The Risky Capital of Emerging Markets*

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Abstract

We use macroeconomic data to build a panel of international capital returns over a long horizon across both developed and developing countries. We document two facts: poor and emerging markets exhibit (1) high average returns to capital and (2) high betas on US returns. We quantitatively explore whether consumption-based risk faced by a US investor can reconcile these patterns. Long-run risks lead to return disparities at least 55% as large as those in the data. Fact (2), although not a sufficient statistic, is informative about the extent of long-run risk in foreign capital, and so about fact (1).

JEL Classification: O4, E22, F21, G12

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1 Introduction

A large body of work has investigated the returns to capital across countries, in particular, whether the cross-section of returns shows significant and systematic differences. In a seminal paper, Lucas (1990) uses the example of India and the United Sates to point out that the data reveal substantial dispersion in the marginal product of capital - one measure of capital returns - despite the fact that neoclassical growth theory predicts return equalization across countries, a fact deemed the 'Lucas Paradox.'[1] A common interpretation of this finding is that return differentials indicate the presence of market inefficiencies, or alternatively, untapped arbitrage opportunities, that lead to a misallocation of capital across countries. Lucas (1990) touched off at least two extensive strands of literature: the first points to various market frictions as hindering capital flows from low to high return countries and so preventing return equalization. However, identifying these forces and measuring their quantitative role has been difficult. A second branch revisits the measurement of returns. For example, in an influential study, Caselli and Feyrer (2007) find that, after a number of adjustments to the Lucas calculation, capital returns are approximately equalized in the year 1996, suggesting that there is in fact no puzzle. Thus, the existence and extent of return differentials and their root causes remain unresolved, with important implications for the efficiency of the world allocation of capital and the associated consequences for global economic performance.

In this paper, we make contributions to both of these strands of the literature. First, we use macroeconomic data to build a panel of international capital returns over a 60-year horizon (1950-2009) and across a sizable cross-section of countries (144), both developed and developing. Our measurement approach uses country-level capital stocks, GDP and prices to infer the marginal return to a US investor on an additional unit of capital invested abroad. We find that there is a good deal of variation in average (expected) returns across countries and that these disparities are systematically related to the level of income - poor and emerging markets tend to offer higher returns than do rich. For example, the difference in expected returns between the US and a set of the poorest countries is about 7 percentage points. These findings are robust to a number of variants on our baseline measurement approach, including different measures of relative prices and capital shares of national income. Further, differences in expected returns persist among countries with open capital accounts, where barriers to investment for international investors (e.g., capital market frictions) are presumably less of a concern, and also manifest themselves in directly observable returns on highly tradable assets such as stocks and sovereign bonds.

[1]The Lucas Paradox is often framed as a puzzle regarding capital flows, rather than rates of return. However, it is Lucas' finding of return differentials that indicates a puzzling lack of flows to equalize returns.

Do persistent differences in rates of return necessarily imply the existence of frictions or a breach of a no arbitrage condition in international capital markets? The answer to this question is affirmative only in the absence of investment risk. In the presence of uncertainty, international investors may face different levels of risk from investing in different locations. We put forward new empirical evidence that these risks are higher in emerging markets. In particular, we document a strong positive relationship between a country's expected return to capital and its exposure to a single common factor, namely, the return to US capital. Countries that offer high expected returns tend to have a high 'beta' on the US return. This is despite the fact that low-income countries tend to have lower correlations with US returns than do high income ones; the large degree of volatility in emerging markets compared to developed ones offsets the lower correlations and leads to higher levels of comovement in a beta (or covariance) sense. Thus, low-income countries tend to be precisely the ones that (1) offer higher expected returns and (2) exhibit a high degree of comovement with the US.[2]

Having established these empirical regularities, the second contribution of this paper is to explore a novel explanation for persistent differences in international capital returns - namely, the risk-return tradeoff implied by asset pricing theory. In particular, we investigate the role of long-run risks à la Bansal and Yaron (2004), i.e., risks due to persistent fluctuations in economic growth prospects. Our motivation for this approach is twofold: first, a recent literature, touched off by Aguiar and Gopinath (2007), has documented the importance of shocks to trend growth rates in accounting for the properties of business cycles in poor/emerging markets and in reconciling differences in the behavior of macroeconomic variables between these countries and developed ones. Second, long-run risks have been shown to have important implications for asset prices and have been able to resolve a number of 'puzzles' in the asset pricing literature. We explore the extent to which heterogeneity in risk arising from volatile and uncertain growth prospects can reconcile international rate of return differentials.[3]

Our point of departure is an international endowment economy along the lines of Colacito and Croce (2011), Colacito and Croce (2013), Lewis and Liu (2015) and Nakamura et al. (2012). A representative US investor is endowed with a stream of consumption and dividends, i.e., payouts from risky capital investments in a number of regions, and a risk-free asset.[4] Economic growth rates feature a small but persistent component, which manifests itself in both consumption growth and growth in dividend payments from invested capital. In each region,

[2]We show that both facts hold for returns on stocks and sovereign bonds.

[3]Two other leading approaches to address the asset-pricing puzzles are habits in utility (Campbell and Cochrane, 1999) and rare disasters (Barro, 2006; Gabaix, 2008). A model of rare disasters may be complementary to our approach. However, disentangling 'rare disasters' from 'normal' fluctuations is not straightforward in poor/emerging markets, which experience large amounts of volatility compared to developed ones.

[4]Relatedly, Lustig and Verdelhan (2007) and Borri and Verdelhan (2012) study the role of US consumption-based risk in international currency and sovereign bond markets.

this component contains both a common 'global' piece and a region-specific idiosyncratic one. Regions differ in their exposure to the common component. With recursive preferences à la Epstein and Zin (1989), asset values respond sharply to persistent shocks that are global in nature. Regions that are more sensitive to these shocks represent riskier investments and so must offer higher risk premia as compensation. Additionally, each region is exposed to both common and idiosyncratic transitory shocks (i.e., shocks that affect growth rates for only a single period), which may also lead to return differentials.

Quantifying the implications of long-run risks in our model is challenging for two reasons: first, we must disentangle common from idiosyncratic shocks. In our framework, the former command risk premia for the US investor whereas the latter do not. Second, even having identified common shocks, we must separate those that affect long-run growth prospects from those that are purely transitory in nature. We design an empirical strategy to overcome these hurdles based on the approach developed in Lewis and Liu (2015). We employ moments in both the persistence and comovement of dividend growth rates and additionally draw on a key prediction of the model that directly links a country's beta on the US return to its exposure to a common long-run shock - specifically, countries that are more sensitive to this shock will have a more volatile response of returns and so exhibit greater comovement with the US return - namely, a higher beta. We exploit this fact and use the comovement of returns - i.e., the betas we found in our empirical work - *relative* to the comovement in dividend growth to infer the degree of common long-run risk and quantify the implications for risk premia. Thus, although not a sufficient statistic, it is precisely fact (2) - the high return betas we find in emerging markets - that is informative about their exposure to shared long-run risks and so about fact (1) - their high average level of returns.

Applying this methodology to the cross-section of countries in our data, we find that long-run risks can account for a significant portion of the large observed return disparities and for the pattern of low income/high return vs high income/low return. In our benchmark specification, which features the US as well as three income-sorted portfolios of countries, the parameterized model accounts for 64% of the spread in the expected return to capital between the US and a portfolio of the poorest countries. We further disaggregate countries into bundles of five and ten portfolios, in which case the model implies return spreads between the US and the lowest income portfolio that are about 60% of their values in the data. At the finest level of granularity, we parameterize the model at the individual country level for a set of 96 countries for which sufficient time-series data are available. The correlation between the model's predicted returns and the actual is about 0.6, confirming the key role of long-run risk in driving return differentials. Moreover, at the country level, the model predicts a negative and statistically significant relationship between returns and income, where the slope of the regression line of the former on the latter amounts to 55% of that observed in the data.

Finally, to gain additional insights behind the risk-return relationship, we decompose predicted returns into their short- and long-run risk components. Our findings here are striking: risk premia stemming solely from short-run risk are actually higher in rich countries than poor and indeed are generally negative in the latter. Because period-by-period growth rates in foreign countries exhibit low comovement with US consumption growth, particularly so in poor countries, investments there actually serve as good hedges for short-run consumption growth risks - put another way, most of international diversification opportunities are with respect to short-run idiosyncratic risks. Hence, long-run risks seem critical to reconciling the high returns from capital investments in poor countries: these risks are systematically higher in poor countries and imply variation in returns across the income spectrum on par with the data. Thus, our findings suggest that long-run risks due to uncertain economic growth prospects are a promising avenue to account for what would appear to be puzzling return differentials and that the persistence of these disparities may not necessarily indicate a 'misallocation' of world capital.

The paper is organized as follows. In Section 2, we describe our data sources and document the key stylized facts. In Section 3, we lay out our quantitative analysis of a risk-based explanation of these facts. In Section 4, we conclude and discuss directions for future research. Details of data work, derivations and additional exercises are in the Appendix.

Related literature. Our paper relates to several branches of literature. The first focuses on measuring the returns to capital across countries using macroeconomic data, for example, Lucas (1990), Caselli and Feyrer (2007) and Hsieh and Klenow (2007).[5] We build on the empirical approaches suggested in these papers to compile a broad database of returns over a long horizon and large cross-section of countries, both developed and developing.

A related strand investigates the failure of return equalization and the implied lack of capital flows from low to high return countries (see Obstfeld and Taylor (2003), Prasad et al. (2007) and Reinhart and Reinhart (2008) for historical and recent patterns of capital flows across rich and poor countries). In a comprehensive empirical study, Alfaro et al. (2008) find that differences in institutional quality play an important role in hindering these flows. Ohanian and Wright (2007) evaluate a number of potential explanations with a focus on capital market frictions, but find the explanatory power of each to be limited, as none reverses the standard forces pushing for return equalization. Gourinchas and Jeanne (2013) document a lack of capital flows towards countries with higher productivity growth and investment and discuss

[5]The development literature also finds high rates of return to investment in low-income countries. See, for example, the comprehensive review in Banerjee and Duflo (2005).

a number of explanations, including domestic financial sector frictions, a mechanism explored in detail in Buera and Shin (2009). Reinhart and Rogoff (2004) point to the effects of serial default in developing countries and Kraay et al. (2005) to sovereign risk. Gourio et al. (2014) link capital flows to expropriation risk. Gourinchas and Rey (2013) offer a comprehensive survey of the theoretical and empirical literatures that examine cross-border capital flows. We depart from this line of work by focusing on the return differentials that are at the heart of the Lucas Paradox and through our quantitative investigation of consumption-based risk as one potentially important factor.

Our modeling of international long-run risks is closely related to Colacito and Croce (2011), Colacito and Croce (2013), Lewis and Liu (2015) and Nakamura et al. (2012). All of these papers find a significant role for shared long-run risk across countries. A key innovation in our analysis is to exploit our constructed dataset to analyze the implications for required returns to capital investments in both developed and emerging markets for a single US-based investor, with a particular emphasis on the implications of heterogenous exposure to common shocks. Our finding of more severe exposure to growth shocks in emerging markets relates our paper to Aguiar and Gopinath (2007), who demonstrate the important role of TFP growth rate volatility in driving observed aggregate dynamics in these countries. Relatedly, Naoussi and Tripier (2013) find that growth shocks play an even more important role in accounting for the behavior of macroeconomic variables in developing and Sub-Saharan African countries.

A broader literature demonstrates the importance of global shocks in driving asset prices and macroeconomic variables. Recent examples include Rey (2015) and Miranda-Agrippino and Rey (2014), who document a 'global financial cycle' in stock and corporate bond returns. Borri and Verdelhan (2012) relate excess returns on foreign sovereign bonds to their comovement with US bonds and Longstaff et al. (2011) find that global factors can account for the majority of sovereign credit spreads. Brusa et al. (2014) find that global currency factors are priced in international stock markets. Colacito et al. (2014) and Lustig et al. (2011) show that heterogenous exposure to global shocks is key in reconciling the cross-section of currency returns. Lustig and Verdelhan (2007) link currency risk premia to US consumption-based risk. Hassan (2013) provides an endogenous mechanism for heterogeneous exposures to global risk, namely, that currencies of large economies are good hedges against consumption risk and so offer lower returns. Closer to our own study, Hassan et al. (2016) link this mechanism to capital returns in a model with endogenous capital accumulation; large countries have lower required rates of return because they have 'safer' currencies. The authors find that country size variation can explain a good portion of cross-country return variation, but that the magnitudes of return differences fall short of those observed in the data.

Papers that focus on quantity dynamics include Kose et al. (2003), who provide evidence of a 'world business cycle.' Neumeyer and Perri (2005) and Uribe and Yue (2006) argue that US interest-rate shocks are of first-order importance in driving emerging market business cycles as they affect domestic variables mostly through their effects on country spreads. Burnside and Tabova (2009) find that about 70% of the cross-sectional variation in the volatility of GDP growth can be explained by countries' differing degrees of sensitivity to global factors and that low-income countries exhibit greater exposure to these factors.

2 The Returns to Capital: Stylized Facts

In this section, we describe our measure of the returns to capital and establish a number of empirical properties of returns - namely, systematic relationships between average returns and level of income across countries and between average returns and the beta on the US return.

2.1 Measuring Returns

We construct a broad panel of returns using macroeconomic data on capital, GDP and relative prices. Our measure builds on Caselli and Feyrer (2007) (CF), Hsieh and Klenow (2007), and Gomme et al. (2011), extended to include an explicit international dimension. This approach allows us to study a large set of countries, both developing and developed, over an extended period of time, which is not possible using data on directly observable asset returns. Additionally, the Lucas Paradox has typically been framed as a puzzle regarding the aggregate return to capital and we view tackling this particular measure as the main contribution of our work. For robustness, however, and to demonstrate the more general nature of our findings, we show below that the key stylized facts regarding the cross-section of returns hold true using data on stocks and sovereign bonds as well.

The world economy consists of the US and J regions, where regions will correspond to countries or bundles of countries in our empirical analysis. The economy consists of both consumption goods and investment goods. We consider a US-based investor who decides whether to pursue an additional capital investment, either at home or abroad. He would purchase a unit of the investment good domestically and invest it either in the US or in some other region. The additional unit of capital represents a claim on some portion of the local income it generates. The payment received by the investor is the rental rate on capital, which represents the period payoff, or 'dividend' from this investment. A portion of the capital depreciates and so the investor is left with only a fraction of the unit at the end of the period, which would continue to hold some value. The (gross) return from this transaction in region j is:

$$R_{j,t} = \frac{D_{j,t}}{P_{I,t}} + (1 - \delta_{j,t}) \frac{P_{I,t+1}}{P_{I,t}}$$

where $D_{j,t}$ denotes the period payoff to a unit of capital, or dividends, $P_{I,t}$ the price of the investment good (in terms of the US consumption good, which serves as numeraire), and $\delta_{j,t}$ the time t rate of depreciation in region j.[6] We assume that investment goods are freely tradable across regions while consumption goods are at least in part not. The law of one price then implies a common price for investment goods (hence, no region subscript). Because the price of consumption goods need not equate, the relative price $\frac{P_{I,t}}{P_{C,j,t}}$ may differ across regions. Although the assumption of freely traded capital goods is a clear simplification, it is motivated by the observation that relative price differences that are systematically related to income are largely driven by differences in the price of consumption goods, which tends to be higher in richer countries, whereas the price of investment goods shows no systematic relationship with income.[7] Our focus on a US-based investor stems in large part from the fact that many countries import a large share of their capital goods and that this is particularly the case in poor countries.[8] Moreover, the question we seek to answer is whether rate of return differentials necessarily point to an untapped arbitrage opportunity on the part of a single investor, and it seems a reasonable first pass to take the perspective of one based in the US.

As shown, for example, in CF, under the assumptions of constant returns to scale and competitive capital markets, the payout to a unit of capital is equal to the (price-adjusted) marginal product of capital:

$$D_{j,t} = \alpha \frac{P_{Y,j,t} Y_{j,t}}{K_{j,t}} \tag{1}$$

where α is the share of total income paid to capital and $P_{Y,j,t}Y_{j,t}$ is region j total income in terms of the numeraire good (US consumption). Putting the pieces together, the return on

[6] We will use country-time specific values of δ in our empirical implementation.

[7] Similar assumptions have been made in the literature, see, for example, the setup in Section I.A. in Hsieh and Klenow (2007). The authors point out that this fact is inconsistent with higher trade frictions in poor countries, but rather may stem from lower productivity of producing investment goods there. We will empirically explore variants of this approach that (1) take into account different levels of P_I across countries and (2) limit our analysis to countries classified as 'open' according to a number of measures so that trade frictions are presumably lower there. We show that our results do not depend on this assumption.

[8] For example, Burstein et al. (2013) document that 80% of the world's capital equipment was produced in just 8 countries in the year 2000; that the median import share of equipment in that year was about 0.75; and that the poorest countries in the world tend to import almost all their equipment. Mutreja et al. (2012) find similarly, and report a correlation between the import to production ratio for capital goods and income of -0.34 (they report, for example, that Malawi imports 39 times as much capital as it produces, and Argentina 19 times as much). Related facts are also in Eaton and Kortum (2001) and Kose (2002), who follow a similar approach in using US investment good prices to measure prices of imported capital goods in developing economies.

capital from region j in period t is given by,

$$R_{j,t} = \alpha \frac{P_{Y,j,t} Y_{j,t}}{P_{I,t} K_{j,t}} + (1 - \delta_{j,t}) \frac{P_{I,t+1}}{P_{I,t}} \tag{2}$$

which measures the marginal return to an additional unit of investment as the number of consumption goods received compared to the number given up.

To measure the quantities in equation (2) we use data from Version 8.0 of the Penn World Tables (PWT),[9] and to measure the relevant prices we rely on data from the US National Income and Product Accounts as reported by the Bureau of Economic Analysis (BEA). Our final sample consists of 144 countries over the period 1950-2009 (so returns are from 1950-2008).[10] For each country, the PWT directly reports real GDP valued at 2005 US dollars, which we will denote $P_{Y,US,2005} Y_{j,t}$, an estimate of the real-valued capital stock $K_{j,t}$ and country-time specific depreciation rates $\delta_{j,t}$. Recall that all prices in (2) are relative to US consumption, as that is the relevant tradeoff being made, and that relative prices may (and do) vary through time. To make this adjustment, we multiply the reported value of GDP by the relative price of output to consumption in the US, $\frac{P_{US,Y,t}}{P_{US,C,t}} = \frac{\frac{P_{US,Y,t}}{P_{US,Y,2005}}}{P_{US,C,t}}$ in each year t, where $P_{Y,US,2005}$ is normalized to 1. The result gives the value of year t GDP in region j in current units of US consumption, which is the object needed to measure $D_{j,t}$. The price index of US output $P_{US,Y,t}$ is constructed as nominal GDP divided by real GDP, with 2005 serving as the base year as noted. To construct the price index of consumption $P_{US,C,t}$, we divide nominal spending on non-durables and services by the corresponding real values. The ratio of these two series is then the relative price of interest. Data for these latter two computations are obtained from the BEA. It remains to specify a value for α, which we set to 0.3 across all regions following Gollin (2002), although with recent work by Karabarbounis and Neiman (2014) in mind, we explore the effects of using time-country specific α's below.

Finally, to compute returns, we need the relative price of investment goods in the US. We compute this price as nominal private spending on investment in equipment and structures divided by the corresponding real values, again with data obtained from the BEA. Our approach to measuring the relevant relative prices follows closely that of Gomme et al. (2011). From an empirical point of view, a beneficial by-product of our focus on a US investor is the ability to measure the relevant prices using a widely used data source thought to be highly reliable.

[9] See Feenstra et al. (2013) for detailed documentation.

[10] Countries need not be present for the entire period to be included. We describe the sample construction in Appendix A.

2.2 Stylized Facts

Figure 1 illustrates the main stylized facts across the full set of 144 countries in our sample. The left hand panel plots the mean (net) return to capital for each country over all available years for that country, denoted by r_j, where returns are computed year by year using expression (2), against the mean level of income over the same period, measured as (log) income per worker and denoted by y_j. The left-hand panel shows the first key fact: capital returns differ significantly around the world and despite a good deal of noise, there is a systematic relationship between returns and income - specifically, returns are generally higher in poorer countries. The relationship between returns and income is negative and highly significant, both in a statistical sense and an economic one: each 10% reduction in income is associated on average with a 1.8 percentage point increase in mean returns.

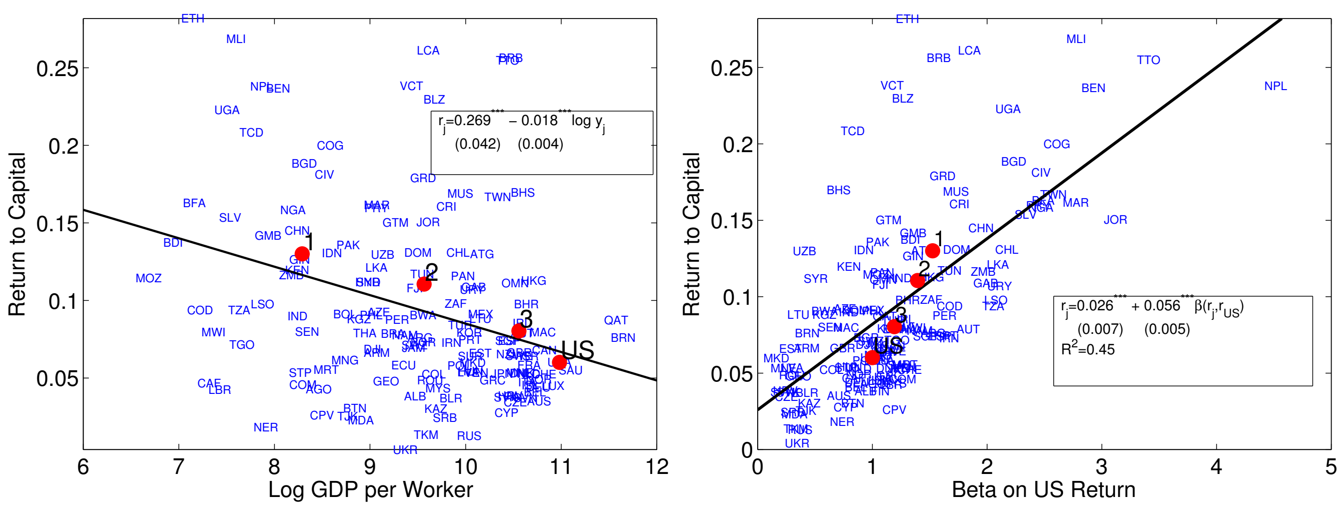

Figure 1: The Returns to Capital

Next, we compute each country's return beta by regressing the time-series of its returns on those in the US. The right-hand panel of Figure 1 plots mean returns against the resulting betas. The figure illustrates the second fact: there is a strong connection between a country's beta and its mean return - countries that exhibit a greater exposure to shocks that move US returns tend to be the same that offer high levels of average returns.

The puzzle we are after is why systematic return differences may persist between low return/rich countries and high return/poor ones. To focus on the link between returns and income, we form bundles, or portfolios, of countries, grouped by levels of income. Our approach follows widespread practice in empirical asset pricing, which has generally moved from addressing variation in individual asset returns to returns on asset portfolios, sorted by factors that are known to predict returns. This procedure proves useful in eliminating asset-specific diversifiable risk (e.g., country-specific idiosyncratic factors that are unrelated to their levels of economic development) and so in honing in on the sources of return variation of interest. Additionally, the portfolio approach also aids in eliminating potential measurement error in country-level variables. Further, we are able to expand the number of countries as data become increasingly available, enabling us to include the largest possible set of countries in our analysis. This is particularly important for poor countries, where time-series coverage is more limited.

We perform our analysis first on 3 portfolios plus the US and then extend it to 5 and 10 portfolios in our quantitative work (with the US always separate). We allocate countries into portfolios based on average income over the sample period. Figure 1 overlays the portfolio returns with those at the country-level.[11] Portfolio 1 contains the poorest set of countries and portfolio 3 the richest, with the US always kept apart, so that higher numbered portfolios are higher income and the US is last, a terminology which will remain consistent throughout the paper. The portfolios eliminate a good deal of the country-level variation in returns even conditional on income level or beta, yet retain the systematic relationships illustrated at the more disaggregate level. We report the levels of average income, expected returns, and beta on the US return across portfolios in the top panel of Table 1. In line with the plot in Figure 1, Portfolio 1 shows average returns of 13% compared to 6% in the US, a spread of 7 percentage points and the highest beta, 1.5.

Second moments. To dig deeper into the betas that we find, Table 1 also reports the correlation of returns in each portfolio with those in the US, as well as the standard deviation of returns. Strikingly, the correlations move in the opposite direction of the return betas and actually tend to be lower in poorer countries. However, betas are a composite of the correlation and standard deviation and the last column of the table shows that returns are much more volatile in poor and emerging markets - generally twice as high in the poorest two portfolios as in the US. The extreme differences in volatility more than offset the pattern in correlations and are largely what drive the disparities in betas. Put another way, when the level of variability differs substantially, correlations may not be indicative of the true factor loadings.

Figure 2 displays these patterns at the country level. In the top row, we plot correlations with US returns against income on the left and average returns against correlations on the right. Correlations are lower in low-income countries and lower correlations are in fact associated with higher returns. The bottom row of Figure 2 shows analogous plots using the standard deviation of returns. Here, the opposite emerges: low-income countries tend to exhibit higher return volatility and the degree of return volatility is strongly positively related to the average level of returns. Again, what we learn is that while low-income countries tend to be less correlated

[11] Appendix F lists the countries by portfolio and year in which they entered the PWT dataset.

Table 1: The Returns to Capital

Returns					
Portfolio	$\mathbb{E}[y_{j,t}]$	$\mathbb{E}[r_{j,t}]$	$\beta(r_{j,t}, r_{US,t})$	$\text{corr}(r_{j,t}, r_{US,t})$	$\text{std}(r_{j,t})$
1	8.29	13.01	1.53	0.71	0.063
2	9.57	11.06	1.39	0.76	0.053
3	10.56	8.04	1.19	0.83	0.042
US	10.98	6.01	1.00	1.00	0.027
Dividend Growth Rates					
Portfolio			$\beta(\Delta d_{j,t}, \Delta d_{US,t})$	$\text{corr}(\Delta d_{j,t}, \Delta d_{US,t})$	$\text{std}(\Delta d_{j,t})$
1			0.47	0.18	0.083
2			0.49	0.21	0.074
3			0.60	0.31	0.064
US			1.00	1.00	0.026
GDP Growth Rates					
Portfolio			$\beta(\Delta y_{j,t}, \Delta y_{US,t})$	$\text{corr}(\Delta y_{j,t}, \Delta y_{US,t})$	$\text{std}(\Delta y_{j,t})$
1			0.18	0.06	0.081
2			0.23	0.10	0.071
3			0.45	0.26	0.059
US			1.00	1.00	0.023

Notes: The top panel of the table reports moments for returns to capital during the 1950-2008 period for three portfolios, sorted by mean income per worker, and the US. The middle panel reports moments for growth rates of dividends from capital during the same period. The last panel reports moments for growth rates of real GDP during the same period.

with the US, their high level of volatility more than offsets this pattern, leading them to have higher return betas.

Dividend and GDP growth rates. Since, in theory, cash flows from capital investments drive valuations of capital goods and therefore returns, it is of interest to examine the properties of the dividends from capital and compare them to the behavior of returns. The center panel of Table 1 reports second moments of the growth rates of dividends as implied by expression (1). Comovement of dividend growth with that in the US, as measured by the beta of foreign dividend growth on US dividend growth, is lower in poorer countries, the opposite pattern to that in returns. The same pattern is true in terms of correlations. Finally, dividend growth is more volatile in lower-income countries, for example, portfolio 1 has three times the standard deviation of the US. The fact that low-income countries show (1) high comovement of returns but (2) low comovement of dividend growth, alongside (3) high levels of volatility, will all play a role in our quantitative analysis of risk-based explanations below.

Lastly, from expression (1), dividend growth comes from changes in income, i.e., GDP, and changes in the capital stock. To get a sense of the role of each, the bottom panel of Table 1

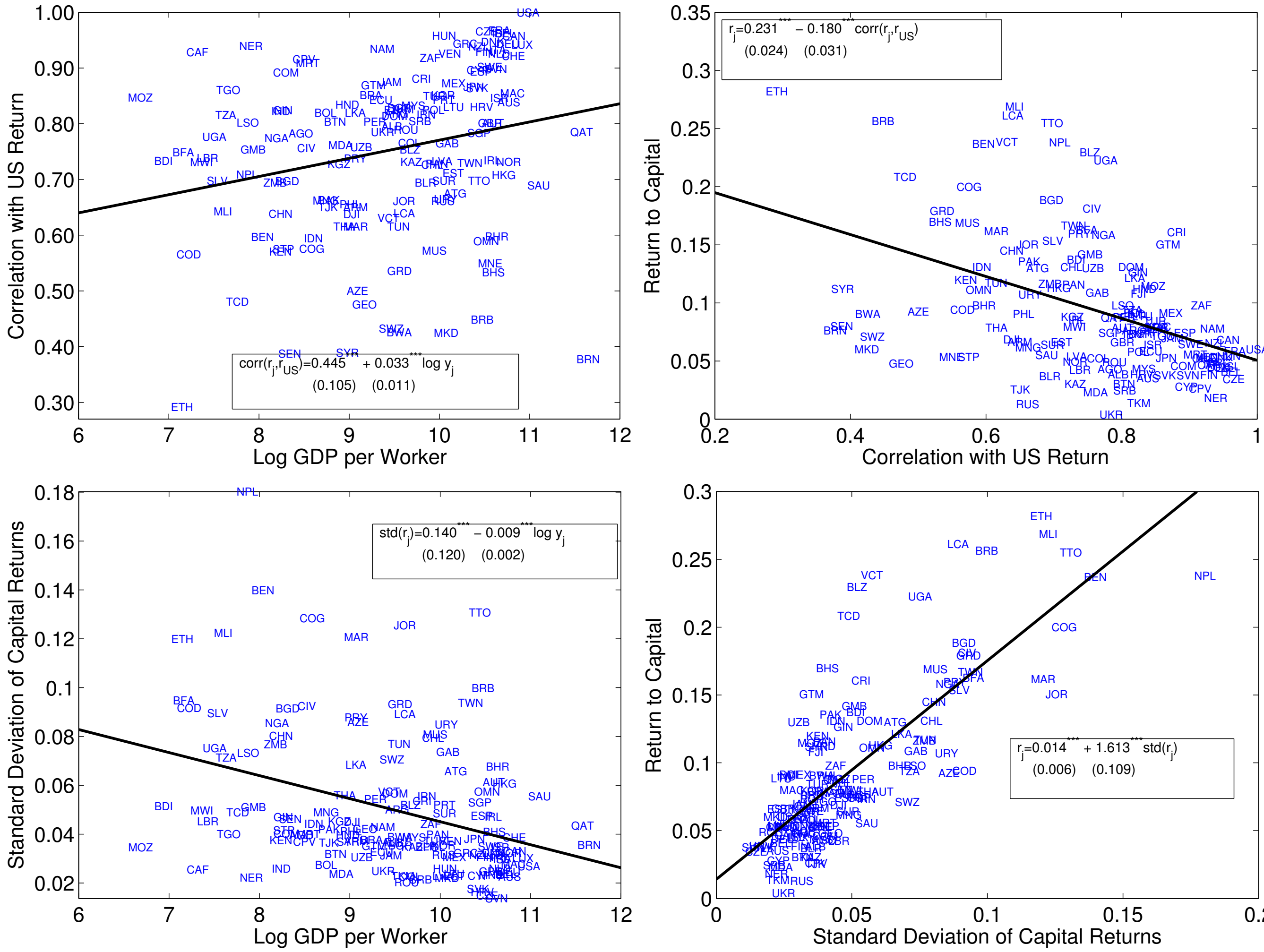

Figure 2: The Returns to Capital - Correlations and Volatilities

reports the second moments of GDP growth rates across the portfolios. These display patterns similar to those in dividend growth - lower betas and correlations with US GDP growth in low-income countries and higher levels of volatility. Dividends clearly inherit much of the properties simply of GDP growth. This is not overly surprising, given the slow-moving nature of the capital stock, which does not tend to be very volatile at short frequencies.

Relation to previous estimates. Our findings of significant (and systematic) variation in capital returns stand in contrast to those in CF. Although the measure of returns in expression (2) builds closely on the insights in that paper in accounting for differences in relative prices when measuring the cross-sectional dispersion in capital returns, there are a number of differences in our approach. First, and most importantly, CF examine the cross-section of returns in a single year, 1996, whereas we study average returns over a longer time period. It turns out that this largely explains the differences in our findings - simply put, the results from 1996 do not seem to generalize to the longer time span.

In addition to expanding the time period under study, our measurement approach differs from CF in several ways. First, we include capital gains, which is in line with Gomme et al. (2011), who point out the importance of changes in the relative price $P_{I,t}$ in driving the time series behavior of capital returns, at least in the US, and in particular, the contribution of this term to the volatility of returns. Second, and also in line with the latter paper, all prices are expressed in units of US consumption, not of region-specific output. The calculations in CF imply that the investor considers his return in units of output received per unit of output invested; here, the investor considers units of consumption received per unit of consumption invested, and a corresponding adjustment must be made when mapping (2) to the data. A third departure from CF is in the cost of the original unit of the investment good: there, investors purchase investment goods locally, that is, in the region where they will be invested; in our setup, the US investor purchases these goods domestically, no matter the location of the investment.[12] However, these variations do not play a large role in driving the differences between our results and theirs.

To reconcile our results with those in CF, we explore a number of variants on our measurement approach that bring our calculations closer to theirs. First, we relax our assumption of a common price of investment goods. To do so, we use country-specific prices as reported in the PWT for all prices in equation (2). This is precisely the price adjustment made in CF. Second, we use country-year specific capital shares, with an adjustment for the shares of non-reproducible capital, again as in CF. To do so, we obtain data on the shares of payments to natural resources in GDP from the World Bank's World Development Indicators (WDI) database. We compute the reproducible capital share as one minus the labor share minus the natural resource (non-reproducible) share.[13] These data are available for 115 of our original 144 countries only over the period 1970-2008. We report the results across the three portfolios in the top panel of Table 2. First, using country-specific prices has only modest effects on our estimates; while the dispersion in returns falls slightly, the differences between the returns on different portfolios and the US remain significant, both economically and statistically.[14] Second, in the more limited time period and country sample for which we can compute country-specific capital shares, differences in returns relative to the US remain large and statistically signifi-

[12] As discussed above, the majority of investment goods are produced in a small number of developed countries.

[13] It should be noted that payments to natural resources include oil rents, natural gas rents, coal rents, mineral rents, and forest rents, and whether or not these are truly 'non-reproducible' is unclear: consider, for example, an investment by Exxon-Mobil in a new oil well.

[14] The US changes most, increasing about 2 percentage points simply from using PWT relative prices, rather than those from the BEA.

cant. Finally, using both country-specific prices and capital shares, dispersion falls modestly, yet, in line with with our main findings, Portfolios 1 to 3 continue to exhibit returns that are significantly different from those in the US.

Table 2: Capital Returns - Alternative Measurement Approaches

Portfolio	Baseline	Country prices	Baseline	Country α's	Country prices & α's
	1950-2008		1970-2008		
1	13.01***	11.94***	9.59***	13.23***	12.85***
2	11.06***	10.44***	7.53***	12.50***	12.27***
3	8.04***	9.30***	6.32**	9.04***	11.10***
US	6.01	8.20	5.21	6.19	9.37
	1996		1996		
1	5.37**	3.32	4.93**	8.36***	6.21
2	5.20*	5.89	3.97	8.11**	9.37
3	3.90	10.03**	3.67	6.55	14.17***
US	3.63	7.23	3.63	5.51	9.55

Notes: Table reports the returns to capital across portfolios under a number of measurement approaches and time periods. Baseline uses US prices from BEA. Country prices uses country-specific P_Y, P_I, P_C from PWT. Country α's uses country-year α from PWT and subtracts from α the share of payments to non-reproducible capital from WDI. Country prices and α's uses country prices and country-year α as described above. Standard errors are reported in parentheses. Asterisks denote significance of difference from US values: *** difference significant at 99%, ** 95%, and * 90%.

Next, we recompute returns for only the year 1996 - the year that CF study - under our baseline approach and each alternative. Under our baseline, the spread in returns in 1996 is much smaller than the average over the period, falling to less than 2% from almost 7%. Although the difference from the US remains statistically significant for Portfolios 1 and 2 (although at lower levels), the economic magnitudes are clearly much smaller. Using country-specific prices, statistical significance as well as the systematic pattern across portfolios disappears.[15] Similar patterns hold with country-specific α's and the combination of the two. Thus, under any of these approaches, differences across portfolios are significant - both economically and statistically - when the entire time-period is under examination, but the returns do not obey any particular pattern in a single year such as 1996. These findings lead us to conclude that differences in the time-period under study is the primary reason why we find systematic cross-country differences in returns whereas CF do not.[16] The risk-based explanations that we explore below are designed

[15]Portfolio 3, which contains the richest countries in the world, enjoys very high returns in 1996 when computed in this fashion.

[16]We should note that one important reason why CF may have chosen to work with year 1996 is because the

to account for these long-run differences, i.e., differences in expected returns over time, not those in any given year based on some particular realization of the stochastic processes that drive returns.[17]

Capital market frictions. Measured returns may differ systematically across countries due to the presence of frictions associated with foreign investments in some countries. These capital market distortions may be explicit (ex. trading limits, taxes, etc.) or implicit—for example, Gourinchas and Jeanne (2013) posit that credit market imperfections, expropriation risk, bureaucracy, bribery, and corruption in poor countries may result in a 'wedge' between social and private returns to physical capital there. Such a wedge may imply that the US investor expects to receive only a fraction of the dividend and/or capital gains yield on investments in poor countries. Hence, in order to invest there, he would demand higher pre-wedge rates of return. This naturally leads to the question, to what extent can these frictions account for the return differentials that we find?

The literature has made attempts to quantify explicit frictions that international investors face, commonly referred to as capital controls, and to categorize countries according to their degree of 'capital account openness.' To understand whether systematic differences in openness can account for the observed return differentials in the data, we have recomputed returns using only the countries that have capital accounts classified as open according to a number of indices (Chinn and Ito, 2006; Quinn, 2003; Grilli and Milesi-Ferretti, 1995). The thought experiment is as follows: if differences in capital controls are the primary source of differences in returns to capital across countries, then returns should be at least approximately equalized among countries with open capital accounts. Relegating the details to Appendix B, we continue to find a strong negative relationship between income and returns among economies typically classified as open (for example, the spread between the US and portfolio 1 exceeds 5 percentage points), suggesting that capital control differences cannot fully account for the differences in

prices in the PWT 6.1 version that they use correspond to 1996—the benchmark year in PWT 6.1. Prices in PWT are obtained from the International Comparison Program (ICP), which collects prices of narrowly-defined and comparable consumer and capital goods across retail locations in a given year. The prices used outside of the benchmark years are interpolated, so they should be interpreted with caution. As noted earlier, we rely on an entirely different version of the PWT—8.0, where the price data were collected in year 2005. Moreover, in our baseline case, where we compute returns from the point of view of a US investor, we rely on price indices from the BEA, which samples prices annually, thus circumventing the problem of interpolated prices between ICP benchmarks. We do use GDP data (in current 2005 PPP prices) from the PWT, so the price of output of each country relative to the US in all years reflects the 2005 PPP adjustment. However, the capital stock in PWT 8.0 is expressed in the same unit; hence, PPP adjustments disappear when we compute dividends and therefore returns.

[17] We should note that the returns across portfolios over the last decade of the PWT data show some convergence compared to earlier periods. However, insufficient data are yet available to determine whether this is a temporary or more permanent change. For example, as we show below, stock and sovereign bond returns continue to show substantial differences over recent periods (1988-2014 and 1995-2009, respectively).

returns between rich and poor countries.[18]

Measuring the types of implicit frictions described above with the intent of adjusting realized returns is very difficult.[19] To the extent that these frictions are correlated with capital controls, the analysis just described is one way to address this issue. Moreover, it is not our intent to rule out the role that these frictions play in explaining return differentials; indeed, we find that a risk-based explanation accounts for only some portion of observed return differences, and it is likely that these alternative factors account for an important piece. Our strategy to identify long-run risks relies primarily on first-differenced variables (and in particular on second moments), which should not be directly affected by country-specific wedges that are not time-varying. Finally, it is worth noting that these mechanisms may not be easily separable in the sense that some of the frictions may be the underlying sources of risk that the investors in our structural model price. For example, weak institutions within a country may be behind the high volatility of macroeconomic variables and, in particular, the excessive responsiveness of these variables to global shocks.[20]

Further Evidence. In this section, we provide further evidence of the key facts using data on directly observable returns on tradable assets - namely, stocks and sovereign bonds. Turning first to stocks, we obtain quarterly country-level stock market returns denominated in US dollars from Morgan Stanley Capital International (MSCI), which we deflate using the US CPI. To ensure a clean comparison across countries, we limit the sample to countries classified as 'Developed' or 'Emerging' by MSCI, which have data available beginning in 1988 (this is the earliest date available for most emerging markets). We additionally include Argentina, which is classified as 'Frontier,' but has data back to 1988. Our final sample consists of a balanced panel of 33 countries over the period 1988-2014, 22 classified as developed (including the US) and 11 as emerging.[21]

For purposes of brevity, we report our detailed results using stock market data in Table 8

[18]In an additional exercise, when considering stock returns, MSCI reports for a few countries and years returns both before and after withholding taxes. Using these to impute a measure of the effective tax rates, we find no significant relationship between the level of taxes and income.

[19]For example, Gourinchas and Jeanne (2013) impute the capital wedge for each country so as to match the discrepancy between actual investment rates in the data and those predicted by a one-sector deterministic neoclassical growth model with a capital tax and fixed world interest rate. The authors find that the imputed capital wedge is higher in poorer countries—an observation that is consistent with the existence of capital market distortions. As the authors note, however, the wedge is consistent with another mechanism: inefficiencies in producing investment goods in poor countries that distort the relative price of capital to consumption goods as argued by Hsieh and Klenow (2007). We follow this line of analysis and adjust our measure of returns for relative prices, without taking a stand on the source of relative price differences.

[20]Relatedly, Alfaro et al. (2008) empirically document the role of institutional quality in hindering capital flows to high return countries.

[21]We provide further details on the data construction in Appendix A.

in Appendix B and illustrate them in Figure 4 (these are analogous to Table 1 and Figure 1). First, we find that average stock returns exhibit a strong negative relationship with average income - the spread between a portfolio of poor countries and the US is about 9 percentage points. Second, countries with higher average stock market returns tend to be those that exhibit high betas on the US stock market return. These are the two main facts reported from our baseline measure in Table 1. We also investigate the second moments of stock market returns and in Figure 5 we display plots analogous to Figure 2. Again, the patterns are similar - low income/high return countries actually have lower correlations with US returns; however, return volatility is extremely high in these countries, which leads to high betas on the US return. Thus, our main empirical findings are confirmed by equity returns, which represent a largely assumption-free measure and are less affected by concerns regarding tradability and other market frictions than our broader measure of the return to the entire capital stock.[22]

Finally, we obtain bond return data from Borri and Verdelhan (2012), who report credit spreads on sovereign bonds for 36 emerging markets. In line with our findings, they show that mean returns on emerging market sovereign bonds are significantly above US bond returns: the average difference is about 5.4% (see Table 6 in their paper). Moreover, they show that (portfolios of) countries with a high beta on US bond returns (measured using the Merrill Lynch US BBB corporate bond index) have higher bond returns - even conditional on default risk. The spread between high and low beta portfolios ranges from 4% to 7%. Thus, our two stylized facts apply to sovereign bond returns as well.

Examining sovereign bonds is useful for two additional reasons. First, they provide one direct way to control for currency risk, since all the bonds under study are denominated in US dollars. The existence of significant spreads suggests that currency risk alone cannot account for a large portion of the differences in returns that we observe. Second, as already noted, the spreads associated with differences in betas are conditional on default risk, measured as the probability of default based on credit ratings from Standard and Poor's. Appendix B summarizes the results from sovereign bond data in more detail.

[22]Harvey (1995), Bekaert and Harvey (1995) and Bekaert and Harvey (1997) report similar results for subsets of the countries in earlier time periods. We rely on equity data for robustness only because stock returns are available for a much smaller set of countries and span a shorter period than our baseline return measure (in large part because stock markets did not exist in the majority of emerging markets). Additionally, stock returns may not be fully representative of the return to capital for a foreign investor, since equity is only one of several ways to invest in foreign markets and only a small fraction of the capital stock in emerging markets tends to be publicly listed.

3 A Long-Run Risk Explanation

Thus far, we have documented two important empirical regularities of capital returns: first, low-income countries tend to offer high average returns. Second, average returns are strongly related to a country's beta on the US return. Further, traditional explanations, for example, frictions in international capital markets, only go some way in accounting for return disparities. In this section, we quantitatively explore a novel explanation for these patterns - namely, the risk-return tradeoff implied by asset pricing theory and specifically, the role of long-run risks due to uncertainty regarding future economic growth prospects.

3.1 The Model

We follow the international long-run risk literature and consider a representative US investor in an international endowment economy.[23] Consumption of the investor and payments to capital in each region (e.g., country or portfolio) experience shocks to expected future growth rates. Each region is exposed to both global and idiosyncratic components of these shocks. Regions differ in their exposure to the global shock process and in the characteristics of the idiosyncratic one. Heterogeneity in exposure to global shocks will play a crucial role in leading to return differences across regions.

Preferences. The representative US investor has recursive preferences à la Epstein and Zin (1989). The investor seeks to maximize lifetime utility

$$V_t = \left[(1-\beta)\, C_t^{\frac{\psi-1}{\psi}} + \beta \nu_t \left(V_{t+1}\right)^{\frac{\psi-1}{\psi}}\right]^{\frac{\psi}{\psi-1}}, \quad \nu_t \left(V_{t+1}\right) = \left(\mathbb{E}_t \left[V_{t+1}^{1-\gamma}\right]\right)^{\frac{1}{1-\gamma}}$$

where ψ denotes the intertemporal elasticity of substitution, γ risk aversion, β the rate of time discount, and $\nu_t\left(V_{t+1}\right)$ the certainty equivalent of period $t+1$ utility. Standard methods give the usual Euler equations, one for each risky asset and one for the risk-free asset:

$$\begin{aligned} 1 &= \mathbb{E}_t \left[M_{t+1} R_{j,t+1}\right] \ \forall \ j \\ 1 &= \mathbb{E}_t \left[M_{t+1} R_{f,t+1}\right] \end{aligned} \tag{3}$$

where $R_{j,t}$ is the (gross) return on capital in region j as defined in equation (2), $R_{f,t}$ is the return on a risk-free bond and M_{t+1} denotes the investor's stochastic discount factor (SDF),

[23] An important exception is Ho et al. (2014) who analyze capital flows in an international production economy featuring long-run risk. We discuss our assumption of an endowment economy in Appendix C.

given by

$$M_{t+1} = \beta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} R_{c,t+1}^{\theta-1}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ and $R_{c,t+1}$ denote the return on an asset that pays aggregate consumption as its dividend, or equivalently, the return to aggregate wealth.

Dynamics of consumption and dividends. The following system lays out the joint dynamics of US consumption and domestic and foreign dividends. We denote with an asterisk a representative foreign region, a convention we follow hereafter.

$$\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_t + \eta_{t+1} \\
x_{t+1} &= \rho x_t + e_{t+1} \\
\Delta d_{t+1} &= \mu_d + \phi x_t + \pi \eta_{t+1} + \mu_{t+1} \\
\Delta d^*_{t+1} &= \mu^*_d + \phi^* x_t + \pi^* \eta_{t+1} + \pi^*_d \mu_{t+1} + \tilde{\phi}^* x^*_t + \mu^*_{t+1} \\
x^*_{t+1} &= \rho^* x^*_t + e^*_{t+1}
\end{aligned} \tag{4}$$

A detailed description of the environment is as follows: turning first to the US, μ_c is the unconditional mean of consumption growth and x_t a time-varying, small but persistent component of the growth rate, so that the conditional expectation at time t of consumption growth in $t+1$ is $\mu_c + x_t$. The persistent component evolves according to an AR(1) process with persistence ρ and variance in the innovations σ^2_e. Consumption growth is also subject to purely transitory shocks η_{t+1} with variance σ^2_η. Dividend growth in the US has unconditional mean μ_d and a levered exposure to the persistent component of consumption growth, x_t, captured by ϕ. Intuitively, the higher the value of ϕ the more responsive are dividend growth rates to innovations in x. The transitory consumption shock η_{t+1} also influences the dividend process, with the magnitude of this relationship governed by π. Dividend growth is also subject to a purely transitory shock μ_{t+1} with variance σ^2_μ. All shocks are i.i.d. and normally distributed.

The dynamics of foreign dividends are similar. Dividend growth has unconditional mean μ^*_d and a levered exposure to a small but persistent component of the growth rate, which is now composed of two pieces. First, there is an exposure to the US long-run shock x, with the degree of exposure governed by ϕ^* and it is in this sense that x represents a 'global' shock. Additionally, there is a region-specific idiosyncratic long-run component x^* (with the degree of exposure governed by $\tilde{\phi}^*$), which evolves according to an AR(1) process with persistence ρ^* and variance in the innovations $\sigma^2_{e^*}$.[24] We allow for transitory shocks to foreign dividend

[24] We model the US x as directly influencing the foreign dividend process. Alternative approaches would be to explicitly include a world x and a region-specific one as in Nakamura et al. (2012), or only region-specific

growth rates to be correlated with temporary shocks to US dividend growth rates μ_{t+1} and US consumption growth η_{t+1}. The strength of these relationships is captured by π_d^* and π^*, respectively. Lastly, each region is also subject to an idiosyncratic transitory shock μ_{t+1}^* with variance $\sigma_{\mu^*}^2$. As in the US, all shocks are i.i.d. and normally distributed.

We do not need to explicitly specify the foreign consumption process. However, a natural way that fits into our framework (and is symmetric with the US process) would be

$$\Delta c_{t+1}^* = \mu_c^* + \xi^* x_t + x_t^* + \pi_c^* \eta_{t+1} + \eta_{t+1}^* \tag{5}$$

and to reformulate the exposure of dividend growth to the long-run process as $\tilde{\phi}^* (\xi^* x_t + x_t^*)$. Then, $\sigma_{\mu^*}^2$ may include some variance coming from an exposure to local consumption shocks η_{t+1}^* and the parameter ϕ^* is a composite of $\tilde{\phi}^*$ and ξ^*. It is straightforward to prove that this distinction has no bearing on our results (and further, that our model does not have any counterfactual implications for the second moments of the empirical consumption process, since there are still free parameters we have not placed values on - for example, π_c^* and $\sigma_{\eta^*}^2$ in (5)).[25] Explicitly modeling the foreign consumption process along with detailed data on foreign consumption would allow one to study how the shocks in our model jointly determine real exchange rates along with risk premia (for example, Colacito and Croce (2011) study how these shocks determine real exchange rates between the US and UK).

The presence of idiosyncratic shocks points to incomplete risk-sharing and can take several interpretations, for example, some form of market incompleteness, or complete markets with complete home bias à la Colacito and Croce (2011). We follow Lewis and Liu (2015) in not taking a stand on the precise market structure at work that leads to this outcome, but rather specify the consumption process directly and work with a general Euler equation, which holds for any level of market integration, and prices both domestic and foreign assets. The consumption process that we measure in the data is an equilibrium outcome based on the true market structure and by working directly with consumption, we avoid having to explicitly specify trading protocols. Additionally, our approach is fairly general, in the sense that the perfect risk-sharing outcome is nested in our framework, and would simply entail a finding of no

x's with some correlation in their innovations as in Colacito and Croce (2011) and Lewis and Liu (2015). It is straightforward to show that these setups are all equivalent (i.e., that ours can be mapped directly to theirs) with a simple change of notation.

[25]This result implies that we do not need to make use of any moments in foreign consumption in our quantitative analysis. This is a significant advantage of our approach, since the limited availability of foreign consumption data would be problematic for our analysis. For example, data on non-durables and services such as those that we obtain from the BEA for the US are not generally available in the full cross-section of countries (particularly developing ones). Only total consumption for each country is available from the PWT, but as has been recognized in the literature, the inclusion of durables makes the connection to the marginal flow utility of consumption (i.e., to the agent's SDF) rather tenuous, and for many countries the series are quite short.

significant idiosyncratic shocks when we take the model to the data.

Risk premia. We solve the model and derive its asset return implications using standard approximation methods.[26] Expected risk premia (in excess of the risk-free rate) on the US and foreign capital assets are, respectively

$$\begin{aligned} \mathbb{E}\left[r_t^e\right] &= \left(\phi - \frac{1}{\psi}\right)\left(\gamma - \frac{1}{\psi}\right)\frac{\kappa_{m,1}}{1-\kappa_{m,1}\rho}\frac{\kappa_1}{1-\kappa_1\rho}\sigma_e^2 + \gamma\pi\sigma_\eta^2 \\ \mathbb{E}\left[r_t^{e*}\right] &= \left(\phi^* - \frac{1}{\psi}\right)\left(\gamma - \frac{1}{\psi}\right)\frac{\kappa_{m,1}^*}{1-\kappa_{m,1}^*\rho}\frac{\kappa_1}{1-\kappa_1\rho}\sigma_e^2 + \gamma\pi^*\sigma_\eta^2, \end{aligned} \tag{6}$$

where κ_1, $\kappa_{m,1}$ and $\kappa_{m,1}^*$ are linearization constants that are endogenous and depend in a non-linear way on the parameters of the US consumption process and those of the US and foreign dividend processes, respectively. The mean risk free-rate is given by:

$$\mathbb{E}\left[r_{f,t}\right] = -\log\beta + \frac{\mu}{\psi} + \frac{1}{2}\left(\frac{1-\gamma}{\psi} - \gamma\right)\sigma_\eta^2 + \frac{1}{2}\left(\theta - 1\right)\left(1 - \frac{1}{\psi}\right)^2\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma_e^2 \tag{7}$$

which is a function only of the parameters governing the US consumption process.

Intuition. Equation (6) shows that excess returns are composed of two pieces, the first relating to long-run risks and the second to short-run. First, notice that setting $\gamma = \frac{1}{\psi}$, which is the case of CRRA preferences, eliminates the long-run component so that risk premia are determined only by the transitory comovement in consumption and dividend growth ($\pi\sigma_\eta^2$), which is 'priced' at γ. The same is true if $\sigma_e^2 = 0$, that is, there is no long-run risk in consumption growth, or if $\rho = 0$, simply with an adjustment to reflect the additional variance σ_e^2, which would then be purely transitory in nature. Thus, both recursive preferences, i.e., the disentangling of γ and ψ, as well as the persistent and stochastic nature of growth rate shocks are necessary for risk premia to differ from the case with no long-run risk.

The sensitivity of dividends to changing global growth conditions, ϕ in the US and ϕ^* abroad, although not sufficient statistics, are key in determining risk premia. Intuitively, the higher this sensitivity, the riskier is the asset and the higher the associated risk premium. An important piece of our empirical work is to pin down the values of these parameters. In contrast, the idiosyncratic portion of the long-run shock abroad (x_t^*) does not enter the return equations anywhere. Because these shocks are by construction only regional, they do not enter the US investor's SDF and so are not risky from his perspective; in other words, idiosyncratic shocks are diversifiable and so do not garner risk premia. This does not mean that we can ignore these

[26] Because these techniques are widely used, we detail the steps in Appendix C.

shocks, however; doing so may bias our estimates of the parameters that do determine returns. We next outline an identification strategy that addresses this challenge, among others.

3.2 Identification

To derive the model's return implications and assess its ability to account for the cross-section of capital returns in the data, we must assign values to the parameters governing the consumption and dividend processes laid out in (4). Here, we outline an empirical strategy to parameterize the model. We demonstrate that moments of US consumption growth, dividend growth in each region, and the comovement of returns in each region with those in the US - closely related to the betas in Section 2 above - enable us to identify all the necessary parameters.

Preferences and US consumption. We begin by assigning values to the preference parameters. We set $\gamma = 10$, $\psi = 1.5$, and $\beta = 0.99$, all standard values in the long-run risk literature. Our choice of β enables the model to approximately match the mean level of the risk-free rate.

Turning to the consumption process, we first assign a value to the persistence parameter ρ. This parameter is notoriously difficult to identify and rather than attempting to do so, we take guidance from the existing literature and set its value to 0.93.[27] This is reported as the mean estimate from annual US data in Ferson et al. (2013) and is quite close to the annual estimate from Bansal et al. (2012b) of 0.91.[28] We determine the values of the remaining parameters of the US consumption process - μ_c, σ_e^2 and σ_η^2 - in order to match the unconditional mean, variance, and autocovariance (i.e., persistence) of US consumption growth. In Appendix C we prove that these three moments identify the three parameters.

US dividends. We pin down the parameters of the US dividend process in a similar fashion. These include: the mean growth rate of dividends μ_d; the exposure to the persistent shock ϕ; the correlation with transitory consumption shocks, governed by π; and the volatility of the transitory shock, σ_μ^2. We set these to match the observed mean growth rate in dividends, the autocovariance of dividend growth relative to that of consumption growth, the covariance of dividend growth with consumption growth, and the variance of dividend growth. In Appendix C we prove that these four moments identify the four parameters.

[27] Because we are interested in the spread in returns between foreign regions and the US, another approach here would have been to choose ρ to match the mean US return. Our model prediction will be quite close to the actual return for the US, lending an additional degree of confidence in the value of ρ.

[28] Much of the long-run risk literature considers monthly decision frequencies and estimates parameters to match moments aggregated to the annual frequency. We abstract from this issue here and focus only on an annual model.

Foreign dividends. Identification of the parameters of the foreign dividend process is complicated by two elements. To see these, recall that returns to both US and foreign assets are in large part driven by their exposure to the global persistent shock, governed by ϕ in the US and ϕ^* abroad. A seemingly natural way to identify ϕ^* would be to follow an approach analogous to the one used above to infer ϕ, i.e., to look at the persistence in foreign dividend growth relative to that in US consumption growth. As we prove in Appendix D, however, due to the presence of local long-run shocks (i.e., x^*), this moment does not deliver the true value of ϕ^*. Alternatively, since x^* is orthogonal to x, it may seem that the comovement between domestic and foreign dividend growth would be an informative moment to identify the exposure of foreign dividends to the common component x. Although this moment is indeed unaffected by the foreign long-run shock x^*, because we also allow for correlation in the transitory movements of dividend growth rates across countries (i.e., through μ_{t+1}), this single moment does not provide enough information to disentangle comovement due to long-run and short-run components. We show in Appendix D that both of these potential biases pointed can be substantial and failure to account for them would lead to misleading conclusions regarding the role of long-run risk.

To overcome these challenges, we employ a strategy that builds on the insight of Lewis and Liu (2015), who face a related problem of having to distinguish correlations in persistent and transitory sources of risk across a few developed economies. Specifically, they show that, in addition to dividend growth comovement, the comovement of returns contains information that can be used to disentangle long-run from short-run correlations - specifically, a high comovement of returns relative to that of dividends is indicative of a greater exposure to common persistent shocks.[29] Although our environment is not identical to theirs, the strategy that we employ is very much in this spirit.

To see this logic, we can derive expressions for the above two moments as

$$\operatorname{cov}\left(\Delta d_t^*, \Delta d_t\right) = \phi\phi^* \frac{\sigma_e^2}{1-\rho^2} + \pi^*\pi\sigma_\eta^2 + \pi_d^*\sigma_\mu^2 \tag{8}$$

$$\begin{aligned} \operatorname{cov}\left(r_t^*, r_t\right) &= \frac{1}{\psi^2}\frac{\sigma_e^2}{1-\rho^2} + \pi^*\pi\sigma_\eta^2 + \pi_d^*\sigma_\mu^2 \\ &+ \frac{\kappa_{m,1}}{1-\kappa_{m,1}\rho}\frac{\kappa_{m,1}^*}{1-\kappa_{m,1}^*\rho}\left(\phi - \frac{1}{\psi}\right)\left(\phi^* - \frac{1}{\psi}\right)\sigma_e^2. \end{aligned} \tag{9}$$

Both the comovement of dividend growth rates (8) and returns (9) depend on both types of common shocks, transitory and persistent. While the former enter both equations in an identical way, return comovement is more sensitive to common long-run shocks than is dividend

[29] A similar insight is in Bansal and Lundblad (2002), who show that exposure to a persistent global shock can account for the excess correlation as well as excess volatility of returns over cash-flow growth rates among five developed economies.

comovement. Intuitively, a persistent shock leads to large revisions in asset valuations, since expected future growth prospects are changed, which serves to increase the comovement of asset returns *relative* to the comovement in period-by-period dividend growth rates.[30] The higher is ϕ^*, the greater is the response of foreign returns to the global shock and the higher is the comovement of returns relative to that in dividends. Guided by this result, we target the covariance of dividend growth rates (8) and the covariance of returns (9), which we normalize by the standard deviation of the US return, i.e., $\frac{\text{cov}(r_t^*,r_t)}{\text{std}(r_t)}$. This moment is clearly closely related to the betas from Section 2 and has the feature of being independent of the variance of US returns.[31]

With this result in hand, we prove in Appendix C that we can identify the remaining parameters of the foreign dividend growth process following a similar strategy as for the US, i.e., using first and second moments of dividend growth rates and their comovement with US dividend and consumption growth. Finally, we require a value for ρ^*, a parameter that is highly difficult to estimate for the US, and more so in emerging markets for which data are significantly more limited. We begin by making the simple assumption that $\rho^* = \rho$.[32]

Moments and Parameters. Table 3 reports the target moments for the 3 portfolio case. For ease of interpretation, we report both covariances and the associated correlations. Dividend and return measures are consistent with those in Section 2.1. US consumption moments are computed using data on nondurables and services over the period 1929-2014, the longest available series from the BEA. The moments for each portfolio represent the mean values for the countries in that portfolio (listed in Appendix F). We provide further details on our empirical work in Appendix A.

In the top panel of Table 3, we display the moments in US consumption and dividend growth rates. The mean growth rate in consumption is about 2%, with a standard deviation of about 0.02 and an autocovariance of 0.00024, which together imply an autocorrelation of 0.50. These values are quite close to those found by other authors over similar time periods, for example, Bansal and Yaron (2004) and Bansal et al. (2012a). Turning to the portfolio moments in the bottom panel, the patterns are largely as discussed in Table 1: portfolios 1 and 2 display a high covariance of returns with those in the US (here we report covariances scaled by the standard

[30]To see this more clearly, subtract (8) from (9). The resulting expression is independent of transitory shocks (i.e., of the terms involving σ_η^2 and σ_μ^2), up to linearization constants.

[31]Because we neither target nor exactly match the US return variance (our estimate is slightly higher than the empirical value, 0.035 vs. 0.027), the estimated covariances will not match the actual. Normalizing both the model-implied and empirical covariances by the standard deviation of US returns ensures that this discrepancy does not affect our estimation.

[32]This assumption is standard in the literature, for example, in Lewis and Liu (2015), Colacito and Croce (2011) and Nakamura et al. (2012). We show below that under our identification strategy, the results are only negligibly affected by even large changes in this parameter.

Table 3: Target Moments - 3 Portfolios

US						
Consumption	$\mathbb{E}\left[\Delta c_t\right]$	$\text{cov}\left(\Delta c_{t+1}, \Delta c_t\right)$	$\text{std}\left(\Delta c_t\right)$			
	0.018	0.00023	0.021			
		$\text{corr}\left(\Delta c_{t+1}, \Delta c_t\right)$				
		0.50				
Dividends	$\mathbb{E}\left[\Delta d_t\right]$	$\frac{\text{cov}(\Delta d_{t+1}, \Delta d_t)}{\text{cov}(\Delta c_{t+1}, \Delta c_t)}$	$\text{cov}\left(\Delta d_t, \Delta c_t\right)$	$\text{std}\left(\Delta d_t\right)$		
	-0.006	4.89	0.00018	0.026		
		$\text{corr}\left(\Delta d_{t+1}, \Delta d_t\right)$	$\text{corr}\left(\Delta d_t, \Delta c_t\right)$			
		0.28	0.60			
Foreign						
Portfolio	$\mathbb{E}\left[\Delta d_t^*\right]$	$\text{cov}\left(\Delta d_{t+1}^*, \Delta d_t^*\right)$	$\text{cov}\left(\Delta d_t^*, \Delta c_t\right)$	$\text{std}\left(\Delta d_t^*\right)$	$\text{cov}\left(\Delta d_t^*, \Delta d_t\right)$	$\frac{\text{cov}(r_t^*, r_t)}{\text{std}(r_t)}$
1	-0.017	0.00122	0.00011	0.083	0.00032	0.041
2	-0.015	0.00156	0.00011	0.074	0.00033	0.037
3	-0.011	0.00075	0.00015	0.064	0.00040	0.032
		$\text{corr}\left(\Delta d_{t+1}^*, \Delta d_t^*\right)$	$\text{corr}\left(\Delta d_t^*, \Delta c_t\right)$		$\text{corr}\left(\Delta d_t^*, \Delta d_t\right)$	$\text{corr}\left(r_t^*, r_t\right)$
1		0.18	0.12		0.18	0.71
2		0.28	0.13		0.21	0.76
3		0.19	0.21		0.31	0.83

Notes: Table reports target moments for baseline parameterization. Consumption is measured as real per-capita consumption of non-durables and services. Consumption moments are computed over the period 1929-2008, the longest available from the BEA. Dividends are measured in exactly the same manner as described in (1). Portfolio moments are computed over the period 1950-2008 using data from PWT and US prices from BEA. The moments for each portfolio represent the mean values for the countries in that portfolio.

deviation of US returns since this is the exact moment we target) alongside a low covariance of dividend growth rates. The high return comovement alongside low dividend growth comovement seen in poorer portfolios is precisely what suggests relatively low contemporaneous correlations in transitory shocks and high exposure to the global long-run shock. Similarly, the covariance of dividend growth rates with US consumption growth tends to increase with income across the portfolios, which again suggests that developed countries co-move more with the US at high frequencies. The correlations of foreign variables with US ones are ordered similarly to the covariances with the exception of returns, for which, as we saw earlier, correlations are ordered in the opposite direction from covariances.[33]

We report the resulting parameter estimates (along with those assigned outside the model) in Table 4. The consumption parameters are relatively standard. Turning to the portfolio-specific parameters, the moments detailed above imply a greater exposure of poor countries to the global long-run shock, captured by a higher value of ϕ. In contrast, the correlation of transitory shocks with the US (captured by π and π_d) is generally increasing in income, and, not

[33]Dividend growth rates tend to be negative, as capital-output ratios, an important component of our return measure, have been increasing.

Table 4: Parameter Values - 3 Portfolios

Preferences:	$\gamma = 10$ $\psi = 1.5$ $\beta = 0.99$					
Consumption:	$\rho = 0.93$ $\mu_c = 0.018$ $\sigma_e = 0.006$ $\sigma_\eta = 0.01$					
Portfolio	μ_d	ϕ	π	π_d	σ_μ	$\tilde{\phi}^* \sigma_{e^*}$
1	-0.017	5.09	-1.16	-0.15	0.074	0.005
2	-0.015	4.20	-0.75	0.00	0.062	0.011
3	-0.011	2.85	0.35	0.29	0.056	0.008
US	-0.006	2.21	0.99	-	0.020	-

Notes: Table reports parameter values that match moments for baseline parameterization reported in Table 3.

surprisingly, is highest in the US. This parameter configuration implies that poor countries are more sensitive to the global long-run shock, even while allowing for richer countries to display the greater period-by-period comovement with the US observed in the data. It is precisely these two forces that our empirical strategy allows us to disentangle. Poor countries also experience more volatile idiosyncratic transitory shocks, captured by σ_μ, a property inherited from the ordering of overall dividend growth volatility.[34] Next, we assess the implication of these cross-region differences for capital returns, that is, do these patterns across income-sorted portfolios lead to differentials in expected returns of the order that we observe in the data?

3.3 Results

Baseline. We report our baseline results in the first two columns of Table 5. The table reports the actual expected return to capital in each portfolio, r, and the expected return predicted by the model, $\hat{r}$, from equations (6) and (7) under the parameter configuration in Table 4. The model predicts returns in line with those in the data and that mimic the decreasing pattern across higher income portfolios. Predicted returns range from about 10.3% for the poorest Portfolio, 1, to about 5.9% for the US, compared to 13% and 6% in the data. The predicted values for the intermediate Portfolios 2 and 3 are 9.1% and 7.0%, respectively, compared to 11% and 8%. Across portfolios, the model predicts a mean level of returns of about 8.1%, slightly below, but in line with, the average of 9.5% observed in the data. Finally, and perhaps most importantly, the model predicts a spread in returns between Portfolio 1 and the US of about 4.5 percentage points, which represents about 64% of the actual spread of 7 percentage points. In other words, given the parameter configuration in Table 4, long-run risk implies a return differential across income-sorted portfolios almost two-thirds of the actual.

[34] In Appendix C, we prove that our estimation only requires us to pin down the composite parameter $\tilde{\phi}^* \sigma_{e^*}$. We report the estimated value for completeness, although because we cannot separate the two components, this value is difficult to interpret in a meaningful way.

Table 5: The Returns to Capital - Predicted vs. Actual

3 Portfolios			5 Portfolios			10 Portfolios		
	$\widehat{r}$	r		$\widehat{r}$	r		$\widehat{r}$	r
1	10.35	13.01	1	10.81	14.37	1	12.13	16.38
2	9.14	11.06	2	10.60	10.88	2	9.46	12.37
3	7.04	8.04	3	8.59	11.39	3	9.77	10.27
US	5.90	6.01	4	8.15	10.06	4	11.10	11.37
			5	6.16	6.74	5	7.33	10.64
			US	5.90	6.01	6	9.84	11.98
						7	7.93	9.74
						8	8.34	10.39
						9	6.47	7.62
						10	5.92	5.99
						US	5.90	6.01
Average:	8.11	9.53		8.37	9.91		8.56	10.25
Spread: 1-US	4.45	6.99		4.91	8.36		6.24	10.37
Percent of actual	64			59			60	
corr($\widehat{r}, r$)	1.00			0.92			0.91	

Notes: Table reports the expected return to capital in each portfolio as measured in the data, r, and as predicted by the model, $\hat{r}$, from equations (6) and (7) under the parameter configuration in Tables 4, 16, and 17 for 3, 5, and 10 portfolio groupings, respectively.

It is important to note that one would reach a very different conclusion from following an alternative empirical strategy, specifically, one that does not explicitly account for idiosyncratic long-run shocks or for correlation in short-run comovement in dividends. In Appendix D, we re-parameterize the model under these alternative cases and show that the implied expected returns may be significantly biased and in fact, lead to substantially smaller return differentials or even a reversal in ordering (i.e., higher expected returns in richer countries). Thus, careful consideration of each element in the model is important to reach accurate inferences regarding the nature of long-run risks across regions.

Disaggregated portfolios. In our baseline analysis, we group countries into 3 income-based portfolios, along with the US. In the remainder of Table 5 we use the richness of our data to examine the implications of our model for more disaggregated groups of countries, specifically, groups of 5 and 10 portfolios (always along with the US). The middle panel reports the results across a 5-portfolio grouping, and the right-hand panel across 10 portfolios.[35] As we move to more disaggregated levels, the spread between the poorest countries in Portfolio 1 and the US widens, going from about 7% to about 8% to about 10%. The increase is due to a rise in returns

[35]We report moments and parameters for the 5 and 10 portfolio cases in Appendix G.

in Portfolio 1 (the US, of course, remains the same). The model captures this feature of the data to a large extent, with the predicted spread also increasing, although not quite in-step with the actual, from 4.5% to 4.9% to 6.2%. The model accounts for about 60% of the observed spread with 5 and 10 portfolios, compared to 64% with 3. As we increase the number of portfolios, the correlation of predicted and actual returns becomes a useful statistic, which remains quite high even in the 10 portfolio case at 0.9. What we glean from Table 5 is that long-run risks seem to play a quantitatively important role in driving return differentials across countries at different stages of development, and that this finding is not an artifact of our baseline choice of 3 portfolios: the model predicts returns that are in line with the data at each of the levels of aggregation that we examine (and indeed, as we show below, continues to hold significant explanatory power even at the country level).

Rebalanced portfolios. Our baseline approach classifies countries according to their mean income over the period. An alternative approach would be to 'rebalance' portfolios by reclassifying countries in each year based on their rank in the income distribution within that particular year. We have also performed this exercise and for purposes of brevity, we report the results in Appendix D. Our results change only minimally under this alternative.

Country-level analysis. Although the portfolio-based approach lends certain advantages, it is nonetheless worth exploring the implications of our model when the parameters are estimated to match moments of individual countries. To do so, we restrict our analysis to countries with sufficiently long time-series of available data. Our empirical strategy relies heavily on time-series moments and short samples are thus problematic. Consequently, we examine only countries for which data availability reaches back at least to 1961, so that at least approximately 50 years of data are available.[36] This gives us 96 countries on which we perform our analysis, still a large number, although less than the 144 we include in our portfolio analyses above. We parameterize the model country-by-country and compute predicted returns on this basis.[37]

We analyze the results in a number of ways. First, we simply ask: does the model predict a relationship between returns and income at the country-level that resembles the one that we observe in the data? To answer this question, we regress country-level returns on income both in the data and as predicted by the model. We obtain a clear negative relationship between capital returns and income in the data: the line of best fit has a slope of -0.023, which is

[36] Countries tend to be added to the PWT in waves, so we are including here the original 1950 wave, and a second wave that spans 1960 and 1961. The next major wave of additions is not until 1970.

[37] We denote by 1 the countries included in the analysis in Appendix F, column 6, titled Ctry An. A handful of countries feature a configuration of moments that imply a negative $\sigma^2_{\mu^*}$ due to its residual nature. In order not to lose these countries, we set $\sigma^2_{\mu^*} = 0.05$, which is the average of the other countries. This choice makes little difference to the results.

significant at the 99% level.[38] The model also predicts a negative relationship: the line of best fit has a slope of -0.013, about 55% the actual, and is significant at the 95% level. In this sense, even when parameterized at the country-level, the model can account for a significant portion (about 55%) of the average relationship between the returns to capital and income.

To get a sense of how the model predictions line up with actual returns on a country-level basis (similar to the correlations reported at the portfolio level above), we display in Figure 3 the predicted vs. actual values, along with the 45 degree line. If the model were a perfect fit to the data, each point would lie exactly on the line. Although there is a good deal of variation at the country level, as should be expected, the model predicts returns that are generally in line with the data: the correlation between the predicted and actual returns is quite high at about 0.61 and is significant at the 99% level. We view this as a strong confirmation of the explanatory power of the theory: the cross-sectional distribution of returns at the country-level is likely determined by a host of factors specific to each country; that our relatively parsimonious theory predicts returns that are highly correlated with the empirical ones suggests that long-run risks indeed play a key role in leading to the variation in returns observed in the data.

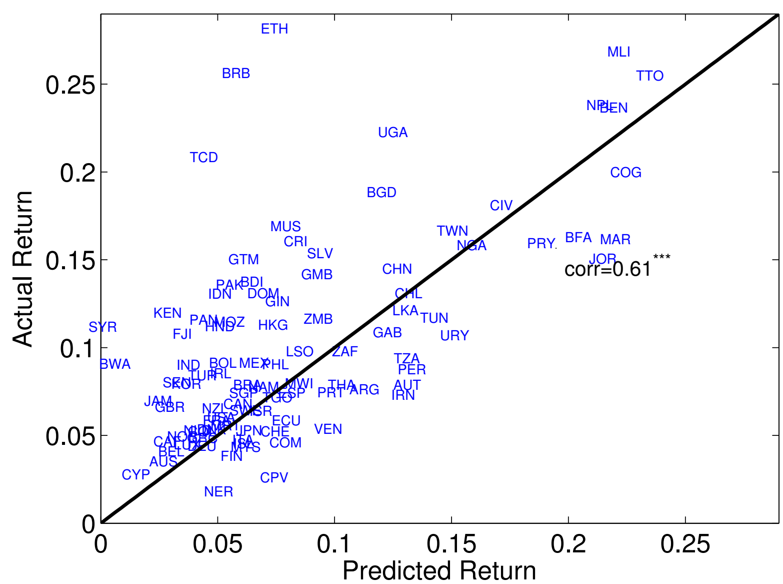

Figure 3: Country-Level Returns - Predicted vs. Actual

Long-run vs short run risk. Expressions (6) and (7) show that we can express predicted returns as the sum of three components: the risk-free rate, i.e., the level of returns in the absence of any risk, excess returns due to short-run risk, i.e., risk derived from period-by-

[38] This statistic is the same as the line of best fit in Figure 1, but the sample here contains only the subset of countries for which we have sufficient data to pass through the model.

period comovement between dividend and consumption growth, and excess returns due to long-run risk, i.e., risk derived from volatility in growth-rate regimes. In Table 6, we report the contribution of each source to the total predicted return.

Table 6: The Composition of Returns

	Actual	Predicted						
Portfolio	r	$\widehat{r}$	$=$	$\widehat{r}^f$	$+$	$\widehat{r}^e_{sr}$	$+$	$\widehat{r}^e_{lr}$
1	13.01	10.35		1.27		−0.25		9.32
2	11.06	9.14		1.27		−0.16		8.02
3	8.04	7.04		1.27		0.07		5.70
US	6.01	5.90		1.27		0.21		4.42

Notes: Table reports actual expected returns, r, and predicted expected returns from the model, $\hat{r}$, computed using the parameters in Table 4. The predicted returns are decomposed into three components: risk-free rate, $\hat{r}^f$, short-run risk, $\hat{r}^e_{sr}$, and long-run risk, $\hat{r}^e_{lr}$ using expressions (6) and (7) in the text.

First, the risk-free rate is only about 1%, as in the data, and by construction, is constant across portfolios due to our focus on a single US investor. Strikingly, excess returns due to short-run risk are negligible and often negative, ranging from about -0.2% to about 0.2%. Negative values indicate a risk compensation: because transitory fluctuations in portfolios 1 and 2 are negatively correlated with US consumption growth, these assets actually represent good hedges for a US investor and so in the presence of only short-run risk, would provide lower returns than in the US. This is intuitive: period-by-period fluctuations in more developed countries are more correlated with those in the US, which implies higher risk premia in those countries, exactly opposite of the patterns actually observed in the data. However, the magnitude of the differences is quite small, with the US demanding 0.5% higher returns than portfolio 1 due to short-run risk. These findings suggest that a model without long-run risks, such as the traditional consumption-based capital asset pricing model with power utility (CCAPM), may struggle to account for the capital returns differentials across rich and poor countries observed in the data. We elaborate further on this point in Appendix D, where we show that an alternative approach to quantifying the CCAPM model (using the covariance of returns with US consumption growth, a sufficient statistic for risk premia in that environment) leads to similar results. Thus, (more than) the entirety of the systematic return differentials predicted by our model is due to long-run risk. The last column in Table 6 shows that long-run risks command excess returns as high as 9.3% in portfolio 1 compared to about 4.4% in the US, leading to a return differential of about 5 percentage points.

Further evidence from stock returns. As an additional exercise, we have also quantified our model using stock market data for two income-sorted portfolios of foreign countries and the US. The results are broadly similar to those in our baseline analysis (details of this exercise are in Appendix D): predicted returns are about 17% in the poorest portfolio compared to about 9% in the US, leading to a spread of about 9 percentage points. The corresponding figures from the data are 18%, 10%, and 9 percentage points, respectively. Thus, both the levels and differences in expected stock market returns generated by the calibrated model are in line with those in the data. Further, in Table 14 we perform a similar decomposition of expected stock returns as in Table 6. We again find that long-run risks play a crucial role in accounting for the empirical return differences - as in our baseline, short-run risk premia are actually higher in more developed countries. For example, these risks alone would suggest a risk premium in the US about 3 percentage points higher than in the emerging markets. These findings confirm the important role of long-run risks in leading to persistent return differences on international investments that we found using our broader baseline measure.

4 Conclusion

In this paper, we have compiled a new panel dataset of international capital returns and documented that poor and emerging markets exhibit (1) high average returns to capital and (2) large exposures to movements in US returns, measured by the beta of the foreign return on the US one. We have found that long-run risk, i.e., risk due to persistent fluctuations in economic growth rates, is a promising channel to reconcile these facts. Key to our results is that emerging markets not only feature large fluctuations in growth rates, but also that the shocks are systemically related across countries, i.e., these markets are highly exposed to global growth-rate shocks.

We leave for future work a more detailed investigation into the sources of the differences in long-run risk that we measure. The implications of such an analysis would clearly be important on many dimensions; from the point of view of our analysis, in reducing required risk premia associated with investments in poor countries and so potentially attracting additional investment flows. Potential avenues of research include understanding the role that high dependence on the production and export of commodities, whose prices are known to be highly volatile, plays in generating volatility in emerging market macro aggregates. Additionally, examining the degree to which institutional differences across countries shape the ability to respond to external shocks may provide further insights into the mechanisms that result in high exposure of emerging markets to global shocks.

We have focused on consumption-based risk due to uncertainty regarding the payoffs to capital investments, both in the short- and long-run. By doing so, we have abstracted from a number of other sources of risk that may play a role in leading to return differences, for example, default risk or expropriation risk. Additionally, our model does not shed light on the fundamental source of long-run risk, i.e., changing prospects for technological progress, low frequency movements in relative prices, etc. Further work investigating these issues and their interaction with rates of return on capital around the world could be quite fruitful.

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For Online Publication: Appendix

A Data

Returns to capital. As described in the text, we use data on relative prices and US per-capita consumption from the BEA. We obtain data from the Penn World Tables Version 8.0 (PWT) to construct dividends and returns in foreign countries. We exclude countries where insufficient data are available, with clear data errors, or that are large outliers. Altogether, these amount to 23 out of 167 countries, leaving us with the 144 used in the main text.

Due to the long time horizon that we analyze, some notes about the PWT country classification are in order. West Germany proxies Germany prior to the unification of East and West Germany. Data for Ethiopia for the period of 1970-1990 refer to the former territory of Ethiopia, including Eritrea. Czechoslovakia is not contained in PWT. Czech Republic and Slovak Republic are added in 1990. USSR is not contained in PWT. Russia, Azerbaijan, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Lithuania, Latvia and Moldova are added in 1990. Yugoslavia is not contained in PWT. Bosnia and Herzegovina, Croatia, Macedonia, Montenegro, Serbia and Slovenia are added in 1990.

We analyze portfolios of countries during the 1950-2009 period. Countries are added to the PWT in waves. In Appendix F we list the countries we use in our benchmark analysis, classified by the portfolio they fall into. In addition, we list the year the country was added to the PWT database and indicate the set of countries we analyze in the country-level exercises as well as those with open capital accounts. As described in the text, mean returns at the country level are computed as the time-series average for each country. To form portfolio returns, these are averaged across countries within each portfolio and through time. All moments for our empirical work are computed analogously, both at the country and portfolio level.

Stock market data. We obtain data from MSCI on quarterly returns denominated in US dollars. The data can be accessed at https://www.msci.com/end-of-day-data-search. We deflate these using the US CPI and limit the sample to countries classified as 'Developed' or 'Emerging' by MSCI, which have data available beginning in 1988 (this is the earliest date available for most emerging markets). We additionally include Argentina, which is classified as 'Frontier,' but has data back to 1988. Our final sample consists of a balanced panel of 33 countries over the period 1988-2014, 22 classified as developed (including the US) and 11 as emerging. The countries included are: Argentina, Australia, Austria, Belgium, Brazil, Canada, Switzerland, Chile, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Hong Kong, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Malaysia, Netherlands, Norway, New Zealand, Phillipines, Portugal, Singapore, Sweden, Thailand, Turkey, and the US.

B Robustness and Further Empirical Findings

Capital market frictions. Chinn and Ito (2006), Quinn (2003), and Grilli and Milesi-Ferretti (1995) provide measures of capital account openness at the country-year level.[39] The

[39] The Grilli/Milesi-Ferretti index covers 61 countries during the 1966-1995 period. Quinn (2003) covers a large number of countries during the 1950-2004 period. Chinn and Ito (2006) build on the work by Quinn (2003) and expand the country coverage to the majority of countries in the world as well as extend the time coverage to 2011.

first two indices provide continuous measures of openness, while the last is an indicator function. For each of the first two indices, we compute the median index value over the covered period and we define a country to be open in a given year if its index value exceeds this threshold. In the case of the Grilli/Milesi-Ferretti index, we define a country to be open in every year in the sample the indicator takes on the value of 1.

Having obtained definitions of openness, we turn to the three portfolios analyzed in the baseline case and examine only the countries that are considered open according to one of the three indices described above. The list of open countries according to each measure, classified by portfolio, are reported in Appendix F. Notice that the number of open countries in Portfolio 1 is significantly smaller than the number of open countries in Portfolios 2 and 3. Thus, there is some evidence that poorer countries are characterized by more strict capital controls. In addition, there is considerable overlap across the different measures of openness, which is reassuring.

Table 7: Capital Returns - Open Countries

	Measure of Openness		
Portfolio	Chinn, Ito	Quinn	Grilli, Milesi-Ferretti
1	10.38***	12.39***	11.48***
2	8.74***	11.27***	10.28***
3	5.61	6.66	7.57**
US	5.22	6.06	5.85

Notes: Table reports the returns to capital across portfolios for economies that are characterized as open according to three indices: Chinn/Ito, Quinn, and Grilli/Milesi-Ferretti, respectively. Chinn/Ito and Quinn openness cutoff is median value in sample. Grilli/Milesi-Ferretti openness indicator is unity. Asterisks denote significance of difference from US values: *** difference significant at 99% and ** 95%.

Table 7 reports the returns in open countries, classified according to each of the three different measures, as well as US returns. US returns differ across columns due to the different time periods covered by each openness measure. Overall, Portfolios 1 and 2 yield significantly higher expected rates of return to US investors, regardless of the measure of openness employed. Returns are monotonically decreasing across portfolios, as in the baseline. Portfolio 3 remains higher than the US, although the difference is somewhat narrower, and is statistically significant in only one case.[40]

[40]Returns are even closer to our baseline as reported in Table 1 if we use the less conservative cutoff for openness in the Quinn database that corresponds to the cutoff used by Lustig and Verdelhan (2007).

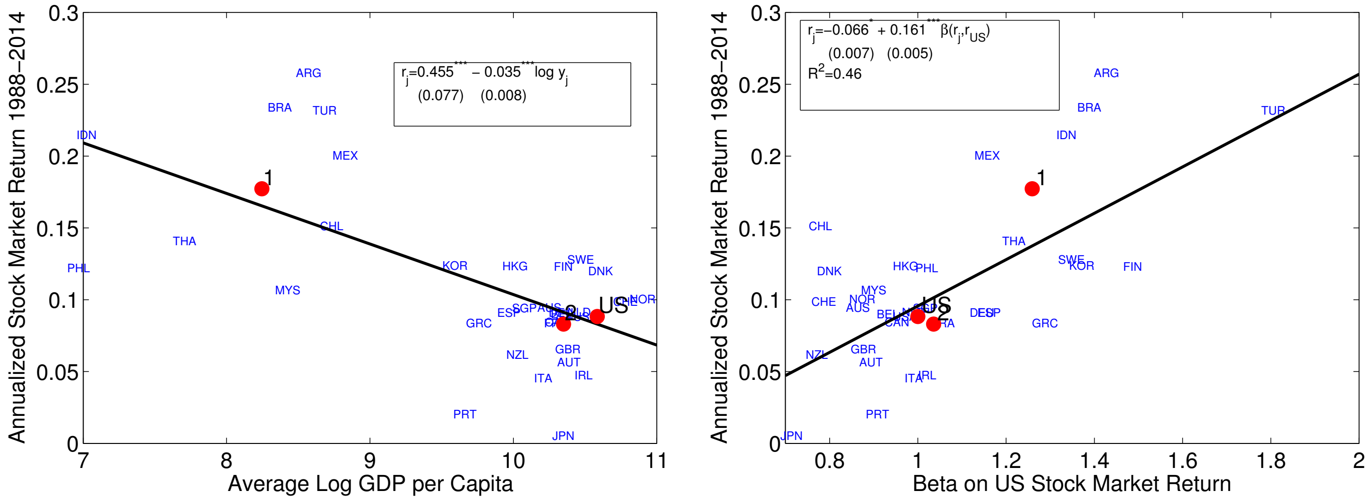

Figure 4: Stock Market Returns

Stock market returns. Figure 4 replicates Figure 1 using annualized stock market returns. The left-hand panel shows that average equity returns exhibit a negative and significant relationship with average income.[41] The right-hand panel shows that high return countries tend to be those that exhibit high betas on the US stock market return. An examination of the plot shows that countries clearly fall into two categories: high-income/low return, with South Korea representing the lower bound along the income dimension, and low-income/high return. We group countries into two portfolios according to this classification and overlay the graph with these portfolios. Additionally, we report the corresponding values in Table 8. At the portfolio level, stock market returns exhibit similar patterns as our baseline measure of returns: low-income countries feature higher mean returns and returns are strongly related to the beta on the US return.

Table 8: Stock Market Returns

Portfolio	log(income)	$\mathbb{E}[r_{j,t}]$	$\beta(r_{j,t}, r_{US,t})$	corr $(r_{j,t}, r_{US,t})$	std $(r_{j,t})$
1	8.25	17.73	1.26	0.46	0.437
2	10.35	8.31	1.04	0.65	0.254
US	10.58	8.84	1.00	1.00	0.156

Notes: Table reports moments for returns to equities. Quarterly returns data are from MSCI and are annualized. Portfolio moments are computed over the period 1988-2014. The moments for each portfolio represent the mean values for the countries in that portfolio.

[41]Since the PWT data end in 2009, average income here is measured using (log) GDP per capita from the World Bank World Development Indicators database over the period 1988-2014.

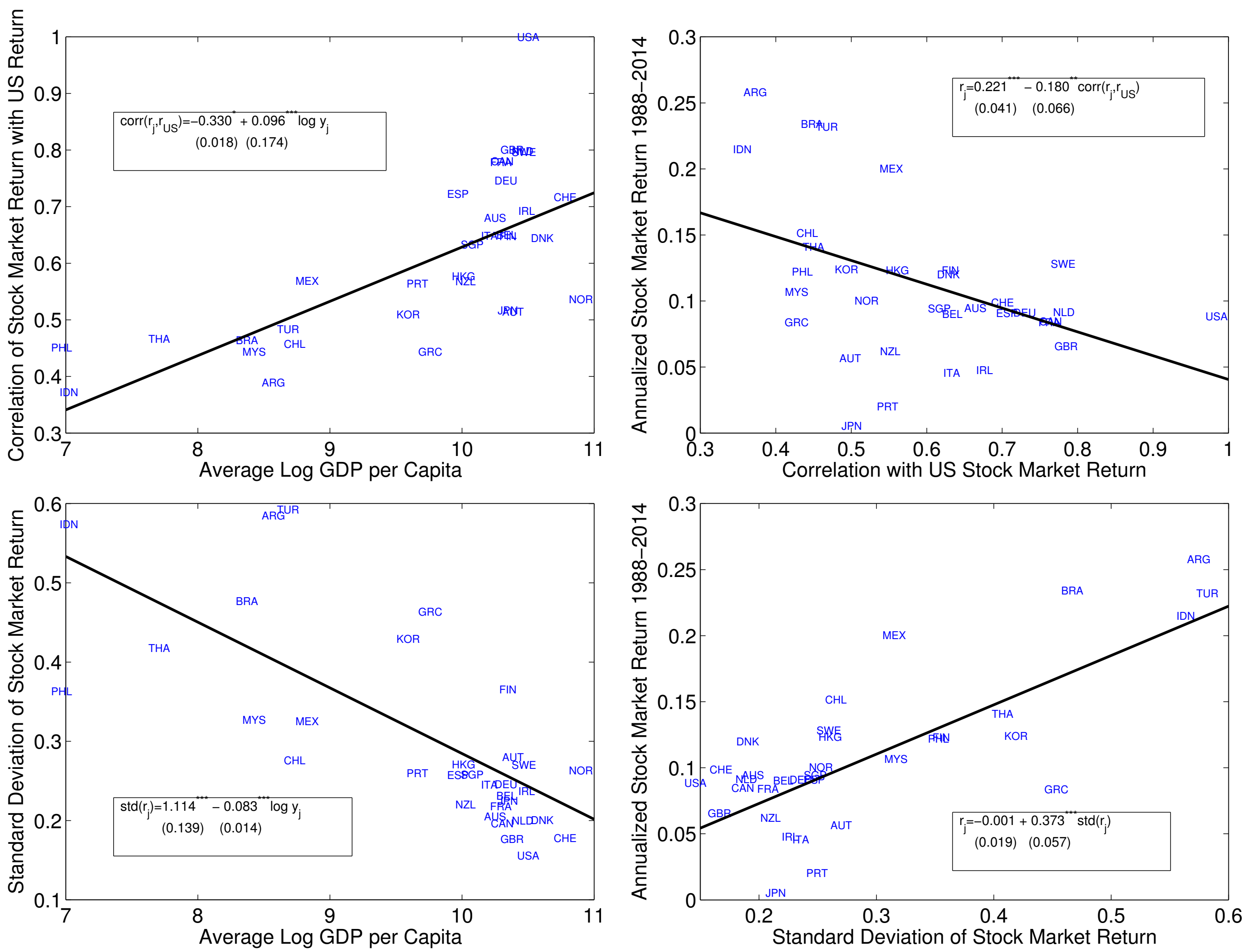

Figure 5: Stock Market Returns - Correlations and Volatilities

Analogous to Figure 2, Figure 5 illustrates the patterns in second moments for stock returns. Precisely the same regularities emerge: first, the correlation of returns with those in the US are actually lower in low-income countries and high correlation countries feature lower average returns. However, these patterns are reversed when examining the volatility of returns: low-income countries are extremely volatile and higher volatility is associated with higher mean returns. This latter finding is what primarily drives the strong relationships between average returns, betas, and income.

Sovereign bonds. We obtain bond return data from Borri and Verdelhan (2012), who report credit spreads on sovereign bonds for 36 emerging markets. First, in line with our findings, they show that mean returns on emerging market sovereign bonds are significantly above US bond returns: the average difference is about 5.4% (see Table 6 in their paper). Next, Borri and

Verdelhan (2012) sort countries into six portfolios along two dimensions: the probability of default based on credit ratings from Standard and Poor's and their beta on a single US bond (the Merrill Lynch US BBB corporate bond index). We summarize their findings in Table 9. Each row in the table shows the credit spreads for one level of default risk, for both high beta and low beta countries. Each column shows the credit spread for one level of beta across the various default probabilities.

In the right-hand column, we calculate the difference in yields between high-beta and low-beta portfolios, conditional on the level of default, that is, within each default group. The differences are substantial, ranging from 4% to almost 7%. In the bottom row, we calculate the difference in yields between high and low default portfolios, conditional on the beta. The differences here are significant as well, ranging from about 3.5% to about 6.5%, but, if anything, are slightly smaller than those due to beta risk. These results suggest that both beta risk and default risk are important in leading to return differentials across sovereign bonds. In our analysis, we focus on the former, and note that return differentials remain large even after controlling for default risk.

Table 9: Emerging Market Sovereign Spreads

Default Rating \ Beta	Low (0.4)	High (1.3)	Beta: High-Low
Low	3.01	7.03	4.02
Medium	5.62	10.15	4.53
High	6.54	13.50	6.96
Default: High-Low	3.53	6.47	

Notes: Table reports credit spreads for emerging markets. Countries are grouped by (i) default risk (each row represents a group) and (ii) beta on US BBB corporate bond index (each column represents a group). All data are from Borri and Verdelhan (2012).

C Model and Identification

Endowment vs production economy. Our choice to work within an endowment economy is an important element of our analysis. There are several motivations for this approach. First, it lends a great deal of tractability in allowing for sharp closed-form expressions for risk premia as well as a transparent identification strategy for pinning down the key parameters. Second, Table 1 shows that the payoffs to capital generally inherit the properties of GDP growth, primarily because the capital stock does not move much at higher frequencies.[42] Finally, the Euler equations that we explore hold no matter the precise mechanisms that give rise to the

[42]The endowment approach is standard when examining stock market returns, which we do in Appendix D.

observed joint dynamics of consumption and dividends. In other words, to the extent that a fully-parameterized production economy is able to generate consumption and dividend processes like those in the data (which we match by construction in our quantitative work), the asset pricing implications will be exactly the same as those in the simpler endowment economy that we analyze.[43] Thus, it is not clear that explicitly modeling production and capital accumulation and the accompanying loss of tractability (and perhaps even loss of computational feasibility given the number of countries that we analyze) would lead to very different results. Moreover, there is some evidence that the underlying mechanisms in our framework go through in an environment with production. For example, Ho et al. (2014) show that a standard two country production economy augmented with Epstein-Zin utility and long-run shocks to productivity growth rates can reconcile some of the key patterns in international capital flows.

Solution. We begin by writing the investor's SDF in logs as

$$m_{t+1} = \theta \log \beta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1} \tag{10}$$

Covariation with m_{t+1} will determine the risk premia on each asset. To characterize the SDF, we solve for the consumption return $r_{c,t+1}$, which we approximate as

$$r_{c,t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta c_{t+1} \tag{11}$$

where $z_t = \log\left(\frac{P_t}{C_t}\right)$ is the log price-consumption ratio and the two κ's are constants of approximation that depend on the unconditional mean of z, $\overline{z}$: $\kappa_1 = \frac{\exp \overline{z}}{1+\exp \overline{z}}$ and $\kappa_0 = \log(1 + \exp \overline{z}) - \overline{z}\kappa_1$. We similarly approximate returns to the US and a representative foreign asset as, respectively,

$$\begin{aligned} r_{m,t+1} &= \kappa_{m,0} + \kappa_{m,1} z_{m,t+1} - z_t + \Delta d_{t+1} \\ r^*_{m,t+1} &= \kappa^*_{m,0} + \kappa^*_{m,1} z^*_{m,t+1} - z^*_t + \Delta d^*_{t+1} \end{aligned}$$

where $z_{m,t} = \log\left(\frac{P_t}{D_t}\right)$ is the US log price-dividend ratio, which has unconditional mean $\overline{z}_m$, and the κ_m's depend on $\overline{z}_m$ in an analogous way to the κ's on $\overline{z}$ above (similar relationships hold for the foreign asset).

Given the endowment nature of the economy, we need find solutions for the price-consumption

[43] Of course, if the production economy does not match the empirical processes, the resulting asset prices will differ, but not necessarily because there is some failure of the Euler equation, the margin on which we focus. Backus et al. (2014) show that the behavior of asset prices changes very little with endogenous consumption and investment.

ratio and the price-dividend ratio for each asset in order to characterize returns. The state variables in the economy are the expected growth rates x_t and x_t^*, and these ratios are approximately linear in the states, i.e.,

$$
\begin{aligned}
z_t &= A_0 + A_1 x_t + A_2 x_t^* \\
z_{m,t} &= A_{m,0} + A_{m,1} x_t + A_{m,2} x_t^* \\
z_{m,t}^* &= A_{m,0}^* + A_{m,1}^* x_t + A_{m,2}^* x_t^*
\end{aligned}
$$

Substituting into the Euler equation (3), we can find

$$
\begin{aligned}
A_1 &= \frac{1-\frac{1}{\psi}}{1-\kappa_1\rho} \\
A_2 &= 0 \\
A_0 &= \frac{\log\beta + \left(1-\frac{1}{\psi}\right)\mu + \kappa_0 + \frac{1}{2}(1-\gamma)\left(1-\frac{1}{\psi}\right)\left(\sigma_\eta^2 + \left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma_e^2\right)}{1-\kappa_1}
\end{aligned} \tag{12}
$$

and for the US asset,

$$
\begin{aligned}
A_{m,1} &= \frac{\phi-\frac{1}{\psi}}{1-\kappa_{m,1}\rho} \\
A_{m,2} &= 0 \\
A_{m,0} &= \frac{\theta\log\beta - \gamma\mu + (\theta-1)\left(\kappa_0 + A_0\left(\kappa_1-1\right)\right) + \mu_d + \kappa_{m,0}}{1-\kappa_{m,1}} \\
&+ \frac{\frac{1}{2}(\pi-\gamma)^2\sigma_\eta^2 + \frac{1}{2}\left((\theta-1)\kappa_1 A_1 + \kappa_{m,1}A_{m,1}\right)^2\sigma_e^2 + \frac{1}{2}\sigma_\mu^2}{1-\kappa_{m,1}}
\end{aligned} \tag{13}
$$

and lastly, for the foreign asset,

$$
\begin{aligned}
A_{m,1}^* &= \frac{\phi^*-\frac{1}{\psi}}{1-\kappa_{m,1}^*\rho} \\
A_{m,2}^* &= \frac{\tilde{\phi}^*}{1-\kappa_{m,1}^*\rho^*} \\
A_{m,0}^* &= \frac{\theta\log\beta - \gamma\mu + (\theta-1)\left(\kappa_0 + A_0\left(\kappa_1-1\right)\right) + \mu_d^* + \kappa_{m,0}^* + \frac{1}{2}\left(\kappa_{m,1}^* A_{m,2}^*\right)^2\sigma_{e^*}^2}{1-\kappa_{m,1}^*} \\
&+ \frac{\frac{1}{2}(\pi^*-\gamma)^2\sigma_\eta^2 + \frac{1}{2}\left((\theta-1)\kappa_1 A_1 + \kappa_{m,1}^* A_{m,1}^*\right)^2\sigma_e^2 + \frac{1}{2}{\pi_d^*}^2\sigma_\mu^2 + \frac{1}{2}\sigma_{\mu^*}^2}{1-\kappa_{m,1}^*}
\end{aligned} \tag{14}
$$

Solving for mean excess returns entails finding the vectors of consumption parameters $\boldsymbol{A}$ and

$\boldsymbol{\kappa}$ and the corresponding vectors of return parameters, $\boldsymbol{A_m}$ and $\boldsymbol{\kappa_m}$, both for the US and each foreign asset. This can be done following a simple iterative procedure. As an example, consider the consumption parameters. First, note that $\overline{z} = A_0$. Then, for a candidate value of $\overline{z}$, we can compute values for $\boldsymbol{\kappa}$. We can then compute the vector $\boldsymbol{A}$ using (12), which produces an updated value for $\overline{z}$. We then iterate until convergence. We use an analogous procedure to solve for the return parameters, both in the US and each foreign region. The mean risk-free rate depends only on consumption and preference parameters.

Identification of parameters for US consumption and dividend growth. The parameters μ_c, σ_e and σ_η are identified by the three moment conditions:

$$\begin{aligned} \mathbb{E}\left[\Delta c_t\right] &= \mu_c \\ \operatorname{cov}\left(\Delta c_t, \Delta c_{t+1}\right) &= \rho\frac{\sigma_e^2}{1-\rho^2} \\ \operatorname{var}(\Delta c_t) &= \frac{\sigma_e^2}{1-\rho^2} + \sigma_\eta^2 \end{aligned} \tag{15}$$

The mean growth rate μ_c is pinned down by its sample value. For a given value of ρ, the autocovariance in consumption growth identifies σ_e^2 and given this value, the variance of consumption growth identifies σ_η^2.

Turning to the US dividend growth process, we rely on the following moment conditions:

$$\begin{aligned} \mathbb{E}\left[\Delta d_t\right] &= \mu_d \\ \sqrt{\frac{\operatorname{cov}\left(\Delta d_{t+1}, \Delta d_t\right)}{\operatorname{cov}\left(\Delta c_{t+1}, \Delta c_t\right)}} &= \phi \\ \operatorname{cov}\left(\Delta d_t, \Delta c_t\right) &= \phi\frac{\sigma_e^2}{1-\rho^2} + \pi\sigma_\eta^2 \\ \operatorname{var}(\Delta d_t) &= \phi^2\frac{\sigma_e^2}{1-\rho^2} + \pi^2\sigma_\eta^2 + \sigma_\mu^2 \end{aligned} \tag{16}$$

The mean growth rate μ_d is identified directly from its sample value. The leverage parameter ϕ is pinned down by the ratio of the autocovariance of Δd to that of Δc. Given the value of ϕ, the covariance of Δd with Δc identifies π. The variance of Δd then pins down the value of σ_μ^2.

Identification of parameters for foreign dividend growth. In addition to the two moment conditions in expressions (8) and (9), we rely on the following four moment conditions to identify the parameters that govern foreign dividend growth:

$$\begin{aligned}
\mathbb{E}\left[\Delta d_t^*\right] &= \mu_d^* && (17)\\
\operatorname{cov}\left(\Delta d_t^*, \Delta c_t\right) &= \phi^* \frac{\sigma_e^2}{1-\rho^2} + \pi^* \sigma_\eta^2 && (18)\\
\operatorname{cov}\left(\Delta d_{t+1}^*, \Delta d_t^*\right) &= \left(\phi^* \sigma_e\right)^2 \frac{\rho}{1-\rho^2} + \left(\tilde{\phi}^* \sigma_{e^*}\right)^2 \frac{\rho^*}{1-\rho^{*2}} && (19)\\
\operatorname{var}\left(\Delta d_t^*\right) &= \frac{\left(\phi^* \sigma_e\right)^2}{1-\rho^2} + \frac{\left(\tilde{\phi}^* \sigma_{e^*}\right)^2}{1-\rho^{*2}} + {\pi^*}^2 \sigma_\eta^2 + {\pi_d^*}^2 \sigma_\mu^2 + \sigma_{\mu^*}^2 && (20)
\end{aligned}$$

Identification proceeds as follows. Because the κ's in (9) are nonlinear functions of the other parameters of the model, we employ a numerical fixed point procedure. We first use (17) to infer the mean dividend growth rate μ_d^* from its sample value. We then guess a candidate value for ϕ^*. Using this guess and the set of US parameters, (18) pins down π^*. With these values in hand, (8) identifies π_d^*. Next, (19) pins down the parameter combination $\tilde{\phi}^* \sigma_{e^*}$ (for a given value of ρ^*) and (20) pins down $\sigma_{\mu^*}^2$. Lastly, we construct the model-implied covariance of returns in expression (9) and iterate on the initial guess of ϕ^* until we match the empirical moment.

As a final note, because (9) depends on $\kappa_{m,1}^*$, we must prove that $\tilde{\phi}^* \sigma_{e^*}$ is sufficient to compute $\kappa_{m,1}^*$, i.e., that we do not need to to separately identify $\tilde{\phi}^*$ and σ_{e^*}. To see this, combine the expressions in (14) to obtain

$$\begin{aligned}
A_{m,0}^* &= \frac{\theta \log \beta - \gamma \mu + (\theta-1)\left(\kappa_0 + A_0\left(\kappa_1 - 1\right)\right) + \mu_d^* + \kappa_{m,0}^* + \frac{1}{2}\left(\frac{\kappa_{m,1}^*}{1-\kappa_{m,1}^* \rho^*}\right)^2 \left(\tilde{\phi}^* \sigma_{e^*}\right)^2}{1-\kappa_{m,1}^*} \\
&+ \frac{\frac{1}{2}\left(\pi^* - \gamma\right)^2 \sigma_\eta^2 + \frac{1}{2}\left((\theta-1)\kappa_1 A_1 + \frac{\kappa_{m,1}^*}{1-\kappa_{m,1}^* \rho}\left(\phi^* - \frac{1}{\psi}\right)\right)^2 \sigma_e^2 + \frac{1}{2}{\pi_d^*}^2 \sigma_\mu^2 + \frac{1}{2}\sigma_{\mu^*}^2}{1-\kappa_{m,1}^*}
\end{aligned}$$

Only $\tilde{\phi}^* \sigma_{e^*}$ appears in the expression. Because $\kappa_{m,1}^*$ is simply a nonlinear function of $A_{m,0}^*$, the same argument goes through.

D Robustness of Quantitative Analysis

Rebalanced Portfolios. As an alternative approach to classifying countries into portfolios, we group countries according to income on an annual basis. Specifically, we 'rebalance' our portfolios on an annual basis, i.e., classify countries in each year based on their rank in the income distribution within that particular year.[44] The main advantage of this approach is that it accounts for the changing place of countries as the income distribution evolves; the drawback is that it introduces a significant degree of turnover in the portfolios, i.e., many countries move in and out of each portfolio, particularly so at finer levels of disaggregation. From our point of view, we are most interested in the robustness of our results to this alternative grouping procedure. We report the results in Table 10.[45] Our results are robust to this alternative grouping procedure. The model predicts a spread in returns between Portfolio 1 and the US of between 4.5% and 5.3%, which accounts for between 60% and 74% of the spread in the data. These results are quite close to those obtained in our baseline approach. The correlation of predicted and actual returns across portfolios ranges upward from a low of about 0.9.

Table 10: The Returns to Capital - Annually Rebalanced Portfolios

3 Portfolios			5 Portfolios			10 Portfolios		
	$\widehat{r}$	r		$\widehat{r}$	r		$\widehat{r}$	r
1	10.36	12.08	1	10.82	12.98	1	11.23	14.89
2	8.58	10.22	2	9.88	10.82	2	10.39	10.90
3	6.91	7.56	3	7.99	10.17	3	9.59	10.48
US	5.90	6.01	4	7.34	8.48	4	10.18	11.15
			5	7.05	7.25	5	8.10	10.50
			US	5.90	6.01	6	7.91	9.86
						7	8.19	8.94
						8	6.50	8.00
						9	7.15	6.86
						10	6.95	7.63
						US	5.90	6.01
Average:	7.94	8.97		8.16	9.29		8.37	9.57
Spread: 1-US	4.46	6.07		4.92	6.97		5.33	8.88
Percent of actual	74			71			60	
corr($\widehat{r}, r$)	1.00			0.96			0.91	

Alternative Identification Strategies. In this section, we perform several exercises to illustrate the important role played by the various elements of the model and our identification strategy in accurately measuring the extent of long-run risks. The key challenge is to identify the parameter that measures the exposure of foreign dividends to the global persistent shock and ultimately governs foreign expected returns, namely ϕ^*.

[44] This approach has been widely used in examining cross-sectional differences in returns. See, for example, Lustig and Verdelhan (2007).

[45] Moments and parameter estimates for this exercise are available upon request.

First, as mentioned in the text, following the same procedure as we do for the US does not identify the desired parameter. To see this, maintaining the assumption that $\rho^* = \rho$, we can derive the following equation from (4), which makes clear the difficulty:

$$\sqrt{\frac{\operatorname{cov}\left(\Delta d^*_{t+1}, \Delta d^*_t\right)}{\operatorname{cov}\left(\Delta c_{t+1}, \Delta c_t\right)}} = \phi^* \sqrt{1 + \left(\frac{\tilde{\phi}^*}{\phi^*}\frac{\sigma_{e^*}}{\sigma_e}\right)^2} \tag{21}$$

This moment identifies the true ϕ^* only if $\tilde{\phi}^*\sigma_{e^*} = 0$, that is, only if there are no regional long-run shocks to dividend growth rates. Otherwise, relying on this moment gives a biased estimate of ϕ^*, with the bias corresponding to the term in square root. This term is weakly larger than 1, implying an upward bias, which would tend to deliver a higher estimate of the risk premium.

To quantify the extent of this bias, we parameterize the model ignoring region-specific idiosyncratic long-run shocks, i.e., under the naive assumption that $\tilde{\phi}^*\sigma_{e^*} = 0$ (or alternatively, that $\rho^* = 0$). In this case, we are clearly able to infer ϕ^* from expression (21). The third column of Table 11 reports the implied returns when following this alternative identification strategy (the US return does not change, since we are only changing assumptions regarding foreign idiosyncratic shocks). The first two columns report the actual returns and those predicted under our baseline approach, respectively. A comparison of the second and third columns shows that ignoring regional long-run shocks would lead to substantial bias in the results. As predicted by expression (21), returns are everywhere biased upward. The magnitude of this bias ranges from 0.7% in portfolio 1 to 2.5% in portfolio 3. Clearly, not accounting for idiosyncratic long-run shocks leads to significant bias under an approach that relies solely on moments in persistence.

In contrast, the fourth column of Table 11 reports the predicted returns under the same assumption of no foreign persistent shocks, i.e. $\tilde{\phi}^*\sigma_{e^*} = 0$, but following our baseline identification strategy. The predicted returns are nearly identical to those obtained from our benchmark approach. Notice this exercise is equivalent to a model where ρ^* is set to zero, and so also serves as a robustness exercise on the value of this parameter. In other words, under our proposed empirical strategy, the results change only negligibly whether we account for local persistent shocks or not, and they are robust to large changes in the persistence of those shocks (recall that the benchmark value of ρ^* is relatively high at 0.93). This robustness to the properties of regional long-run shocks is an attractive feature of our approach and is intuitive when examining our identification equations (8)-(9) and (17)-(20) and the expressions for predicted returns (6) and (7). The parameters of the foreign shock processes (ρ^* and $\sigma^2_{e^*}$) do not enter anywhere into the latter two, implying that they do not directly impact expected returns; their only effect is indirect by affecting $\kappa^*_{m,1}$, and so our estimate of ϕ^* (through expression (14)). However, these indirect effects are quantitatively negligible.

Because we allow for correlation in both the transitory and persistent movements of dividend growth rates across countries, the comovement of domestic and foreign dividend growth does not provide enough information to identify ϕ^*. Expression (8) shows that even if we knew the value of π^*, which measures the exposure of foreign dividend growth to the transitory component of US consumption growth, we cannot separately identify ϕ^* from π^*_d. Failure to account for the portion of the comovement of dividend growth rates that is due to temporary shocks - π^*_d - may bias the estimate of ϕ^*.

In the last column of Table 11, we compute predicted returns under the assumption that there is no transitory comovement between dividend growth rates, i.e., $\pi^*_d = 0$. Imposing this restriction implies that correlations in dividend growth rates across countries are due only to exposure to the common long-run shock, and to their common dependence on the transitory consumption shock governed by π^* and π. In this case, the covariance of dividend growth rates with those in the US and with US consumption growth (expressions (8) and (18)) are clearly sufficient to tease out ϕ^*. The implications are very stark: Portfolio 3 now yields the highest returns while Portfolio 1 yields the lowest. As discussed earlier, since period-by-period comovement between dividend growth in developed economies and the US is higher than in less developed countries, attributing this comovement only to persistent components would result in the misleading conclusion that developed countries are actually riskier, leading to a full reversal in the ordering of implied risk premia.

Finally, we note that using foreign consumption data and specifying a foreign consumption process as in expression (5) in order to use a strategy exactly analogous to that in the US - i.e., the ratio of the autocovariance of foreign dividend to foreign consumption growth - is also not sufficient. Using the notation from expression (5), this moment exactly identifies $\tilde{\phi}^*$, but does not hold any information regarding ξ^* and therefore does not pin down ϕ^*, as can be seen from the following expression:

$$\sqrt{\frac{\operatorname{cov}\left(\Delta d^*_{t+1}, \Delta d^*_t\right)}{\operatorname{cov}\left(\Delta c^*_{t+1}, \Delta c^*_t\right)}} = \tilde{\phi}^* \tag{22}$$

In other words, this ratio tells us the translation from persistence in local consumption growth to dividend growth, but does not identify how the local consumption process itself depends on the global long-run shock.

Table 11: Predicted Returns - Alternative Empirical Strategies

Portfolio	r	$\widehat{r}$	$\sigma_{e^*}=0$ $\widehat{r}_{autocov}$	$\widehat{r}_{baseline}$	$\widehat{r}_{\pi_d^*=0}$
1	13.01	10.35	11.00	10.36	8.69
2	11.06	9.14	12.00	9.16	9.18
3	8.04	7.04	9.54	7.05	10.47

Notes: The first two columns of the Table report actual expected returns, r, and predicted expected returns from the model, $\hat{r}$, computed using the parameters in Table 4. The third column, denoted by $\widehat{r}_{autocov}$ reports predicted expected returns when $\sigma_{e^*} = 0$ and ϕ^* satisfies expression (21); all remaining parameters satisfy moment conditions as in baseline. The fourth column, denoted by $\widehat{r}_{baseline}$ reports predicted expected returns when $\sigma_{e^*} = 0$ and all remaining parameters satisfy moment conditions as in baseline. The fifth column, denoted by $\widehat{r}_{\pi_d^*=0}$ reports predicted expected returns when $\pi_d^* = 0$ and all remaining parameters satisfy moment conditions as in baseline.

E Consumption CAPM

In this section, we take an alternative approach to illustrate the implications of the traditional power-utility CCAPM model - namely, we use the covariance of returns with consumption growth, which is a sufficient statistic for risk premia in that framework. Consider a representative US investor with CRRA preferences

$$u(c_t) = \frac{c_t^{1-\gamma} - 1}{1-\gamma}$$

where γ is the coefficient of relative risk aversion (here also the inverse of the intertemporal elasticity of substitution).

Euler equations of the form in expression (3) continue to hold with the investor's SDF now given by $M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}$. To simplify matters, we linearize the SDF around its unconditional mean as $\frac{M_{t+1}}{\mathbb{E}[M_{t+1}]} \approx 1 + m_{t+1} - \mathbb{E}[m_{t+1}]$ where $m_t = \log M_t$. Using the definition of m_t along with the unconditional expectation of (3) gives the standard covariance formula

$$\mathbb{E}\left[r_{j,t}^e\right] = \gamma \mathrm{cov}\left(\Delta c_t, r_{j,t}\right) \tag{23}$$

which relates the mean excess return on an asset to the covariance of its returns with log consumption growth. The degree of risk aversion γ governs the strength of this relationship, that is, it determines how much additional compensation is demanded for each additional unit of covariance risk.

To assess the ability of the CCAPM to account for the patterns in international capital returns, it remains to construct the objects in equation (23). Mean excess returns are computed as the average of annual returns less the annual return on a 3 month treasury bond. US consumption is measured as real per-capita consumption of non-durables and services.[46] The covariance for each portfolio is calculated as the average covariance of the countries within that portfolio (recall that in our baseline approach, countries do not change portfolios).

We report the results in Table 12. First, we set a value for γ and evaluate the right hand side of (23). This is the excess return predicted by the CCAPM. We set $\gamma = 10$, which is towards the higher end of the range commonly deemed to be reasonable.[47] Excess returns range from a low of 0.10% to a high of 0.27%. Quantitatively, these are essentially negligible: the model generates excess returns orders of magnitude below the actual, and only a minimal spread between portfolios. Clearly, the CCAPM cannot rationalize the patterns of capital returns observed in the data, at least not for this level of risk aversion.

Table 12: Capital Returns in the Consumption CAPM

						$\widehat{r}^e$	
Portfolio	r^e	$\text{cov}\,(r_{j,t}, \Delta c_{US,t})$	$\text{corr}\,(r_{j,t}, \Delta c_{US,t})$	$\text{std}\,(r_{j,t})$	$\gamma =$	10	480
1	11.79	0.00027	0.30	0.063		0.27	12.75
2	9.84	0.00019	0.25	0.053		0.19	8.96
3	6.82	0.00012	0.23	0.042		0.12	5.95
US	4.79	0.00010	0.31	0.027		0.10	4.94
Spread: 1-US	6.99	-	-	-		0.16	7.81

Notes: Table reports excess returns across portfolios, r^e, the covariance and correlation of returns with US consumption growth, the volatility of returns and the predicted excess returns from the CCAPM model under two alternative levels of risk aversion.

Next, we ask what level of risk aversion is needed to best fit the observed levels of returns across portfolios? To answer this, we compute the slope of the line of best fit (with a constant term of zero) across portfolios, which gives a value of 480. The associated excess returns are reported in the last column of the table, which shows that to generate levels of returns on par with the data within this framework requires an unreasonably high level of risk aversion.[48]

Long-run risk and international stock market returns. Our approach to analyzing stock market returns is quite similar to that in our baseline analysis . Moments in US consumption growth are exactly the same. Rather than estimating ϕ in the US, we follow the literature and assign the well-accepted value of $\phi = 3$ (see, for example, Bansal and Yaron (2004) and many more). The remainder of the calibration follows the same strategy as in the baseline,

[46]Data on treasury returns are obtained from the Federal Reserve Bank of St. Louis FRED database.
[47]See, for example, Mehra and Prescott (1985).
[48]We have also performed this exercise using stock market returns. The results are similar.

but employing moments from stock market data. We use annual data for both returns and dividends (hence, the return values differ slightly from those in Table 8, which were annualized from quarterly data). Return data are as described in Appendix A. Due to known problems with imputing dividend series from the return and price indices provided by MSCI, see, for example, the discussion and references in Rangvid et al. (2014), we follow these authors and use dividend data obtained from Datastream. Datastream reports quarterly dividend yields and price indices in US dollars for most of the countries in our sample, from which we can compute the level of dividends.[49] We deflate quarterly dividends using the US CPI and because of well-known seasonality in dividend payouts, we aggregate to an annual frequency.

Both the dividend and returns series exhibit a handful of extreme outliers. As has been recognized in the literature, emerging stock markets are prone to extremely large short-term fluctuations, due, for example, to events such as currency crises, default episodes, movements in commodity prices etc. Given our rather short time frame and small number of countries, even one of these episodes can have a large influence on the results (for example, returns exceeding 100% within a single quarter or fluctuations in dividend growth rates of over 300% in a year). The dividend series are also subject to at least two other considerations: first we are only able to compute total dividends from the Datastream data, not dividends per share. To the extent that the number of firms in the Datastream index is changing, this may affect the resulting moments for reasons unrelated to changes in dividends per share, which is the object of interest. Second, countries may differ in terms of the dividend policy of firms - i.e., to what extent firms smooth dividends or decide to use retained earnings to finance increased investment rather than distribute profits to shareholders - and these differences may be independent of actual differences in the underlying fundamentals of firms. To address this concern we exclude observations where dividends fluctuate by more than 50% in a single year, roughly the 2% tails of the distribution. We accordingly do the same for stock returns, where we trim the 3% tails of returns in each country. We choose this more systematic approach, rather than take a stand on whether particular episodes represent outliers or not, given their relatively more frequent occurrence in emerging markets. Our trimming approach tends to be conservative for our quantitative work, in the sense of generally leading to lower predicted returns from our model.

The top panel of Table 13 reports the target moments. Even after trimming extreme outliers, the dividend data show very large differences in mean growth rates across countries. This may be due in part to the shortness of the time-series available and differences in dividend policies across countries unrelated to fundamentals. With this in mind, we make the admittedly rough

[49]Brazil and Switzerland are only available in local currency. For these countries, we convert dividends from local currency to US dollars using end of quarter exchange rates obtained from the Federal Reserve Bank of St. Louis FRED database.

adjustment of setting all mean growth rates to the US value of 0.02. This has very little effect on the results, since mean growth rates do not directly affect risk premia.[50]

Table 13: Stock Market Returns - Predicted vs. Actual

Moments						
Portfolio	$\mathbb{E}\left[\Delta d_t^*\right]$	$\operatorname{cov}\left(\Delta d_{t+1}^*, \Delta d_t^*\right)$	$\operatorname{cov}\left(\Delta d_t^*, \Delta c_t\right)$	$\operatorname{std}\left(\Delta d_t^*\right)$	$\operatorname{cov}\left(\Delta d_t^*, \Delta d_t\right)$	$\frac{\operatorname{cov}(r_t^*, r_t)}{\operatorname{std}(r_t)}$
1	0.020	0.00812	-0.00002	0.191	0.00213	0.132
2	0.020	0.00655	0.00044	0.155	0.00254	0.087
US	0.020		0.00032	0.062		
		$\operatorname{corr}\left(\Delta d_{t+1}^*, \Delta d_t^*\right)$	$\operatorname{corr}\left(\Delta d_t^*, \Delta c_t\right)$		$\operatorname{corr}\left(\Delta d_t^*, \Delta d_t\right)$	$\operatorname{corr}\left(r_t^*, r_t\right)$
1		0.20	-0.01		0.17	0.35
2		0.25	0.21		0.25	0.43
US		0.54	0.44		1.00	1.00
Parameters						
Portfolio	μ_d	ϕ	π	π_d	σ_μ	$\tilde{\phi}^* \sigma_{e^*}$
1	0.020	7.75	-14.14	0.20	0.131	0.021
2	0.020	3.68	1.88	0.48	0.127	0.028
US	0.020	3.00	0.83	-	0.055	-
Returns						
Portfolio	$\widehat{r}$	r				
1	17.27	18.24				
2	11.50	8.89				
US	8.44	9.60				
Average:	12.40	12.25				
Spread: 1-US	8.83	8.64				
Percent of actual	102					

Notes: Table reports target moments, calibrated parameters, and expected stock returns as reported in the data, r and predicted by the model, $\hat{r}$. Consumption is measured as real per-capita consumption of non-durables and services. Consumption moments are computed over the period 1929-2008, the longest available from the BEA. Dividend data are from Datastream and returns data are from MSCI. Portfolio moments are computed over the period 1988-2014. The moments for each portfolio represent the mean values for the countries in that portfolio.

The center panel of Table 13 reports the parameter estimates and the bottom panel the predicted mean returns. The model generates expected returns of 17.3% for the low-income countries and 8.4% for the US, representing a spread of 8.8 percentage points. The corresponding values in the data are 18.2% and 9.6%, so a spread of 8.6%; although the levels of returns in the model are about 1% lower than the data, the model-implied spread between the poorest countries and the US is almost exactly that in the data. The higher-income countries exhibit an intermediate level of returns, both in the model and data, although here the model generates returns that are quite a bit higher than the data: 11.5% versus 8.9%. In sum, the long-run risk model leads to stock market returns across income groups very much in line with those in

[50]For example, setting the growth rate of the low-income portfolio as high as 0.05 changes the risk premium there only negligibly.

the data and perhaps most importantly, suggests risk premia on the order of those observed. Indeed, the model seems to fit equity returns more closely than our baseline measure of returns; this may not be surprising, given that the LRR model was built with equity markets in mind.

Table 14 performs the analogous exercise as Table 6 and decomposes stock market returns into their risk-free, short-run and long-run components. The results are similar to those in our baseline analysis - short-run risks are generally small and ordered in the reverse direction, i.e., they are higher in developed countries than developing. Thus, long-run risks account for (more than) the entirety of the return differentials predicted by the model.

Table 14: Stock Market Returns - Decomposition

	Actual	Predicted						
Portfolio	r	$\widehat{r}$	$=$	$\widehat{r}^f$	$+$	$\widehat{r}^e_{sr}$	$+$	$\widehat{r}^e_{lr}$
1	18.24	17.27		1.27		-2.99		18.98
2	8.89	11.50		1.27		0.40		9.83
US	9.60	8.44		1.27		0.18		6.99

Notes: Table reports actual expected returns, r, and predicted expected returns from the model, $\hat{r}$, computed using the parameters in Table 13. The predicted returns are decomposed into three components: risk-free rate, $\hat{r}^f$, short-run risk, $\hat{r}^e_{sr}$, and long-run risk, $\hat{r}^e_{lr}$ using expressions (6) and (7) in the text.

F List of Countries

Country	3 Letter code	Init. year	Portfolio number 3 portf.	5 portf.	10 portf.	Ctry An.	α	Openness CI-2004	Q-2004	GMF-1995
Albania	ALB	1970	2	3	5	0	0	1	0	0
Angola	AGO	1970	1	2	3	0	0	0	0	0
Antigua/Barbuda	ATG	1970	3	4	8	0	0	1	0	1
Argentina	ARG	1950	2	3	5	1	1	1	0	1
Armenia	ARM	1990	2	2	4	0	1	1	0	0
Australia	AUS	1950	3	5	10	1	1	1	1	1
Austria	AUT	1950	3	5	9	1	1	1	1	1
Azerbaijan	AZE	1990	2	2	4	0	1	0	0	0
Bahamas	BHS	1970	3	5	9	0	1	0	0	0
Bahrain	BHR	1970	3	5	9	0	0	1	0	1
Bangladesh	BGD	1959	1	1	2	1	0	0	0	0
Barbados	BRB	1960	3	4	8	1	1	0	0	0
Belarus	BLR	1990	2	3	6	0	1	0	0	0
Belgium	BEL	1950	3	5	10	1	1	1	1	1
Belize	BLZ	1970	2	3	6	0	0	0	0	0
Benin	BEN	1959	1	1	2	1	1	0	0	0
Bhutan	BTN	1970	1	2	3	0	0	0	0	0
Bolivia	BOL	1950	1	2	3	1	1	1	1	1
Botswana	BWA	1960	2	3	5	1	1	1	0	0
Brazil	BRA	1950	2	2	4	1	1	1	1	0
Brunei	BRN	1970	3	5	10	0	0	0	0	0
Bulgaria	BGR	1970	2	3	5	0	1	0	1	0
Burkina Faso	BFA	1959	1	1	1	1	1	0	0	0
Burundi	BDI	1960	1	1	1	1	0	0	0	0
Canada	CAN	1950	3	5	10	1	1	1	1	1
Cape Verde	CPV	1960	1	2	3	1	0	0	0	0
Central Afr. Rep.	CAF	1960	1	1	1	1	1	0	0	0
Chad	TCD	1960	1	1	1	1	0	0	0	0
Chile	CHL	1951	2	3	6	1	1	1	1	0
China	CHN	1952	1	1	2	1	1	0	1	0
Colombia	COL	1950	2	3	6	1	1	1	1	0
Comoros	COM	1960	1	1	2	1	0	0	0	0
Congo, Dem. Rep.	COD	1970	1	1	1	0	0	0	0	0
Congo, Rep. of	COG	1960	1	2	3	1	0	0	0	0
Costa Rica	CRI	1950	2	3	6	1	1	1	1	1
Cote d‘Ivoire	CIV	1960	1	2	3	1	1	0	0	0
Croatia	HRV	1990	3	4	8	0	1	1	0	0
Cyprus	CYP	1950	3	4	8	1	1	1	0	0
Czech Republic	CZE	1990	3	5	9	0	1	1	1	0

Country	3 Letter code	Init. year	Portfolio number 3 portf.	5 portf.	10 portf.	Ctry An.	α	Openness CI-2004	Q-2004	GMF-1995
Denmark	DNK	1950	3	5	9	1	1	1	1	1
Djibouti	DJI	1970	1	2	4	0	1	1	0	1
Dominican Rep.	DOM	1951	2	3	5	1	1	1	0	0
Ecuador	ECU	1951	2	2	4	1	1	1	1	1
El Salvador	SLV	1950	1	1	1	1	0	1	1	0
Estonia	EST	1990	3	4	7	0	1	1	0	1
Ethiopia	ETH	1950	1	1	1	1	0	0	0	0
Fiji	FJI	1960	2	3	5	1	1	0	0	0
Finland	FIN	1950	3	4	8	1	1	1	1	1
France	FRA	1950	3	5	10	1	1	1	1	1
Gabon	GAB	1960	3	4	7	1	0	0	0	0
Gambia, The	GMB	1960	1	1	2	1	0	1	0	1
Georgia	GEO	1990	2	2	4	0	1	1	0	0
Germany	DEU	1950	3	5	10	1	1	1	1	1
Greece	GRC	1951	3	4	8	1	1	1	1	0
Grenada	GRD	1970	2	3	5	0	0	0	0	0
Guatemala	GTM	1950	2	2	4	1	1	1	1	1
Guinea	GIN	1959	1	1	2	1	0	0	0	0
Honduras	HND	1950	1	2	4	1	1	1	0	1
Hong Kong	HKG	1960	3	5	10	1	1	1	1	1
Hungary	HUN	1970	2	4	7	0	1	1	1	0
Iceland	ISL	1950	3	5	10	1	1	1	0	0
India	IND	1950	1	1	2	1	1	0	1	0
Indonesia	IDN	1960	1	2	3	1	1	1	1	1
Iran	IRN	1955	2	3	6	1	1	1	0	0
Ireland	IRL	1950	3	5	9	1	1	1	0	1
Israel	ISR	1950	3	5	9	1	1	1	1	0
Italy	ITA	1950	3	5	9	1	1	1	1	1
Jamaica	JAM	1953	2	3	5	1	1	1	1	0
Japan	JPN	1950	3	4	8	1	1	1	1	0
Jordan	JOR	1954	2	3	6	1	1	1	0	0
Kazakhstan	KAZ	1990	2	3	6	0	1	0	0	0
Kenya	KEN	1950	1	1	2	1	1	1	1	0
Korea, Rep. of	KOR	1953	2	4	7	1	1	1	1	0
Kyrgyzstan	KGZ	1990	1	2	3	0	1	1	0	0
Latvia	LVA	1990	2	4	7	0	1	1	0	1
Lesotho	LSO	1960	1	1	2	1	1	0	0	0
Liberia	LBR	1964	1	1	1	0	0	1	0	0
Lithuania	LTU	1990	3	4	7	0	1	0	0	1
Luxembourg	LUX	1950	3	5	10	1	1	0	0	0
Macao	MAC	1970	3	5	10	0	1	1	0	0

Country	3 Letter code	Init. year	Portfolio number 3 portf.	5 portf.	10 portf.	Ctry An.	α	Openness CI-2004	Q-2004	GMF-1995
Macedonia	MKD	1990	3	4	7	0	1	1	0	0
Malawi	MWI	1954	1	1	1	1	0	0	0	0
Malaysia	MYS	1955	2	3	6	1	1	1	0	1
Mali	MLI	1960	1	1	1	1	0	0	0	0
Mauritania	MRT	1960	1	2	3	1	1	0	0	0
Mauritius	MUS	1950	2	4	7	1	1	1	0	0
Mexico	MEX	1950	3	4	8	1	1	1	1	0
Moldova	MDA	1990	1	2	3	0	1	0	0	0
Mongolia	MNG	1970	1	2	3	0	1	1	0	0
Montenegro	MNE	1990	3	5	9	0	0	1	0	0
Morocco	MAR	1950	2	2	4	1	1	0	0	0
Mozambique	MOZ	1960	1	1	1	1	1	0	0	0
Namibia	NAM	1960	2	3	5	1	0	0	0	0
Nepal	NPL	1960	1	1	1	1	0	0	0	0
Netherlands	NLD	1950	3	5	9	1	1	1	1	1
New Zealand	NZL	1950	3	4	8	1	1	1	1	1
Niger	NER	1960	1	1	2	1	1	0	0	1
Nigeria	NGA	1950	1	1	2	1	0	0	1	0
Norway	NOR	1950	3	5	10	1	1	1	1	1
Oman	OMN	1970	3	5	9	0	0	1	0	1
Pakistan	PAK	1950	1	2	3	1	0	0	0	0
Panama	PAN	1950	2	4	7	1	1	1	0	1
Paraguay	PRY	1951	1	2	4	1	1	1	0	0
Peru	PER	1950	2	2	4	1	1	1	1	1
Philippines	PHL	1950	1	2	4	1	1	1	1	0
Poland	POL	1970	2	3	6	0	1	1	1	0
Portugal	PRT	1950	2	4	7	1	1	0	1	1
Qatar	QAT	1970	3	5	10	0	0	1	0	1
Romania	ROU	1988	2	3	6	0	1	1	0	0
Russia	RUS	1990	2	4	7	0	1	0	1	0
S.Tome/Principe	STP	1970	1	1	2	0	1	1	0	0
Saudi Arabia	SAU	1970	3	5	10	0	0	1	0	1
Senegal	SEN	1960	1	1	2	1	1	0	1	0
Serbia	SRB	1990	2	3	6	0	1	1	0	0
Singapore	SGP	1960	3	4	8	1	1	1	1	1
Slovak Rep.	SVK	1990	3	4	8	0	1	1	0	0
Slovenia	SVN	1990	3	5	9	0	1	1	0	0
South Africa	ZAF	1950	2	3	6	1	1	0	1	0
Spain	ESP	1950	3	4	8	1	1	1	1	1
Sri Lanka	LKA	1950	2	2	4	1	1	1	1	0
St. Lucia	LCA	1970	2	3	6	0	0	1	0	0

Country	3 Letter code	Init. year	Portfolio number 3 portf.	5 portf.	10 portf.	Ctry An.	α	CI-2004	Openness Q-2004	GMF-1995
St.Vincent/Gren.	VCT	1970	2	3	5	0	0	0	0	0
Suriname	SUR	1970	2	4	7	0	1	0	0	0
Swaziland	SWZ	1970	2	3	5	0	1	0	0	0
Sweden	SWE	1950	3	5	9	1	1	1	1	1
Switzerland	CHE	1950	3	5	10	1	1	1	0	1
Syria	SYR	1960	1	2	4	1	0	0	0	0
Taiwan	TWN	1951	3	4	8	1	0	1	0	0
Tajikistan	TJK	1990	1	2	3	0	1	0	0	0
Tanzania	TZA	1960	1	1	1	1	1	0	0	0
Thailand	THA	1950	1	2	3	1	1	1	0	0
Togo	TGO	1960	1	1	1	1	0	0	0	0
Trinidad/Tobago	TTO	1950	3	4	8	1	0	0	0	1
Tunisia	TUN	1960	2	3	5	1	1	0	1	0
Turkey	TUR	1950	2	4	7	1	1	0	1	0
Turkmenistan	TKM	1990	2	3	5	0	0	0	0	0
Uganda	UGA	1950	1	1	1	1	0	1	1	0
Ukraine	UKR	1990	2	3	5	0	1	0	0	0
United Kingdom	GBR	1950	3	5	9	1	1	1	1	1
United States	USA	1950	4	6	11	1	1	1	1	1
Uruguay	URY	1950	2	4	7	1	1	1	1	0
Uzbekistan	UZB	1990	2	2	4	0	0	0	0	0
Venezuela	VEN	1950	3	4	7	1	1	0	1	0
Zambia	ZMB	1955	1	1	2	1	0	1	0	0

G Additional Tables

Table 16: Target Moments and Parameter Values, 5 Portfolios

Moments						
Portfolio	$\mathbb{E}[\Delta d_t^*]$	$\text{cov}\left(\Delta d_{t+1}^*, \Delta d_t^*\right)$	$\text{cov}(\Delta d_t^*, \Delta c_t)$	$\text{std}(\Delta d_t^*)$	$\text{cov}(\Delta d_t^*, \Delta d_t)$	$\frac{\text{cov}(r_t^*, r_t)}{\text{std}(r_t)}$
1	−0.016	0.00148	0.00014	0.084	0.00042	0.045
2	−0.016	0.00160	0.00005	0.078	0.00010	0.036
3	−0.016	0.00116	0.00014	0.077	0.00039	0.037
4	−0.013	0.00102	0.00015	0.070	0.00046	0.037
5	−0.011	0.00058	0.00015	0.060	0.00038	0.028
Parameters						
Portfolio	μ_d	ϕ	π	π_d	σ_μ	$\tilde{\phi}^* \sigma_{e^*}$
1	−0.016	5.37744	−0.96821	−0.00010	0.074	0.00715
2	−0.016	5.33112	−2.07645	−0.57545	0.062	0.00846
3	−0.016	3.83740	−0.27666	0.14880	0.069	0.00918
4	−0.013	3.51331	0.01263	0.35320	0.061	0.00887
5	−0.011	2.39233	0.58129	0.27506	0.054	0.00715

Table 17: Target Moments and Parameter Values, 10 Portfolios

Moments						
Portfolio	$\mathbb{E}[\Delta d_t^*]$	$\text{cov}\left(\Delta d_{t+1}^*, \Delta d_t^*\right)$	$\text{cov}(\Delta d_t^*, \Delta c_t)$	$\text{std}(\Delta d_t^*)$	$\text{cov}(\Delta d_t^*, \Delta d_t)$	$\frac{\text{cov}(r_t^*, r_t)}{\text{std}(r_t)}$
1	−0.019	0.00138	0.00016	0.089	0.00041	0.049
2	−0.014	0.00161	0.00013	0.079	0.00043	0.041
3	−0.018	0.00107	0.00005	0.087	0.00009	0.033
4	−0.015	0.00208	0.00005	0.069	0.00009	0.038
5	−0.017	0.00114	0.00016	0.082	0.00042	0.033
6	−0.014	0.00116	0.00012	0.072	0.00037	0.041
7	−0.017	0.00113	0.00012	0.074	0.00041	0.035
8	−0.010	0.00091	0.00017	0.066	0.00052	0.039
9	−0.013	0.00069	0.00014	0.060	0.00037	0.029
10	−0.009	0.00047	0.00016	0.059	0.00039	0.027
Parameters						
Portfolio	μ_d	ϕ	π	π_d	σ_μ	$\tilde{\phi}^* \sigma_{e^*}$
1	−0.019	6.45374	−1.33225	−0.18904	0.073	0.01000
2	−0.014	4.35358	−0.62409	0.19171	0.067	0.01123
3	−0.018	4.77576	−1.77650	−0.51733	0.078	0.00516
4	−0.015	5.65472	−2.24257	−0.62392	0.044	0.01100
5	−0.017	3.07385	0.30829	0.29047	0.074	0.01061
6	−0.014	4.66260	−0.90714	0.02476	0.062	0.00672
7	−0.017	3.46198	−0.25718	0.29270	0.065	0.00981
8	−0.010	3.55182	0.24894	0.42668	0.057	0.00783
9	−0.013	2.59247	0.32249	0.25836	0.053	0.00788
10	−0.009	2.23859	0.79737	0.28864	0.054	0.00631