is the vector of asset returns, $r_{i,t}$; α is the vector of constants, α_i ; β_1 is the vector of $\beta_{i,1}$'s; β_2 is the vector of $\beta_{i,2}$'s, and β_3 is the vector of $\beta_{i,3}$'s from the regional regressions. Also, let μ_1 , μ_2 , and μ_3 be the unconditional means of the three risk factors. Then, define the vector function of data and parameters

$$g_t(\alpha, \beta, \mu) = \begin{pmatrix} \varepsilon_t \\ \varepsilon_t \times r_{US,t}^e \\ \varepsilon_t \times r_{US,t}^b \\ \varepsilon_t \times r_{US,t}^{vs} \\ r_{US,t}^e - \mu_1 \\ r_{US,t}^b - \mu_2 \\ r_{US,t}^{vs} - \mu_3 \end{pmatrix},$$

and the orthogonality conditions are

$$E[g_t(\alpha, \beta, \mu)] = 0.$$

The proportion of the expected return that is attributable to exposure to the variance risk is a

non-linear function of the underlying β 's and μ 's. We calculate the standard errors of these proportions by applying the delta method. That is, if θ is the vector of parameters, if Ω is the usual GMM estimate of the asymptotic covariance matrix of the parameters that allows for conditional heteroskedasticity, and if $H(\theta)$ is the proportion of the expected return due to variance risk, then the standard error of the proportion is

$$\left(\frac{dH(\theta)^\top}{d\theta} \Omega \frac{dH(\theta)}{d\theta} \right)^{0.5}.$$

APPENDIX FOR CHAPTER 3

C1 Mapping Cash Flows and Expected Returns to State Variables

C1.1 Mapping Cash Flows and Expected Returns to X_t and ν_{t+1}

Assume $X_t^w = (g_{w,t} \mu_{w,t} r_{f,t})'$ and $X_t^i = (TI_{i,t} FI_{i,t} EVR_{i,t} LF_{i,t})'$, with $X_t = (X_{w,t}' X_{i,t}')'$. Let e_i be a vector of zeros with a 1 in the i^{th} place and let $\nu_{t+1} = [\varepsilon_{w,t+1}^d \varepsilon_{i,t+1}^d]'$, with $\nu_{i,t+1} \sim N(0, \Sigma_\nu)$.

Cash flows can then be mapped to X_t and ν_{t+1} :

$$\begin{aligned} \Delta d_{i,t+1} &= \kappa_{i,0} + \kappa_1 TI_{i,t} + \gamma_{i,0} g_{w,t} + \gamma_1 TI_{i,t} g_{w,t} + \varphi_{i,0} LF_{i,t} + \varphi_1 TI_{i,t} LF_{i,t} \\ &\quad + \gamma_{i,0} \varepsilon_{w,t+1}^d + \gamma_1 TI_{i,t} \varepsilon_{w,t+1}^d + \varepsilon_{i,t+1}^d \\ &= \kappa_{i,0} + (\kappa_1 e_4 + \gamma_{i,0} e_1 + \varphi_{i,0} e_7)' X_t + X_t' (\gamma_1 e_4 e_1' + \varphi_1 e_4 e_7') X_t \\ &\quad + (\gamma_{i,0} e_2 + e_1)' \nu_{t+1} + X_t' (\gamma_1 e_4 e_2') \nu_{i,t+1} \\ &= \alpha_1 + \xi_1' X_t + X_t' \Omega_1 X_t + \Gamma_1 \nu_{i,t+1} + X_t' \Lambda_1 \nu_{i,t+1} \end{aligned} \tag{C1}$$

where α_1 is a scalar, $\xi_1 = [\gamma_{i,0} \ 0 \ 0 \ \kappa_1 \ 0 \ 0 \ \varphi_{i,0}]'$ is a $K \times 1$ vector, Ω_1 is a $K \times K$ symmetric matrix given by

$$\Omega_1 = \begin{bmatrix} 0 & 0 & 0 & \gamma_1/2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_1/2 & 0 & 0 & 0 & 0 & 0 & \varphi_1/2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \varphi_1/2 & 0 & 0 & 0 \end{bmatrix}, \quad (C2)$$

$\Gamma_1 = [\gamma_{i,0} \ 1]'$ is a 2×1 vector, and Λ_1 is a $K \times 2$ matrix given by

$$\Lambda_1 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \gamma_1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}. \quad (C3)$$

Using the same notation, expected discount rates can be mapped to X_t :

$$\begin{aligned} \mu_{i,t} &= r_{f,t} + \theta_{i,0} + \theta_1 F I_{i,t} + \beta_{i,0} \mu_{w,t} + \beta_1 F I_{i,t} \mu_{w,t} + \lambda_{i,0} V R_{i,t} + \lambda_1 F I_{i,t} V R_{i,t} \\ &= \theta_{i,0} + (e_3 + \theta_1 e_5 + \beta_{i,0} e_2 + \lambda_{i,0} e_6)' X_t + X_t' (\beta_1 e_5 e_2' + \lambda_1 e_5 e_6') X_t \\ &= \alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t \end{aligned} \quad (C4)$$

where α_2 is a scalar, $\xi_2 = [0 \ \beta_{i,0} \ 1 \ 0 \ \theta_1 \ \lambda_{i,0} \ 0]'$ is a $K \times 1$ vector and Ω_2 is a $K \times K$ symmetric matrix

given by:

$$\Omega_2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta_1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \beta_1/2 & 0 & 0 & 0 & 0 & \lambda_1/2 \\ 0 & 0 & 0 & 0 & \lambda_1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (C5)$$

C1.2 Mapping Expected Returns to X_t in Simplified Model

Assume $X_t = (\mu_{w,t} \ r_{f,t} \ \Delta d_{i,t} \ FI_{i,t} \ EVR_{i,t})'$, and let e_i be a vector of zeros with a 1 in the i^{th} place. Expected discount rates can then be mapped to X_t :

$$\begin{aligned} \mu_{i,t} &= r_{f,t} + \theta_0 + \theta_1 FI_{i,t} + \beta_0 \mu_{w,t} + \beta_1 FI_{i,t} \mu_{w,t} + \lambda_0 VR_{i,t} + \lambda_1 FI_{i,t} VR_{i,t} \\ &= \theta_0 + (e_2 + \theta_1 e_4 + \beta_0 e_2 + \lambda_0 e_5)' X_t + X_t' (\beta_1 e_4 e_2' + \lambda_1 e_4 e_5') X_t \\ &= \alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t \end{aligned} \quad (C6)$$

where α_2 is a scalar, $\xi_2 = [\beta_0 \ 1 \ 0 \ \theta_1 \ \lambda_0]'$ is a $K \times 1$ vector and Ω_2 is a $K \times K$ symmetric matrix given by:

$$\Omega_2 = \begin{bmatrix} 0 & 0 & 0 & \beta_1/2 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ \beta_1/2 & 0 & 0 & 0 & \lambda_1/2 \\ 0 & 0 & 0 & \lambda_1/2 & 0 \end{bmatrix} \quad (C7)$$

C2 The Pricing Equation

The price-dividend ratio of country i under the framework outlined in Section 3.2 and imposing the transversality condition is

$$\frac{P_{i,t}}{D_{i,t}} = E_t \left[\sum_{n=1}^{\infty} \exp \left(\sum_{j=0}^{n-1} -\mu_{i,t+j} + \Delta d_{i,t+j+1} \right) \right]$$

Let $v_t(n) = E_t \left[\exp \left(\sum_{j=0}^{n-1} -\mu_{i,t+j} + \Delta d_{i,t+j+1} \right) \right]$, such that $\frac{P_{i,t}}{D_{i,t}} = \sum_{n=1}^{\infty} v_t(n)$. I conjecture

$$v_t(n) = \exp \left(a(n) + b(n)' X_t + X_t' H(n) X_t \right).$$

To solve this expectation, I use the following lemma to take the expectation of a quadratic Gaussian (proven in [Ang and Liu \(2004\)](#)). **Lemma:** let ϵ be a $K \times 1$ vector, where $\epsilon \sim N(0, \Sigma)$, A a $K \times 1$ vector and Ω a symmetric $K \times K$ matrix. If $(\Sigma^{-1} - 2\Omega)$ is strictly positive definite, then

$$E[\exp(A\epsilon + \epsilon'\Omega\epsilon)] = \exp \left(-\frac{1}{2} \ln \det(I - 2\Sigma\Omega) + \frac{1}{2} A'(\Sigma^{-1} - 2\Omega)^{-1} A \right)$$

Initial Conditions

For $n = 1$,

$$\begin{aligned} v_t(1) &= E_t [\exp(-\mu_t + \Delta d_{t+1})] \\ &= E_t \left[\exp \left(-(\alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t) + (\alpha_1 + \xi_1' X_t + X_t' \Omega_1 X_t + \Gamma_1' \nu_{i,t+1} + X_t' \Lambda_1 \nu_{i,t+1}) \right) \right] \\ &= \exp \left((\alpha_1 - \alpha_2) + (\xi_1 - \xi_2)' X_t + X_t' (\Omega_1 - \Omega_2) X_t \right) E_t \left[\exp \left(\Gamma_1' \nu_{i,t+1} + X_t' \Lambda_1 \nu_{i,t+1} \right) \right] \\ &= \exp \left((\alpha_1 - \alpha_2) + (\xi_1 - \xi_2)' X_t + X_t' (\Omega_1 - \Omega_2) X_t \right) \exp \left(\frac{1}{2} \Gamma_1' \Sigma_\nu \Gamma_1 + \Gamma_1' \Sigma_\nu \Lambda_1' X_t + \frac{1}{2} X_t' \Lambda_1 \Sigma_\nu \Lambda_1' X_t \right) \end{aligned}$$

Matching coefficients, the initial conditions are:

$$a(1) = \alpha_1 - \alpha_2 + \frac{1}{2} \Gamma_1' \Sigma_\nu \Gamma_1$$

$$b(1)' = (\xi_1 - \xi_2)' + \Gamma_1' \Sigma_\nu \Lambda_1'$$

$$H(1) = \Omega_1 - \Omega_2 + \frac{1}{2}\Lambda_1\Sigma_\nu\Lambda_1'$$

Recursive Conditions

Using induction for an arbitrary time $t+n+1$, it is possible to characterize the recursive equations describing $a(n)$, $b(n)$, and $H(n)$.

$$\begin{aligned} v_t(t+n+1) &= E_t \left\{ \exp \left(- \left(\alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t \right) + \left(\alpha_1 + \xi_1' X_t + X_t' \Omega_1 X_t + \Gamma_1' \nu_{i,t+1} + X_t' \Lambda_1 \nu_{i,t+1} \right) \right) \right. \\ &\quad \left. E_t \left[\exp \left(a(n) + b(n)' X_{t+1} + X_{t+1}' H(n) X_{t+1} \right) \right] \right\} \\ &= \exp \left(a(n) + \alpha_1 - \alpha_2 + (\xi_1 - \xi_2)' X_t + X_t' (\Omega_1 - \Omega_2) X_t \right) E_t \left\{ \exp \left(\Gamma_1' \nu_{i,t+1} + X_t' \Lambda_1 \nu_{i,t+1} \right) \right. \\ &\quad \left. \exp \left(b(n)' (c + \Phi X_t + \epsilon_{t+1}) + (c + \Phi X_t + \epsilon_{t+1})' H(n) (c + \Phi X_t + \epsilon_{t+1}) \right) \right\} \\ &= \exp \left(a(n) + \alpha_1 - \alpha_2 + (\xi_1 - \xi_2)' X_t + X_t' (\Omega_1 - \Omega_2) X_t + b(n)' (c + \Phi X_t) + (c + \Phi X_t)' H(n) (c + \Phi X_t) \right) \\ &\quad E_t \left\{ \exp \left((\Gamma_1 + \Lambda_1' X_t)' \nu_{i,t+1} \right) \exp \left(\left(b(n) + 2H(n)' (c + \Phi X_t) \right)' \epsilon_{t+1} + \epsilon_{t+1}' H(n) \epsilon_{t+1} \right) \right\} \end{aligned}$$

Taking this expectation involves using the assumption that ϵ_{t+1} and $\nu_{i,t+1}$ are independent and the lemma to take the expectation of a quadratic Gaussian on the ϵ_{t+1} terms:

$$\begin{aligned} &= \exp \left(a(n) + \alpha_1 - \alpha_2 + (\xi_1 - \xi_2)' X_t + X_t' (\Omega_1 - \Omega_2) X_t + b(n)' (c + \Phi X_t) + (c + \Phi X_t)' H(n) (c + \Phi X_t) \right) \\ &\quad \exp \left(\frac{1}{2} \Gamma_1' \Sigma_\nu \Gamma_1 + \Gamma_1' \Sigma_\nu \Lambda_1' X_t + \frac{1}{2} X_t' \Lambda_1 \Sigma_\nu \Lambda_1' X_t \right) \exp \left(- \frac{1}{2} \ln \det \left(I - 2 \Sigma H(n) \right) \right) \\ &\quad + \frac{1}{2} \left(b(n) + 2H(n)' (c + \Phi X_t) \right)' \left(\Sigma^{-1} - 2H(n) \right)^{-1} \left(b(n) + 2H(n)' (c + \Phi X_t) \right) \end{aligned}$$

$$\begin{aligned}
&= \exp\left(a(n) + \alpha_1 - \alpha_2 + \frac{1}{2}\Gamma_1'\Sigma_\nu\Gamma_1 + b(n)'c + c'H(n)c - \frac{1}{2}\ln \det(I - 2\Sigma H(n))\right) \\
&\quad + \frac{1}{2}\left(b(n) + 2H(n)'c\right)'(\Sigma^{-1} - 2H(n))^{-1}\left(b(n) + 2H(n)'c\right) \\
&\quad \exp\left((\xi_1 - \xi_2)'X_t + \Gamma_1'\Sigma_\nu\Lambda_1'X_t + b(n)'\Phi X_t + 2c'H(n)\Phi X_t\right) \\
&\quad + 2\left(b(n) + 2H(n)'c\right)'(\Sigma^{-1} - 2H(n))^{-1}\Phi X_t \\
&\quad \exp\left(X_t'(\Omega_1 - \Omega_2)X_t + \frac{1}{2}X_t'\Lambda_1\Sigma_\nu\Lambda_1'X_t + X_t'\Phi'H(n)\Phi X_t + X_t'\Phi'H(n)(\Sigma^{-1} - 2H(n))^{-1}H(n)'\Phi X_t\right)
\end{aligned}$$

Matching coefficients, I find that the coefficients $a(n)$, $b(n)$ and $H(n)$ are given by the recursions:

$$\begin{aligned}
a(n+1) &= a(n) + \alpha_1 - \alpha_2 + \frac{1}{2}\Gamma_1'\Sigma_\nu\Gamma_1 + b(n)'c + c'H(n)c - \frac{1}{2}\ln \det(I - 2\Sigma H(n)) \\
&\quad + \frac{1}{2}\left(b(n) + 2H(n)'c\right)'(\Sigma^{-1} - 2H(n))^{-1}\left(b(n) + 2H(n)'c\right) \\
b(n+1)' &= (\xi_1 - \xi_2)' + \Gamma_1'\Sigma_\nu\Lambda_1' + b(n)'\Phi + 2c'H(n)\Phi + 2\left(b(n) + 2H(n)'c\right)'(\Sigma^{-1} - 2H(n))^{-1}H(n)'\Phi \\
H(n+1) &= (\Omega_1 - \Omega_2) + \frac{1}{2}\Lambda_1\Sigma_\nu\Lambda_1' + \Phi'H(n)\Phi + 2\Phi'H(n)'(\Sigma^{-1} - 2H(n))^{-1}H(n)\Phi
\end{aligned}$$

Note on converged values of $\mathbf{a(n)}$, $\mathbf{b(n)}$, $\mathbf{H(n)}$

We calibrate the model with state variables represented as deviations from the mean (i.e. $\tilde{X}_t \equiv X_t - \bar{X}$), although we could have done the following adjustment to have everything in terms of X_t :

$$\begin{aligned}
P(n) &= a(n) + b(n)'\tilde{X}_t + \tilde{X}_t'H(n)\tilde{X}_t \\
&= a(n) + b(n)'(X_t - \bar{X}) + (X_t - \bar{X})'H(n)(X_t - \bar{X}) \\
&= \left(a(n) - b(n)\bar{X} + \bar{X}'H(n)\bar{X}\right) + \left(b(n)' - 2\bar{X}'H(n)\right)X_t + X_t'H(n)X_t
\end{aligned}$$

Also note that we assume c is simply a vector of zeros, as variables are demeaned.

C3 The Pricing Equation: Simplified Model

This model makes two simplifying assumptions: (1) we assume state variables are demeaned, such that $\tilde{X}_t = X_t - \bar{X}$, with $\tilde{X}_t = (\tilde{\mu}_{w,t} \tilde{r}_{f,t} \tilde{g}_{i,t} \tilde{F}I_{i,t} E_t(\tilde{V}R_{i,t+1}))$, and (2) expected log returns, $\mu_{i,t}$, follow a quadratic Gaussian structure given by

$$\mu_{i,t} = \alpha_2 + \xi_2' \tilde{X}_t + \tilde{X}_t' \Omega_2 \tilde{X}_t, \quad (\text{C8})$$

such that α_2 captures the mean local discount rate. In this simplified version of the model, cash flows do not follow a quadratic gaussian process, and are simply another state variable in the system.

Initial Conditions

For $n = 1$,

$$\begin{aligned} v_t(1) &= E_t [\exp(-\mu_t + \Delta d_{t+1})] \\ &= E_t \left[\exp(-(\alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t) + e_3' X_{t+1}) \right] \\ &= \exp\left(-\alpha_2 - \xi_2' X_t - X_t' \Omega_2 X_t\right) E_t \left[\exp\left(e_3'(c + \Phi \tilde{X}_t + \epsilon_{t+1})\right) \right] \\ &= \exp\left(-\alpha_2 + e_3' c + \frac{1}{2} e_3' \Sigma e_3 + (-\xi_2 + e_3' \Phi)' \tilde{X}_t - \tilde{X}_t' \Omega_2 \tilde{X}_t\right) \end{aligned}$$

Matching coefficients (and define $\alpha_1 = e_3' c$), the initial conditions are:

$$a(1) = \alpha_1 - \alpha_2 + \frac{1}{2} e_3' \Sigma e_3$$

$$b(1)' = -\xi_2' + e_3' \Phi'$$

$$H(1) = -\Omega_2$$

Recursive Conditions

Using induction for an arbitrary time $t+n+1$, it is possible to characterize the recursive equations describing $a(n)$, $b(n)$, and $H(n)$.

$$\begin{aligned}
v_t(t+n+1) &= E_t \left\{ \exp \left(-(\alpha_2 + \xi_2' X_t + X_t' \Omega_2 X_t) + e_3' X_{t+1} \right) \right. \\
&\quad \left. E_t \left[\exp \left(a(n) + b(n)' \tilde{X}_{t+1} + \tilde{X}_{t+1}' H(n) \tilde{X}_{t+1} \right) \right] \right\} \\
&= \exp \left(a(n) - \alpha_2 - \xi_2' \tilde{X}_t - \tilde{X}_t' \Omega_2 \tilde{X}_t + e_3' c + (e_3 + b(n))' \Phi \tilde{X}_t + \tilde{X}_t' \Phi' H(n) \Phi \tilde{X}_t \right) \\
&\quad E_t \left\{ \exp \left((e_3 + b(n))' \varepsilon_{t+1} + 2(\Phi \tilde{X}_t)' H(n) \varepsilon_{t+1} + \varepsilon_{t+1}' H(n) \varepsilon_{t+1} \right) \right\} \\
&= \exp \left(a(n) - \alpha_2 - \xi_2' \tilde{X}_t - \tilde{X}_t' \Omega_2 \tilde{X}_t + e_3' c + (e_3 + b(n))' \Phi \tilde{X}_t + \tilde{X}_t' \Phi' H(n) \Phi \tilde{X}_t \right) \\
&\quad \exp \left(-\frac{1}{2} \ln \left(\det(I - 2\Sigma H(n)) \right) \right) \\
&\quad + \frac{1}{2} \left(e_3 + b(n) + 2H(n)\Phi \right)' \left(\Sigma^{-1} - 2H(n) \right)^{-1} \left(e_3 + b(n) + 2H(n)\Phi \right)'
\end{aligned}$$

Matching coefficients, I find that the coefficients $a(n)$, $b(n)$ and $H(n)$ are given by the recursions:

$$\begin{aligned}
a(n+1) &= a(n) + \alpha_1 - \alpha_2 - \frac{1}{2} \ln \left(\det(I - 2\Sigma H(n)) \right) + \frac{1}{2} \left(e_3 + b(n) \right)' \left(\Sigma^{-1} - 2H(n) \right)^{-1} \left(e_3 + b(n) \right) \\
b(n+1) &= -\xi_2 + \Phi \left(e_3 + b(n) \right)' + 2\Phi H(n) \left(\Sigma^{-1} - 2H(n) \right)^{-1} \left(e_3 + b(n) \right) \\
H(n+1) &= -\Omega_2 + \Phi' H(n) \Phi + 2\Phi' H(n)' \left(\Sigma^{-1} - 2H(n) \right)^{-1} H(n) \Phi
\end{aligned}$$