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RISK, VOLATILITY, AND THE GLOBAL CROSS-SECTION OF GROWTH RATES

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ABSTRACT

We reconsider the empirical links between volatility and growth between 1970 and 2007. There is a strong and significant correlation between individual country growth rates and global factors that are arguably exogenous with respect to their economies. The amount of volatility driven by these external factors is highly correlated, cross-sectionally, with the overall amount of volatility in GDP growth. There is also a strong correlation between a country's average growth rate and the magnitude and sign of its exposure to global factors. We interpret our findings as a partial answer to the question "Why doesn't capital flow from rich to poor countries?" We argue that low-income countries that grow slowly are riskier from the perspective of the marginal international investor.

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Ramey and Ramey (1995) established that countries with volatile growth tend to have lower average growth. They studied a panel of 92 countries over the period 1962–85 and found a statistically significant negative relationship between the standard deviation of a country's annual growth rate, and its average growth rate, over the same period. We reconsider the empirical links between volatility and growth, but in doing so we focus on the effects of arguably exogenous global risk factors on relatively small economies. In our benchmark analysis we consider six factors: US real GDP growth, the ex-post short term real interest rate in the US, the change in the relative prices of oil and two commodity price indices (for metals and agriculture), and the US stock market excess return. Our key new findings are as follows:

- In the time series dimension, there is a strong and significant correlation between individual country growth rates and the global factors, but the sign, magnitude and degree of correlation varies widely across countries.
- The degree of volatility for each country predicted by our time series analysis is highly correlated with the overall level of volatility in each country. Overall we can explain about 70 percent of the cross-sectional variation in the volatility of GDP growth in terms of countries' differing degrees of sensitivity to aggregate volatility.
- Our most novel finding is that there is a strong correlation between a country's average growth rate and the magnitude and sign of its exposure to aggregate factors. This is revealed by a cross-sectional regression of average country-specific growth rates on country-specific factor "betas".

Our findings provide a partial answer to a long-standing question in the macroeconomics of growth: "Why doesn't capital flow from rich to poor countries?" As Lucas (1990) argued, if countries have access to the same constant returns to scale production technology, which is a function of capital and labor, then if output per worker differs between the two countries it must be due to them having different levels of capital per worker, which would imply higher returns to capital in the poor country. If trade in capital goods is free then capital should flow from the rich to the poor economy until returns are equated across countries. This process is instantaneous in the absence of adjustment costs to capital (Barro and Sala-i-Martin, 2004, p. 163). The notion that returns should be equated across countries, either instantaneously, or in the long-run, rests on a deterministic view of the world. In contrast, in financial economics, it is common to explain *indefinitely* persistent differences in rates of return across assets in terms of differences in exposure of these assets to aggregate risk factors. Assets that are more exposed to aggregate risk earn higher average returns. Our empirical analysis demonstrates that low-income countries (with presumably high returns to capital) that exhibit surprisingly low growth (relative to the predictions of the neoclassical model) tend to be more heavily exposed to our measure of global risk. Under the assumption that our measure of global risk is related to the stochastic discount factor of the relevant international investors, we can explain, at least partially, why more capital does not flow to these countries.

In our sample, when we replicate Ramey and Ramey's benchmark regression, we too find evidence of a significant negative association between volatility and growth in the cross-section. In fact, in our sample, which spans the period 1970–2007 for 107 countries, the relationship is stronger than in Ramey and Ramey's case. Their benchmark point estimates imply that for each additional percentage point of volatility, a country's average growth rate is 0.15 percentage points lower. Our point estimate implies an effect that is twice as large: for each additional percentage point of volatility, a country's average growth rate is 0.31 percentage points lower. Apart from the possibility that the magnitude of the effect could vary with the time period, we attribute this difference in magnitude to the fact that our sample includes more countries that are not high-income members of the OECD. Like Ramey and Ramey, we find that the effect of volatility on growth is mainly observed among low and middle-income countries.

Our estimates of country exposure to global risk factors vary widely in the cross-section, and for many countries they are statistically significant at the five or ten percent level. For example, Mexico has a strong negative and statistically significant exposure to US interest rates, and a strong positive and statistically significant exposure to oil prices. When the US interest rate is one standard deviation above its mean, holding everything else equal Mexico's growth rate is about 1.3 percentage points below its mean. When the change of the relative price of oil is one standard deviation above its mean, holding everything else equal Mexico's growth rate is about 1.2 percentage points above its mean. The signs of Mexico's exposure are not surprising given its proximity to the United States and its status as an oil producer. Chile's real GDP growth, in contrast, is approximately uncorrelated with both variables. China's exposures have the opposite signs but similar magnitudes. We attribute

China's significant negative exposure to oil prices to its status as a large net importer of energy.

The R^2 statistics of our time series regressions are typically quite low (about 0.23), indicating that the global factors that we have identified do not account for much of the time series variation in the typical country's growth rate. Despite this, the degree of exposure to external factors is significant in determining which countries have high volatility and which ones have low volatility. When we run a cross-sectional regression of the standard deviation of GDP growth on the standard deviation of predicted GDP growth, we obtain an R^2 statistic of 0.70.

The fact that our estimates of country exposure to global risk factors vary significantly in the cross-section is crucial to our cross-sectional regression analysis. Absent cross-country variation in the degree of exposure to global factors we would not be able to identify the effects of such exposure on growth. Our results indicate that a country's exposures to US GDP growth, US interest rates, world oil prices, metals prices and agricultural prices, as measured by the "betas" in our time series regressions, have a statistically and economically significant effect on a country's average growth rate.[1] This suggests that while volatility has an effect on economic growth, the effects of volatility are not necessarily symmetric. As an example, countries with positive exposure to US interest rate fluctuations grow faster than countries with negative exposure.

Our results are closely related to a large literature on the effects of commodity prices and external shocks in developing countries. This literature has largely studied the dynamic effects of commodity prices on economic performance, with parameter restrictions imposed across countries. Typically the literature has studied the relationship between GDP growth and other aggregate time series and country-specific export-weighted commodity price series.[2] In effect, the evidence in the literature is akin to dynamic versions of our time series regressions, but with cross-country restrictions on the slope coefficients that determine the

[1] The degree of statistical significance of some variables changes across specifications of our regressions.

[2] Deaton and Miller (1995) find modest evidence that country-specific export-weighted measures of commodity prices are positively correlated with growth in Sub-Saharan African countries. Raddatz (2007) concludes that external shocks (to rich country growth, world interest rates, and country-specific trade indices) are relatively unimportant contributors to volatility in low-income countries. The previous two studies both use panel regressions that impose common parameters across countries. Dehn (2000) and Dehn and Collier (2001), measure country-specific "extreme" commodity price shocks, but enter these as explanatory variables in growth regressions that impose common parameters across countries. They find significant responses to negative shocks, but insignificant responses to positive shocks.

growth dynamics. Here we eschew examining dynamic responses in favor of identifying country-specific exposures to common shocks. This allows us to identify long-run effects of exposure to shocks on growth using our cross-sectional regressions.

Our empirical methodology owes much to a technique, pioneered by Fama and MacBeth (1973), that is used in the finance literature to explain cross-sectional variation in expected returns across firms. Fama and MacBeth take a two step approach to estimating linear factor models. The first step is a group of time series regressions of the returns to n portfolios on a $k \times 1$ vector of aggregate risk factors. The second step is a single cross-sectional regression, with a sample size of n, of average portfolio returns on the estimated betas. Our approach mimics Fama and MacBeth's, with country growth rates replacing portfolio returns in the regressions. In our case, there is no formal asset pricing theory underlying the estimation, but we are able to exploit the approach in order to correctly compute standard errors for the cross-sectional regressions given that they use generated regressors. We also provide an interpretation of our empirical work that relates growth rates, rates of return, and risk.

In Section 1 we revisit the evidence on the links between volatility and growth by re-examining and extending Ramey and Ramey's (1995) evidence. In Section 2 we consider the time series relationship between country growth rates and global risk factors. We examine the strong correlation between a country's overall level of volatility and its volatility due to external factors. Section 3 introduces our cross-sectional analysis that links average country growth rates to risk exposures. Section 4 provides the details of how we interpret our findings in terms of risk. It also extends our cross-sectional analysis in ways that account for the role of tranisiton dynamics in explaining growth rates. Section 5 provides some interpretation of our measure of risk. We show that it is not equivalent to a risk factor defined as the difference between average high-income country growth rates and average low-income country growth rates. It has additional explanatory power. Section 6 concludes.

1 Volatility and Growth Revisited

To begin, we revisit the basic regression in Ramey and Ramey's article. We define the *real growth rate* as $g_{it} = 100 \times \Delta \ln y_{it}$, where y_{it} is per capita GDP measured in constant US dollars. For each country in our data set, we calculate the mean and the standard deviation of the real growth rate as $g_i = \frac{1}{T}\sum_{t=1}^{T} g_{it}$ and $\sigma_i = \left[\frac{1}{T}\sum_{t=1}^{T}(g_{it} - g_i)^2\right]^{1/2}$. We measure growth at the annual frequency for 32 high-income countries, and 75 low and middle-income countries over the sample period 1971–2007.[3] The criterion for inclusion in our data set is that we must have data for the country over the entire sample period.[4] Consistent with the World Bank definition, a high-income country is one whose gross national income (GNI) per capita in 2007 exceeded 11,456 US dollars.

Figure 1 shows a scatter plot of the mean growth rate, g_i, against the standard deviation of the growth rate, σ_i, for our full sample. The negative relationship between the two variables is clear from the graph. When we regress the mean growth rate on the standard deviation of the growth rate we obtain the following estimates for the full sample:

$$g_i = \underset{(0.30)}{2.95} - \underset{(0.06)}{0.31}\sigma_i \tag{1}$$

($R^2 = 0.20$, heteroskedasticity-consistent standard errors in parentheses). Our estimate of the slope coefficient is twice as large as Ramey and Ramey's and has a greater degree of statistical significance (our t statistic is 5.2, while Ramey and Ramey's is 2.3). Additional results are presented in Table 1, for, exclusively, the low and middle-income countries, and the high-income subsample. Consistent with Ramey and Ramey's findings, if we only consider high-income countries the basic relationship between growth and volatility is small and statistically insignificant. For low and middle-income countries the results are similar to what we obtain for the full sample.

One pattern that is clear from inspection of Figure 1 is that there are many East Asian countries with low volatility and high growth, while there are many Sub-Saharan African and other low-income countries with high volatility and low growth. Indeed, if one includes dummy variables for Sub-Saharan Africa (SSA) and East Asia (EAS) in regression (1), the coefficient on volatility becomes considerably smaller, but it remains statistically significant, as indicated in Table 1. We do not view the smaller coefficient as a criticism of regression (1). High volatility may be an important reason, among others, that growth is low in Sub-Saharan Africa, while countries in East Asia may have grown faster, in part, due to low volatility.

A more serious issue is whether regression (1) reflects measurement problems. High volatility may partly reflect errors in measuring output. If countries with lower growth also have less accurate statistical data, the relationship between growth and volatility could be

[3] The list of countries in our sample is provided in the Appendix.

[4] We eliminated Georgia and Latvia from consideration, even though they appear from 1970–2007 in the World Bank database. We also eliminate Germany and Kiribati due to German unification and the split of the Gilbert and Ellice Islands which both occurred within our sample period.

spurious. It is hard to know which countries have better data, but one might imagine that income level is strongly correlated with data quality. With this in mind we include the logarithm of per capita GDP in 1970, $\ln y_{i0}$, in regression (1). It has no virtually no effect on the relationship between growth and volatility, as shown in Table 1. We conclude that any correlation between measurement error variance and income level does not significantly bias the observed relationship between growth and volatility.

Another concern is that using the standard deviation of output growth as a measure of volatility might focus too much attention on output's high frequency behavior. To address this concern we also ran a Ramey and Ramey-style regression using the standard deviation of HP-filtered output as our measure of volatility.[5] As Table 1 indicates, the negative correlation between growth and volatility is robust to this alternative.

2 Global Risk Factors and Volatility

We now explore the relationship between global risk factors and economic growth in a subset that includes 104 of the countries from our original sample. We exclude the United States and Japan from consideration because they accounted for around 30 and 15 percent of world GDP, respectively, in 2000. We also exclude Saudi Arabia from the sample because it is by far the largest oil producer in our sample and a key member of OPEC. We consider six global risk factors.

1. The growth rate of per-capita real GDP in the United States. We include this factor as an indicator of global demand conditions. We expect most countries in the sample to have a positive exposure to this risk factor.

2. The ex-post short term real interest rate in the United States, as measured by the average 3-month T-bill rate minus the rate of inflation measured using the US Producer Price Index (PPI). We include this factor as an indicator of the cost of borrowing in international markets, and, to some extent, liquidity conditions. We expect to find that most countries have a negative exposure to this risk factor, as a previous and large body of empirical work suggests that world interest rates and developing country growth rates are negatively correlated.[6] In small open economy models positive shocks to the world interest rate also tend to drive down investment and output, although the magnitudes of the effects depend

[5] The HP-filter is defined in Hodrick and Prescott (1997).

[6] See, for example, Agénor, McDermott and Prasad (2000), and Neumeyer and Perri (2004).

on a country's net foreign asset position.[7]

3–5. We include the rates of change of three commodity price series relative to US PPI inflation. The three commodities are crude oil, a primary metals index, and an agricultural commodity index. We include these series as indicators of possible terms of trade shocks at the global level. Some countries may be net importers of these commodities, while other may be net exporters. When countries are net importers of commodities which are used as inputs into production, a rise in the price of these commodities acts like a negative technology shock in that firms will respond by reducing their demand for inputs into production. This would tend to indicate negative exposures for net importers, and, possibly symmetric, positive exposures for net importers. But other factors come into play as well. Commodity prices may also acts as indicators of global demand conditions. In this situation rising commodity prices may be associated with a tendency towards positive exposure for all countries.

6. Finally, we include the excess return to the value weighted United States stock market as an indicator of financial conditions. We do not have strong priors as to the sign of the correlation between this variable and real growth rates in our sample of 104 countries.

Graphs of the time series of our six risk factors are provided in Figure 2. The graphs indicate that the commodity price indices are highly volatile, and far from perfectly correlated with each other. They are also not synchronous with the United States-specific variables in any obvious way. Summary statistics that confirm these visual impressions are provided in Table 2. In all cases, we believe it is reasonable to treat our six global factors as exogenously determined. All of the countries in our sample accounted for small fractions of world GDP in 2000.[8] Thus we think it is reasonable to take the US growth rate, the US interest rate and US stock returns as exogenous. While some of the countries in our sample are oil producers, we think it is arguable that none of them are price setters in the global oil market. Similarly, while several of the countries in our sample are commodity producers we think it is reasonable to assume that their individual economies do not have a significant influence on our overall indices of metals and agricultural prices.

[7] See Correia, Neves and Rebelo (1995). In a different model Mendoza (1991) finds that interest rate shocks only have modest effects on economic activity.

[8] The largest 12 of the 104 countries in our data set accounted for a total of 29 percent of global GDP in 2000. The remaining countries individually account for less than 1 percent of global GDP, and most are much smaller than that.

2.1 Time Series Regressions

The first step in our analysis is a time series regression of each country's real growth rate, g_{it}, on each of the six risk factors, which we denote generically with the scalar f_t:

$$g_{it} = a_i + f_t' \beta_i + \epsilon_{it}, \quad t = 1, \ldots, T, \text{ for each } i = 1, \ldots, n, \tag{2}$$

where $T = 37$ is the sample size in the time dimension, and $n = 104$ is the sample size in the country dimension. We estimate the system of 104 equations represented by (3) equation-by-equation using OLS, and do this separately for each of the six risk factors. Table 3 and Figure 3 contain summary information regarding the estimated betas (β_i). The median R^2 of the typical time series regression is quite low, ranging from 0.036 when the agricultural price index is the right-hand side variable, to 0.017 when the US market return is the right-hand side variable. This means that each of the global factors that we have identified explains a modest amount of the variation in GDP growth for individual countries. Figure 3 shows histograms of the betas for each factor. The frequency of estimates within each bin is reported, as well as the number of estimates within each bin that are statistically significant at the 5 percent level. The graphs and the summary information in Table 3 show that there is considerable spread in the betas across countries. Betas are also statistically significant for a substantial fraction of the countries.

We interpret the betas as measures of a country's exposure to specific risk factors. One concern, in this regard, is that we could be focusing too much attention on the very high frequency behavior of output and the various risk factors. To address this concern we also run time series regressions of HP-filtered per capita output, denoted y_{it}^H, on HP-filtered versions of the risk factors, which we denote, generically, as f_t^H.[9] Let β_i^H denote the beta from a time series regression of y_{it}^H on f_t^H. Figure 4 presents a scatter plot of $\hat{\beta}_i^H$, the estimated beta obtained using HP-filtered data, against $\hat{\beta}_i$, the estimated beta from equation (2).[10] The scatter plots show that the exposures measured using growth rates are similar to those obtained using HP-filtered data, given that the pairs of estimated betas are clustered close to the 45 degree line. Therefore, we are confident that what our time series regressions pick up is not just a high-frequency phenomenon.

[9] The HP-filtered risk factors are the cyclical components of the log-level of real per capita US GDP, the logarithm of the cumulative real return to holding US treasuries, the logarithm of each of our commodity price series minus the logarithm of the US PPI and the logarithm of the cumulative excess return to the US stock market.

[10] Full summary information on the estimates of β_i^H is provided in the Appendix.

The next step in our analysis is a time series regression of each country's real growth rate, g_{it}, on our 6×1 vector of risk factors, which we denote $\mathbf{f}_t$:

$$g_{it} = a_i + \mathbf{f}_t' \boldsymbol{\beta}_i + \epsilon_{it}, \quad t = 1, \ldots, T, \text{ for each } i = 1, \ldots, n. \tag{3}$$

We again estimate the system of 104 equations represented by (3) equation-by-equation using OLS.

Table 4 and Figure 5 contain summary information regarding the estimated betas ($\boldsymbol{\beta}_i$). The median R^2 of the time series regressions is 0.30, indicating that the global factors that we have identified explain a modest amount of the variation in GDP growth for individual countries.[11] Figure 5 shows histograms of the betas for each factor. The frequency of estimates within each bin is reported, as well as the number of estimates within each bin that are statistically significant at the 5 percent level. The graphs and the summary information in Table 4 show that there is considerable spread in the betas across countries. Between roughly 15 and 30 percent of the estimated betas are individually statistically significant at the 5 percent level. For 74 of the 104 countries the F-test of the entire regression indicates statistical significance at the 5 percent level.

There is also economically significant variation across countries in the size of the betas. Table 4 gauges the economic significance of the most extreme beta estimates by scaling them by the standard deviations of the individual factors. These scaled betas indicate that the effects of fluctuations in global factors on economic activity in the most sensitive economies are quantitatively large.

2.2 Volatility Stemming from Global Factors

Regression (3) allows us to decompose the variance of GDP growth in each country into two components. For each country the sample variance of GDP growth, is equal to

$$\sigma_i^2 = \gamma_i^2 + \kappa_i^2, \tag{4}$$

where $\gamma_i^2 = \hat{\boldsymbol{\beta}}_i' \hat{\Sigma}_{\mathbf{f}} \hat{\boldsymbol{\beta}}_i$ is the sample variance of the predicted values from regression (3), $\hat{\boldsymbol{\beta}}_i$ is the least squares estimate of $\boldsymbol{\beta}_i$, $\hat{\Sigma}_{\mathbf{f}}$ is the sample covariance matrix of the vector of factors, $\mathbf{f}_t$, and κ_i^2 is the sample variance of the residual from the regression.

[11] Raddatz (2007) suggests a more modest role for exogenous external shocks. At a forecast horizon of one year he argues that shocks to exogenous factors explain only 1 percent of GDP growth. One explanation for this lower R^2 (compared to our median R^2 of 0.30) is that Raddatz obtains his results by imposing common slope coefficients in a dynamic panel VAR model. The long-run R^2 is 0.11. When he uses a mean-group estimator that allows for country-specific slope coefficients the long-run R^2 rises to 0.24.

We refer to γ_i as the "volatility due to global factors" and σ_i as "overall volatility". The two measures of volatility, σ_i and γ_i are highly correlated with one another in the cross-section. Of course, this need not be true by construction. For example, suppose that there was no spread among the betas across i, so that $\hat{\boldsymbol{\beta}}_i = \hat{\boldsymbol{\beta}}$ for all i. Then, obviously, there would be no cross-sectional correlation between σ_i and $\gamma_i = \gamma = \left(\hat{\boldsymbol{\beta}}' \hat{\Sigma}_{\mathbf{f}} \hat{\boldsymbol{\beta}}\right)^{1/2}$.

As it turns out, the volatility due to external factors can explain about 70 percent of the cross-sectional spread in overall volatility. To see this, we run a cross-sectional regression of σ_i on γ_i:

$$\sigma_i = \underset{(0.30)}{0.18} + \underset{(0.14)}{2.09}\gamma_i \tag{5}$$

($R^2 = 0.70$, heteroskedasticity-consistent standard errors in parentheses). A plot of overall volatility, σ_i, against the fitted values from this regression (Figure 6) shows that countries with more volatility due to external factors tend to have more overall volatility, and the relationship is close to linear. If the relationship were exactly linear the dots in Figure 6 would line up perfectly on the 45 degree line. There are four volatile countries that are obvious exceptions to this pattern: Gabon (GAB), Guinea-Bissau (GNB), Rwanda (RWA) and the Solomon Islands (SLB).[12] It is worth noting that these outliers are not responsible for the estimated effect of volatility on growth found in regression (1). If these four countries are excluded from the regression the results are just as strong, with the slope coefficient becoming -0.36 with a standard error of 0.07.

Finally, we also find that the point estimate of the slope coefficient in the basic growth-volatility regression, (1), is robust if we replace actual volatility, σ_i, with predicted volatility due to external factors, $\hat{\sigma}_i = 0.18 + 2.09\gamma_i$:

$$g_i = \underset{(0.38)}{2.76} - \underset{(0.08)}{0.27}\hat{\sigma}_i, \tag{6}$$

($R^2 = 0.10$, heteroskedasticity-consistent standard errors in parentheses). We think that the robustness of the point estimate adds to the strength of the results from the basic regression reported in equation (1). It does not appear that the relationship between volatility and

[12] At least in the case of Rwanda this is not surprising: its exceptionally high level of volatility is due to two observations: the 64 log-percent drop in per capita GDP in 1994, during the genocide, and the 31 log-percent increase in GDP in the subsequent year. Gabon had extremely volatile real growth in the 1970s, and is highly dependent on oil exports, yet fluctuations in its real GDP do not coincide closely on a year-to-year basis with the price of oil. Guinea-Bissau suffered a 36 log-percent drop in per capita GDP in 1998 during a bloody civil war. The Solomon Islands suffered big declines in economic activity during a period of civil unrest in 2000-01.

growth is driven entirely by classical measurement error. If it were, then we would expect the relationship between volatility and growth to disappear once real GDP growth was projected on external factors using our time series regressions, (3).[13]

3 Global Risk Factors and Economic Growth

We turn, now, to our main results, which concern the relationship between a country's exposure to global risk factors and its average growth rate. To identify this relationship we run a cross-sectional regression of average growth rates on the estimated betas from the time series regression, (3):

$$g_i = \lambda_0 + \hat{\boldsymbol{\beta}}_i' \boldsymbol{\lambda} + u_i, \qquad i = 1, \ldots, n, \tag{7}$$

where $\hat{\boldsymbol{\beta}}_i$ is the OLS estimate of $\boldsymbol{\beta}_i$ obtained in the time series regression, and u_i is an error term. Table 5 presents our estimates of λ_0 and $\boldsymbol{\lambda}$. In computing standard errors for λ_0 and λ we take into account the fact that the right-hand side variables in the regression, $\hat{\boldsymbol{\beta}}_i$, are generated regressors.[14]

As Column (1) of Table 5 indicates, we find that the λ coefficients corresponding to three of our global risk factors are statistically significant at the 5 or 10 percent level depending on which correction of the standard errors we adopt. The US real interest rate enters with a positive sign, while the rates of change of the relative prices of crude oil and metals enter the estimated equation with negative signs. The cross-sectional R^2 is 0.15, indicating that we can explain 15 percent of the cross-sectional variation in country growth rates using the spread in the betas, which measure country exposures to the global factors.

In Column (2) of Table 5 we include regional dummy variables for Sub-Saharan Africa and East Asia in the regression. Although the statistical significance of our results is somewhat diminished, the signs and magnitude of the coefficients are quite similar across the two regressions.

We cannot give $\boldsymbol{\lambda}$ the same structural interpretation that it has in financial economics. There, the left-hand side variables are rates of return on different assets, so the elements of $\boldsymbol{\beta}_i$ can be interpreted as the quantity of each type of risk exhibited in the return to asset i.

[13] Of course, if errors in measuring GDP were correlated with the external factors then the growth-volatility link might still be driven by measurement error.

[14] We present two sets of standard errors. One is based on the correction proposed by Shanken (1992). The other is a correction proposed by Jagannathan and Wang (1998) that allows for more general forms of heteroskedasticity. Both corrections are described in detail in Cochrane (2005).

The elements of $\boldsymbol{\lambda}$ measure the price, or risk premium, associated with each source of risk. Nonetheless, we think our findings can be interpreted broadly as linking country growth rates to risk exposures for reasons we explain in Section 4.

In the case of the US interest rate, the positive λ estimate indicates that countries with more negative exposures to increases in US interest rates grow more slowly, on average, than countries with positive exposures. Our point estimate for the λ associated with US interest rates is 2.0. The minimum value of the interest rate beta in our sample is -0.77 while the maximum value is 0.65. Taking our point estimates seriously, our cross-sectional regression predicts a growth rate differential of 2.9 percentage points for the two countries with these betas, holding the other betas equal.

In standard small open economy models it would not be surprising to find that an increase in US interest rates would lower growth.[15] These models can also produce a variety of sensitivies to interest rate shocks (i.e. spread in the betas), if they are calibrated to allow for different levels of net foreign assets across countries. Countries with more debt would have more negative betas with respect to interest rates. However, since these models are usually solved by linear approximation in the the neighborhood of non-stochastic steady states, they have no implications for average growth rates, which are determined entirely by the assumed rate of technical progress. One interpretation of our finding is that countries with more negative exposure to world interest rates are riskier, in a sense that we will make more precise below. Consequently, they may attract less investment (physical, human and financial), and grow more slowly. Alternatively, the positive coefficient on interest rates may be a reflection of debt overhang effects that are not present in standard models, or nonlinearities that are not preserved by conventional solution techniques.[16]

In the case of oil and metals prices we obtain negative λ estimates. Countries with more positive exposures to changes in these commoidty prices grow more slowly, on average, than countries with negative exposures. Our point estimate for the λ associated with oil price changes is -18. The minimum value of the oil price beta in our sample is -0.13 while the maximum value is 0.09. Our cross-sectional regression predicts a growth rate differential of 4.0 percentage points for the two countries with these betas, holding the other betas constant. Our point estimate for the λ associated with metals price changes is -9. The minimum value of the oil price beta in our sample is -0.14 while the maximum value is 0.35.

[15] See Correia, Neves and Rebelo (1995).

[16] Sachs (1984) and Krugman (1985) provide early analyses of debt overhang related to sovereign debt.

Our cross-sectional regression predicts a growth rate differential of 4.4 percentage points for the two countries with these betas, holding the other betas constant.

In standard open economy models changes in the prices of commodities affect growth in two ways. To the extent that the commodities are used in the production of final goods, increases in their relative price affect the producers of final goods in much the same way as negative shocks to the production technology. To this extent we would expect negative betas to emerge from the time series regressions. On the other hand, when commodity production represents a significant source of national income, relative commodity price increases induce positive wealth effects that expand domestic demand, at least to the extent that the prices changes do not reflect shocks to the cost of commodity production. Thus, for major commodity producers we might expect positive betas to emerge. Nonetheless, as in the case of interest rates, simple linearized small open economy models do not predict non-zero values of λ in the cross-section. As in the case of interest rates, one interpretation of our finding is that countries with more positive exposure to oil and metals prices are risky, and therefore attract less investment of all kinds. Another possibility is that it reflects the so-called "resource curse".[17]

4 Risk, Returns to Capital and Growth

4.1 International Investors, Risk and Rates of Return

As we alluded to above, one interpretation of our findings is that countries with more negative exposures to US interest rates, and more positive exposures to changes in oil and metals prices, are riskier. We now make more precise what we mean by *risky*. Suppose there is a representative international investor who can lend to country i, or can own capital installed in country i, where $i = 1, \ldots, n$. Let the international investor's stochastic discount factor for payments in constant international dollars received at time t be denoted m_t^*. With no barries to capital, the following moment condition must hold:

$$0 = E_t(R_{it+1} m_{t+1}^*), \quad i = 1, \ \ldots, n. \tag{8}$$

Here R_{it+1} measures the real excess return (over the risk free rate) to investments made in country i at time t. By the law of iterated expectations, the unconditional version of (8) is

$$0 = E(R_i m^*), \quad i = 1, \ \ldots, n, \tag{9}$$

[17] See Auty (1993) and Sachs and Warner (1995).

where we have dropped time subscripts for convenience. We can rewrite the moment condition, (9), in terms of covariances:

$$0 = E(R_i)E(m^*) + \mathrm{cov}(R_i, m^*), \quad i = 1, \ \ldots, n. \tag{10}$$

This means that the difference between average rates of return across two countries can be explained by differences in covariances between rates of return and the international investor's SDF:

$$E(R_i) - E(R_j) = -\left[\mathrm{cov}(R_i, m^*) - \mathrm{cov}(R_j, m^*)\right]. \tag{11}$$

Equation (11) highlights a key difference between deterministic and explicitly stochastic models. In a deterministic model there are no expected values, and no covariance terms. Rates of return are non-stochastic and equal across countries. Differences in marginal products of capital can only exist in the presence of adjustment costs or some kind of capital market friction.

Ideally we would assess whether risk explains differences in rates of return across countries by gathering data on rates of return to investment, and estimating an explicit model of the international investor's stochastic discount factor. Unfortunately we regard this approach as frought with difficulty. We might, for example, assume a Cobb-Douglas production technology and measure the marginal product of capital in each country and at each point in time, using assumptions about model parameters and data on output and capital stocks.[18] However, if rates of return are inclusive of adjustment costs, we would need to make further assumptions about functional forms. Measuring returns to investment in human capital would be even more difficult. Rather than pursuing an empirical approach explicitly based on rates of return, we take a different approach which is loosely guided by theoretical considerations. Consequently, we do not view our empirical results as providing explicit estimates of the international investor's stochastic discount factor.

4.2 Growth Rates versus Rates of Return

Our approach is to replace rates of return, in equation (11), with growth rates of per capita GDP. When doing this we expect the relationship between the objects on the left and right-

[18] Measure capital stocks is non-trivial. See, for example, Klenow and Rodriguez-Clare's (1997) analysis of the neoclassical growth model, in which they measure capital stocks by accumulating investment data in the Penn World Tables.

hand sides of (11) to change sign. That is, we expect

$$E(g_i) - E(g_j) \propto \mathrm{cov}(g_i, m^*) - \mathrm{cov}(g_j, m^*). \tag{12}$$

How do we come to this conclusion? Recall that the covariances that appear on the right-hand side of (11) and (12) are time-series statistics. In standard stochastic growth models rates of return and growth rates of GDP are highly correlated in the time series dimension because changes in technology and labor inputs (as opposed to the slow-moving changes in capital inputs) drive the comovements. Improvements in technology and increases in labor inputs due to other shocks increase growth and the marginal product of capital, and, hence, the rate of return to investments in capital. Consequently we expect, at a minimum, the sign of $\mathrm{cov}(R_i, m^*)$ to be the same as the sign of $\mathrm{cov}(g_i, m^*)$.

The sign switch in going from (11) to (12) comes from the left hand side of equation (12). To arrive at this conclusion, we again derive intuition from the open-economy neoclassical growth model with adjustment costs. In the deterministic version of the model, if two countries share the same preferences and technology, and have the same initial capital stocks, rates of return will be the same in the two countries, and they will grow at the same rate. Now suppose one country is riskier, in these sense explained above: its rate of return to capital is more negatively correlated with m^*. Then it will attract less capital, the rate of return to capital will be higher, and economic growth will be slower. So riskier countries will grow more slowly and compensate for their riskiness by paying higher returns to capital on average. Hence we expect and inverse relationship between $E(R_i) - E(R_j)$ and $E(g_i) - E(g_j)$.

One subtle complication in our analysis is that in moving from equation (11) to equation (12) we lose the equality sign. Since our empirical work effectively imposes the equality in (12), we cannot claim to be identifying m^*, but rather, at best, a proxy for it, that we denote m. A second complication is that the intuition we have just given applies to two countries with same initial conditions. If transition dynamics driven by countries' different initial conditions are important, we must somehow take them into account in our empirical work.

4.3 Taking Transition Dynamics into Account

To take transition dynamics into account we note that in a standard deterministic open-economy neoclassical growth model with adjustment costs the transition dynamics are linear up to a first order approximation:

$$g_{it} - g \cong -\rho \hat{y}_{it-1}, \tag{13}$$

where g is the long-run steady state growth rate, corresponding to the rate of technical progress, ρ is a small positive scalar, and $\hat{y}_{it}$ is the percentage deviation of initial income from the long-run steady state growth path of output. The steady state growth path of output can be written as $ye^{tg/100}$, for some constant y. Therefore, we define $\hat{y}_{it} = 100 \times [\ln(y_{it}/y) - tg/100]$. Given this discussion, we choose to work with a modified version of g_{it}:

$$\begin{aligned} \hat{g}_{it} &= g_{it} + \rho \hat{y}_{it-1} \\ &= g_{it} + \rho \times 100 \times \ln(y_{it}/y) - \rho g t \end{aligned} \tag{14}$$

We set y and g so that the average of $\hat{y}_{it}$ is zero for the US.[19]

4.4 Our Implicit Measure of Global Risk

Our implicit measure of risk, is defined in terms of a linear combination of the vector of six factors: $m_t = (\mathbf{f}_t - \boldsymbol{\mu})' \mathbf{b}$, where $\boldsymbol{\mu}$ and $\mathbf{b}$ are 6×1 vector of coefficients and $\boldsymbol{\mu} = E(\mathbf{f}_t)$. We impose the identifying restrictions

$$E(\hat{g}_{it}) = E(\lambda_0 + \hat{g}_{it} m_t), \quad i = 1, \ \ldots, n, \tag{15}$$

where λ_0 is an unknown constant. Since m_t is zero mean by construction, the moment restriction, (15), can be rewritten as

$$E(\hat{g}_{it}) = \lambda_0 + \mathrm{cov}(\hat{g}_{it}, m_t). \tag{16}$$

If we consider the difference in growth rates across two countries, dropping time subscripts we obtain

$$E(\hat{g}_i) - E(\hat{g}_j) = \mathrm{cov}(\hat{g}_i, m) - \mathrm{cov}(\hat{g}_j, m), \tag{17}$$

which is a version of (12) written as an equality, and with g_i replaced by $\hat{g}_i$ and m^* replaced by m. Of course, m_t is, at best, a proxy for the stochastic discount factor of the international investor, m^*.

[19] The normalization of y is completely irrelevant to our empirical work because it has no effect on the estimated betas. It only affects the constant in the time series regressions. The choice of g affects the betas but affects them all by amounts that do not vary in the cross-section. Therefore it only affects the constant in the cross-sectional regression.

Given our expression for m_t, (16) can, in turn, be rewritten as

$$E(\hat{g}_{it}) = \lambda_0 + \mathrm{cov}(\hat{g}_{it}, \mathbf{f}_t)\mathbf{b}. \tag{18}$$

Finally, (18) can be written in terms of betas and lambdas:

$$E(\hat{g}_{it}) = \lambda_0 + \underbrace{\mathrm{cov}(\hat{g}_{it}, \mathbf{f}_t)\mathbf{\Sigma}_{\mathbf{f}}^{-1}}_{\boldsymbol{\beta}_i'}\underbrace{\mathbf{\Sigma}_{\mathbf{f}}\mathbf{b}}_{\boldsymbol{\lambda}}. \tag{19}$$

Once we have estimated $\boldsymbol{\lambda}$, we can construct an estimated time series for our measure of risk:

$$\hat{m}_t = \left(\mathbf{f}_t - \bar{\mathbf{f}}\right)' \hat{\mathbf{b}} = \left(\mathbf{f}_t - \bar{\mathbf{f}}\right)' \hat{\mathbf{\Sigma}}_{\mathbf{f}}^{-1}\boldsymbol{\lambda}, \tag{20}$$

where $\bar{\mathbf{f}} = \frac{1}{T}\sum_{t=1}^{T} \mathbf{f}_t$ and $\hat{\mathbf{\Sigma}}_{\mathbf{f}} = \frac{1}{T}\sum_{t=1}^{T} \left(\mathbf{f}_t - \bar{\mathbf{f}}\right)\left(\mathbf{f}_t - \bar{\mathbf{f}}\right)'$.

4.5 Empirical Results

There are three steps in our empirical analysis.

1. Rather than estimate ρ, we consider a range of plausible values, $\rho \in [0, 0.02]$. For each value of ρ we measure $\hat{g}_{it}$.

2. For each $i = 1, \ldots, n$, we regress, $\hat{g}_{it}$, on $\mathbf{f}_t$:

$$\hat{g}_{it} = a_i + \mathbf{f}_t'\boldsymbol{\beta}_i + \epsilon_{it}, \quad t = 1, \ldots, T. \tag{21}$$

When $\rho = 0$ the estimated betas are the same ones we presented in Table 4 and Figure 5.

3. We run a cross-sectional regression of average growth rates on the estimated betas from the time series regression, (21):

$$\hat{g}_i = \lambda_0 + \hat{\boldsymbol{\beta}}_i'\boldsymbol{\lambda} + u_i, \qquad i = 1, \ldots, n, \tag{22}$$

where $\hat{g}_i = \frac{1}{T}\sum_{t=1}^{T} \hat{g}_{it}$, $\hat{\boldsymbol{\beta}}_i$ is the OLS estimate of $\boldsymbol{\beta}_i$ obtained in the time series regression, and u_i is an error term. When $\rho = 0$ the estimated elements of $\boldsymbol{\lambda}$ are the same as those presented in Table 5.

The value of ρ that maximizes the R^2 of the cross-sectional regression is 0.005. One problem in using the R^2 as a criterion for choosing ρ is that the definition of the left-hand side variables changes as ρ changes. If we, instead, use a criterion that judges the models on how well they fit the average unmodified growth rates, the “best” value of $\rho \in [0, 0.02]$ is actually 0. This is not surprising, because over our sample period, the average high-income country grew much faster than the average low-income country. Consequently, were we to estimate ρ, the estimate would be negative. Rather than select a preferred value of ρ we present the results for different values of ρ and interpret the R^2 of each regression as the extent to which taking risk into account improves the fit of the neoclassical model. We explain this intepretation in the Appendix.

In Table 6, we present results of estimating the cross-sectional regression with several values of $\rho \in [0, 0.02]$. As before, when $\rho = 0$ we see that US interest rates, oil price changes and metals price changes enter the cross-sectional regression in a statistically significant way. The degree of statistical significance depends on which correction of the standard errors is used. For larger values of ρ, US GDP growth and agricultural raw materials, which both enter positively in the cross-sectional regression, begin to become statistically significant, while changes in metals prices begin to lose their significance. Overall, our results suggest that we can explain about 15 percent of the cross-sectional variation in country growth rates in terms of these countries' differing exposures to global risk factors. While this may seem like a modest effect, it is quantitatively significant compared to benchmark growth regressions in the literature.[20]

5 Interpreting our Measure of Risk

5.1 Measuring Risk

Given our estimates of $\boldsymbol{\lambda}$ we can construct the estimated measure of risk given in equation (20): $\hat{m}_t = \left(\mathbf{f}_t - \bar{\mathbf{f}}\right)' \hat{\boldsymbol{\Sigma}}_{\mathbf{f}}^{-1} \hat{\boldsymbol{\lambda}}$. When $\hat{m}_t$ rises it indicates that our proxy for the marginal valuation of payoffs by the international investor goes up. The measures of $\hat{m}_t$ corresponding to two cases ($\rho = 0$ and $\rho = 0.005$) are shown in Figure 7. The variance of the $\hat{m}_t$ series for $\rho = 0.005$ has greater variance, but the two measures of $\hat{m}_t$ are highly correlated with one another—the correlation coefficient being 0.97—reflecting the fact that small corrections for possible transition dynamics do not greatly affect the estimates of the betas in the time series regressions. With further increases in ρ, the variance of $\hat{m}_t$ increases further, but the the general pattern in the variation of $\hat{m}_t$ over time remains similar.

To develop intuition about $\hat{m}_t$ we consider "M-betas", that is the regression coefficient obtained when $\hat{g}_{it}$ is regressed on $\hat{m}_t$. In population, this coefficient is given by $\beta_{mi} =$

[20] For example, Barro and Sala-i-Martin (2004, p. 522) report R^2 of around 0.5 in cross-sectional regressions over 10 year time periods. Levine and Renelt (1992) report similar results over a 30 year time interval.

$\mathrm{cov}(\hat{g}_i, m)/\,\mathrm{var}(m)$. The predicted growth rate of a country is given by (16), so it can also be written as $E(\hat{g}_{it}) = \lambda_0 + \beta_{mi}\,\mathrm{var}(m)$, in population. The variance of m_t measures how much the investor values a unit of risk, while β_{mi} measures the riskiness of a country. Countries with higher values of β_{mi} are *less* risky because their growth rates are more highly correlated with m. Figure 8 plots average growth rates, relative to the mean across all countries in our sample, against the M-beta, $\hat{\beta}_{mi}$, for the case where $\rho = 0.005$. If risk exposure could explain the entire cross-sectional pattern in growth rates the dots in Figure 8 would line up on the red line, which corresponds to our estimate of the portion of growth explained by exposure to risk, $\hat{\boldsymbol{\beta}}_i'\boldsymbol{\lambda} = \hat{\beta}_{mi}\hat{\sigma}_m^2$.

Risk exposure is highly correlated with initial income. The highest-income countries tend to have roughly zero M-betas, while below-median-income countries tend to have negative betas. To illustrate this point, we calculate the M-beta of each country and average these betas within quartiles of our data set sorted according to average per capita GDP in 1970. These averaged M-betas are reported in Figure 9, plotted against the average initial income of each income quartile. The average growth rates (relative to the sample wide average) of each income quartile are also reported. The graphs show that there is a general pattern of betas increasing by income, with a similar pattern observed for $\rho = 0$ and $\rho = 0.005$. We also see a pattern of growth being more rapid for the high-income countries. This pattern becomes sharper as we consider larger values of ρ. The reason is simple. Larger values of ρ imply faster transition dynamics, and these, in turn, imply larger downward growth-rate adjustments for poor countries. That is, since $\hat{g}_{it} - g_{it} = \rho\hat{y}_{it-1}$ is more negative the lower is a country's income level, it becomes more sharply related to income for larger values of ρ.[21]

5.2 Sorted Factors and Portfolios

In our sample period high-income countries (defined by per capita GDP in 1970) have grown faster than low-income countries. In this section we investigate whether our measure of risk, $\hat{m}_t$, is equivalent to risk factors created by sorting our 104 countries by income and forming "portfolios" by income group, or whether it has additional explanatory power. In forming our new risk factors, we mimic the common practice in the finance literature of sorting firms by characteristics that appear to be systematically associated with rates of return, and then

[21] Of course, there are exceptions to these patterns. For example, Botswana, whose per capita income was \$425 in 1970, has grown very rapidly, at an annual pace of 6.5 percent. But it is also exceptional in being a low-income country with a large M-beta.

creating risk factors by grouping firms with similar characteristics.[22] We also investigate whether $\hat{m}_t$ and our new income-based risk factors can explain the cross-sectional variation in a set of 26 income-sorted portfolios.

We construct our income-based risk factors in two ways. To construct our first factor, we sort the 104 countries in our data set into two groups of 52 countries, ordered by initial income in 1970. In each time period, we average the growth rates of the countries within the high-income and low-income categories. Our constructed risk factor, which we refer to as the SHL (static high-income minus low-income) factor, is the difference between these average growth rates.

To construct our second factor, in every year, t, we sort the 104 countries in our data set into two groups of 52 countries, ordered by income in the previous year, $t-1$. We compute the difference between the average growth rates of these two groups of countries and refer to it as the DHL (dynamic high-income minus low-income) factor. In the second approach there is some change in the content of the two portfolios over time.

We construct two sets of income-sorted portfolios in an analogous way. The first set of 26 portfolios is constructed by sorting the 104 countries in our data set into 26 groups of 4 countries, ordered by initial income in 1970. In each time period, each portfolio growth rate is the simple average of the growth rates of the countries within that portfolio. Since the identity of the countries in each portfolio is fixed over time, we refer to these as "static" sorted portfolios. The second set of 26 portfolios is constructed by, in each time period, sorting the 104 countries in our data set into 26 groups of 4 countries, ordered by income in the previous time period. Again, the portfolio growth rate is the simple average of the growth rates of the countries within that portfolio. Since the identity of the countries in each portfolio varies over time, we refer to these as "dynamic" portfolios.

As our results in Table 7 indicate, the SHL and DHL factors are able to explain substantial fractions of the cross-sectional variation in average growth rates within our sample. This is true for our original 104-country sample, but is also true for the 26 static and dynamic sorted portfolios. Our measure of risk from Section 5.1 (measured using $\rho = 0$), denoted $\hat{m}$, also has significant explanatory power for the different sets of growth rates.

In Table 8, we ask whether our measure of risk, $\hat{m}$, has explanatory power that goes

[22] A classic example is Fama and French (1993), where firms are sorted on the basis of size (market capitalization) and the ratio of book value to market value, and the constructed risk factors are the average return differentials between the small and big firms, and high book-to-market and low book-to-market value firms.

beyond picking up the variation in growth rates that is explained by SHL and DHL. We estimate two factor models that pair $\hat{m}$ together with SHL and DHL. Our results indicate that in all cases, $\hat{m}$ has significant explanatory power in the cross-section over and above that provided by the SHL or DHL factors. This suggests that $\hat{m}$ is not just picking up whatever factors explain the observation that high-income countries have grown faster than low-income countries since 1970. It is actually able to explain variation in growth rates within these groups. Together, the $\hat{m}$ and DHL factors can explain 78 percent of the cross-sectional variation of the growth rates of the 26 dynamically-sorted portfolios. This case is also illustrated in Figure 10, where we compare model-predicted growth rates (the predicted values in the cross-sectional regression) with average growth rates in the data. Given the fit of this model, we think additional research into the economic factors underlying the DHL variable will be fruitful for explaining, further, why low-income countries have grown more slowly that high-income countries since 1970.

6 Conclusions

In this paper we have reconsidered the empirical links between volatility and growth, with a focus on the role of arguably exogenous global risk factors. We have shown that there is a strong relationship, over time, between individual country growth rates and US GDP growth, US interest rates, growth rates of three commodity price series and US stock returns, but that this relationship varies across countries. We have shown that countries with greater exposures to these factors also display more overall volatility in GDP growth. Ramey and Ramey's (1995) result that more volatile countries grow slower is robust to replacing the volatility of GDP growth with the volatility of GDP growth explained by exogenous global factors. This suggests that global risk factors play an important role in the link between volatility and growth.

Our most important result is that there is a strong correlation between a country's average growth rate and the magnitude and sign of its exposure to aggregate risk factors. This is revealed by a variety of cross-sectional regressions of average country-specific growth rates on country-specific factor "betas". A long-standing question in macroeconomics is "Why doesn't capital flow from rich to poor countries?" Our results suggest that part of the answer is that low-income countries are "riskier".

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Appendix

Data Sources Our measure of real GDP per capita in constant 2000 US dollars is taken from the World Development Indicators database. We measure the US real interest rate as the difference between the 3 month T-bill rate (from the International Financial Statistics [IFS] database) and the rate of inflation of the US producer price index (PPI) (from the IFS database). We obtained the oil, metals, and agricultural products price indices from the IFS database, and converted them to relative prices using the US PPI. The excess return on the US stock market was taken from the Fama/French factors file available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Rates of change were measured as log first differences multiplied by 100. Our country list is found in Table A1.

Interpreting the R^2 Statistic Denote the predicted values of $\hat{g}_i$ in the cross-sectional regression as $\hat{g}_i^p = \hat{\lambda}_0 + \hat{\boldsymbol{\beta}}_i^{\prime}\boldsymbol{\lambda}$. Given the definition of $\hat{g}_{it}$, $\hat{g}_i = g_i + \rho\hat{y}_i$ where $\hat{y}_i = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_{it-1}$. Therefore the predicted values for the original growth rates are $g_i^p = \hat{g}_i^p - \rho\hat{y}_i$. The R^2 measured in terms of modified growth rates is

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{g}_i - \hat{g}_i^p)^2}{\sum_{i=1}^{n}(\hat{g}_i - \hat{g})^2}$$

where $\hat{g} = \frac{1}{n}\sum_{i=1}^{n}\hat{g}_i$. Letting $\bar{g} = \frac{1}{n}\sum_{i=1}^{n} g_i$, the R^2 measured in terms of unmodified growth rates is

$$\tilde{R}^2 = 1 - \frac{\sum_{i=1}^{n}(g_i - g_i^p)^2}{\sum_{i=1}^{n}(g_i - \bar{g})^2}.$$

Since $g_i - g_i^p = \hat{g}_i - \hat{g}_i^p$ the $\tilde{R}^2$ is related to R^2 according to

$$\tilde{R}^2 = 1 - (1 - R^2)\frac{\sum_{i=1}^{n}(\hat{g}_i - \hat{g})^2}{\sum_{i=1}^{n}(g_i - \bar{g})^2}.$$

A cross-sectional regression with no risk terms has predicted values equal to $\hat{g}$ for all i and an R^2 of 0. Therefore, its alternate R^2 is

$$\tilde{R}^2_{\text{no risk}} = 1 - \frac{\sum_{i=1}^{n}(\hat{g}_i - \hat{g})^2}{\sum_{i=1}^{n}(g_i - \bar{g})^2}.$$

Comparing the fit of the models with and without risk terms we see that

$$\tilde{R}^2 - \tilde{R}^2_{\text{no risk}} = R^2\frac{\sum_{i=1}^{n}(\hat{g}_i - \hat{g})^2}{\sum_{i=1}^{n}(g_i - \bar{g})^2}$$

Thus, the improvement in fit in terms of unmodified growth rates is proportional to the R^2 of the cross-sectional regression in terms of modified growth rates.

TABLE A1: Country List

Australasia & Pacific	**Latin Amer. & Caribbean**	**South Asia**
Australia*	Argentina	Bangladesh
Fiji	Belize	India
New Zealand*	Bolivia	Nepal
Papua New Guinea	Brazil	Pakistan
Solomon Islands	Chile	Sri Lanka
East Asia	Colombia	**Sub-Saharan Africa**
China	Costa Rica	Benin
Hong Kong*	Dominican Rep.	Botswana
Indonesia	Ecuador	Burkina Faso
Japan*†	El Salvador	Burundi
Korea*	Guatemala	Cameroon
Malaysia	Guyana	Central African Rep.
Philippines	Haiti	Chad
Singapore*	Honduras	Congo, Dem. Rep.
Thailand	Jamaica	Congo, Rep.
Europe	Mexico	Côte d'Ivoire
Austria*	Nicaragua	Gabon
Belgium*	Panama	Gambia, The
Denmark*	Paraguay	Ghana
Finland*	Peru	Guinea-Bissau
France*	St. Vincent & the Gren.	Kenya
Greece*	Trinidad & Tobago*	Lesotho
Hungary*	Uruguay	Liberia
Iceland*	Venezuela	Madagascar
Ireland*	**Middle East & N. Africa**	Malawi
Israel*	Algeria	Mali
Italy*	Egypt	Mauritania
Luxembourg*	Iran	Niger
Malta*	Morocco	Nigeria
Netherlands*	Saudi Arabia*†	Rwanda
Norway*	Syria	Senegal
Portugal*	Tunisia	Seychelles
Spain*	**North America**	Sierra Leone
Sweden*	Bahamas*	South Africa
Switzerland*	Bermuda*	Sudan
Turkey	Canada*	Swaziland
United Kingdom*	United States*†	Togo
		Zambia

* Indicates a high-income country as designated by the World Bank.
† Indicates a country not included in our analysis of global factors, but included in our growth and volatility regressions.

TABLE 1: Cross-Sectional Regressions of Average Growth Rates on Volatility

	Right-hand side variables					
	Constant	Volatility	Regional dummies		Initial Income	R^2
			SSA	East Asia		
A) *Regressions with the full sample*						
Volatility only	2.95 (0.30)	−0.31 (0.06)				0.203
Volatility and regional dummies	2.14 (0.33)	−0.21 (0.06)	−1.04 (0.32)	2.41 (0.48)		0.433
Volatility and initial income	2.26 (0.93)	−0.30 (0.06)			0.08 (0.11)	0.207
Volatility of HP-filtered output	2.88 (0.30)	−0.50 (0.10)				0.187
B) *Regressions with income-based subsamples*						
Low & middle-income	2.68 (0.42)	−0.30 (0.07)				0.177
High-income	2.54 (0.43)	−0.02 (0.14)				0.001

Notes: Annual data, 1971–2007. The table summarizes results of estimating cross-sectional regressions of average growth rates of real per capita GDP on volatility, and other variables. Volatility is measured as the standard deviation of the growth rate of real per capita GDP, except in the one case indicated, where it is measured as the standard deviation of the cyclical component of the logarithm of real per capita GDP, as defined by the HP-filter (Hodrick and Prescott, 1997). The full list of countries is provided in the Appendix, along with the delineation by income category and region. Initial income is measured as the logarithm of real per capita GDP in 1970. Real GDP is measured in constant (2000) US dollars.

TABLE 2: Summary Statistics for Risk Factors

	Standard Deviations					
	US growth	US interest rate	Oil price	Metals prices	Agricultural prices	US market return
	1.90	4.39	28.1	16.9	10.4	17.0

	Correlation Matrix					
	US growth	US interest rate	Oil price	Metals prices	Agricultural prices	US market return
US growth	1	0.11	−0.11	0.29	0.39	−0.02
US interest rate	0.11	1	−0.65	−0.32	−0.25	0.21
Oil price	−0.11	−0.65	1	0.26	0.13	−0.33
Metals prices	0.29	−0.32	0.26	1	0.58	−0.09
Agricultural prices	0.39	−0.25	0.13	0.58	1	−0.41
US market return	−0.02	0.21	−0.33	−0.09	−0.41	1

Notes: Annual data, 1971-2007. The table provides summary statistics for the six risk factors described in more detail in the main text: US GDP growth, the US real interest rate, the rates of change of the relative prices of oil, metals, and agricultural products, and the excess return to the US stock market. For the US interest rate and the US market return the units of the standard deviations are in percentage points. For the other variables they are percent changes.

TABLE 3: Time Series Regressions of Individual Country Growth Rates on Individual Risk Factors

	Beta Estimates			Scaled Beta Estimates		Number of Statistically Significant Betas		Median R^2
	Minimum ($\beta_{\min}$)	Median (β_{med})	Maximum ($\beta_{\max}$)	$\beta_{\min} \times \sigma_f$	$\beta_{\max} \times \sigma_f$	5% level	10% level	
US growth	−1.22	0.21 (0.34)	2.31	−2.32	4.39	25	32	0.029
US interest rate	−0.76	−0.12 (0.13)	0.54	−3.33	2.36	30	41	0.035
Oil price	−0.07	0.02 (0.02)	0.08	−2.00	2.18	19	31	0.021
Metals prices	−0.09	0.03 (0.04)	0.23	−1.50	3.83	27	34	0.030
Agricultural prices	−0.21	0.04 (0.05)	0.42	−2.18	4.31	37	48	0.036
US market return	−0.16	−0.00 (0.04)	0.15	−2.80	2.58	5	10	0.017

Notes: Annual data, 1971–2007. The table summarizes results of estimating the time series regressions described in the note to Figure 3. Summary information about the estimated βs across the 104 countries in our data set is presented. The median of the heteroskedasticity consistent standard errors is presented in parentheses below the median estimate of β.

TABLE 4: Time Series Regressions of Individual Country Growth Rates on the Vector of Risk Factors

	Beta Estimates			Scaled Beta Estimates		Number of Statistically Significant Betas	
	Minimum (β_{min})	Median (β_{med})	Maximum (β_{max})	$\beta_{\text{min}} \times \sigma_f$	$\beta_{\text{max}} \times \sigma_f$	5% level	10% level
US growth	−1.25	0.23 (0.32)	2.63	−2.38	5.01	24	31
US interest rate	−0.77	−0.12 (0.16)	0.65	−3.36	2.84	23	29
Oil price	−0.13	0.00 (0.02)	0.09	−3.65	2.59	12	21
Metals prices	−0.14	0.01 (0.04)	0.35	−2.33	5.89	13	20
Agricultural prices	−0.57	0.02 (0.07)	0.35	−5.91	3.62	24	31
US market return	−0.14	0.01 (0.04)	0.21	−2.30	3.64	14	19

Notes: Annual data, 1971–2007. The table summarizes results of estimating the time series regressions described in the note to Figure 5. Summary information about the estimated βs across the 104 countries in our data set is presented. The median of the heteroskedasticity consistent standard errors is presented in parentheses below the median estimate of β.

TABLE 5: Cross-Sectional Regressions of Average Country Growth Rates on Betas with respect to Global Risk Factors

Right-hand side variables	(1)	(2)
Constant (λ_0)	1.94	2.10
	(0.18)	(0.17)
	[0.18]	[0.17]
US GDP growth	0.18	0.04
	(0.50)	(0.48)
	[0.45]	[0.43]
US real interest rate	2.03	1.70
	(1.07)	(1.02)
	[1.22]	[1.11]
Oil price change	−18.3	−13.4
	(8.36)	(7.57)
	[9.45]	[8.47]
Metals price change	−9.01	−11.3
	(5.02)	(4.92)
	[4.61]	[4.49]
Agriculture price change	2.20	−1.34
	(2.44)	(2.33)
	[2.07]	[2.03]
US market excess return	0.83	2.89
	(4.26)	(4.02)
	[3.25]	[3.61]
Sub-Saharan Africa		−1.26
		(0.29)
		[0.24]
East Asia		2.96
		(0.52)
		[0.46]
R^2	0.15	0.46
MAE	1.25	0.99

Notes: In column (1) we present the results of estimating cross-sectional regressions of the form, $g_i = \lambda_0 + \hat{\boldsymbol{\beta}}_i' \boldsymbol{\lambda} + u_i$, $i = 1, \ldots, n$, with $n = 104$. Here g_i is the average growth rate of a country in the period 1971–2007, and $\hat{\boldsymbol{\beta}}_i$ is a 6×1 vector of estimated betas from the time series regressions described in the note to Figure 5. The betas measure the exposure of country i's growth rate with respect to six risk factors: US GDP growth, the US real interest rate, the rates of change of the relative prices of oil, metals, and agricultural products, and the excess return to the US stock market. Standard errors that correct for estimation of the betas are presented below the point estimates: Shanken (1992) standard errors are in parentheses; Jagannathan and Wang (1998) standard errors are in brackets. Column (2) presents a similar regression in which we add dummy variables for whether a country is located in Sub-Saharan Africa or East Asia.

TABLE 6: Cross-Sectional Regressions of Modified Growth Rates on Betas with respect to Global Risk Factors

Right-hand side variables	$\rho = 0$	$\rho = 0.005$	$\rho = 0.01$	$\rho = 0.015$	$\rho = 0.02$
US GDP growth	0.18	0.50	0.82	1.10	1.35
	(0.50)	(0.54)	(0.60)	(0.65)	(0.71)
	[0.45]	[0.45]	[0.46]	[0.47]	[0.49]
US real interest rate	2.03	2.60	3.22	3.86	4.53
	(1.07)	(1.17)	(1.28)	(1.41)	(1.55)
	[1.22]	[1.40]	[1.58]	[1.80]	[2.03]
Oil price change	−18.3	−21.8	−25.3	−29.0	−32.6
	(8.36)	(9.26)	(10.3)	(11.5)	(12.6)
	[9.45]	[10.6]	[12.0]	[13.5]	[15.1]
Metals price change	−9.01	−9.81	−10.1	−9.98	−9.28
	(5.02)	(5.44)	(5.91)	(6.38)	(6.83)
	[4.61]	[5.02]	[5.51]	[6.01]	[6.48]
Agriculture price change	2.20	3.88	5.63	7.44	9.29
	(2.44)	(2.62)	(2.82)	(3.05)	(3.28)
	[2.07]	[2.15]	[2.28]	[2.44]	[2.61]
US market excess return	0.83	0.98	1.22	1.55	1.97
	(4.26)	(4.59)	(4.99)	(5.41)	(5.85)
	[3.25]	[3.23]	[3.31]	[3.49]	[3.77]
R^2	0.149	0.164	0.159	0.150	0.141

Notes: We present the results of estimating cross-sectional regressions of the form, $\hat{g}_i = \lambda_0 + \hat{\boldsymbol{\beta}}_i' \boldsymbol{\lambda} + u_i$, $i = 1, \ldots, n$, with $n = 104$. Here $\hat{g}_i$ is the average growth rate of a country in the period 1971–2007 modified to take into account transition dynamics (see the main text), and $\hat{\boldsymbol{\beta}}_i$ is a 6×1 vector of estimated betas from the time series regressions described in the note to Figure 4. The parameter ρ determines the magnitude of the correction for transition dynamics. The betas measure the exposure of country i's modified growth rate with respect to six risk factors: US GDP growth, the US real interest rate, the rates of change of the relative prices of oil, metals, and agricultural products, and the excess return to the US stock market. Standard errors that correct for estimation of the betas are presented below the point estimates: Shanken (1992) standard errors are in parentheses; Jagannathan and Wang (1998) standard errors are in brackets.

TABLE 7: CROSS-SECTIONAL REGRESSIONS OF GROWTH RATES ON BETAS WITH RESPECT TO OUR MEASURE OF RISK AND INCOME-SORTED FACTORS

	104 countries			26 portfolios static sorting		26 portfolios dynamic sorting	
Factor:	$\hat{m}$	SHL	DHL	$\hat{m}$	SHL	$\hat{m}$	DHL
λ	0.99	0.88	0.91	1.32	0.71	0.89	1.04
	(0.41)	(0.29)	(0.30)	(0.54)	(0.23)	(0.29)	(0.29)
	[0.31]	[0.24]	[0.25]	[0.52]	[0.22]	[0.32]	[0.23]
R^2	0.15	0.21	0.21	0.29	0.27	0.27	0.70

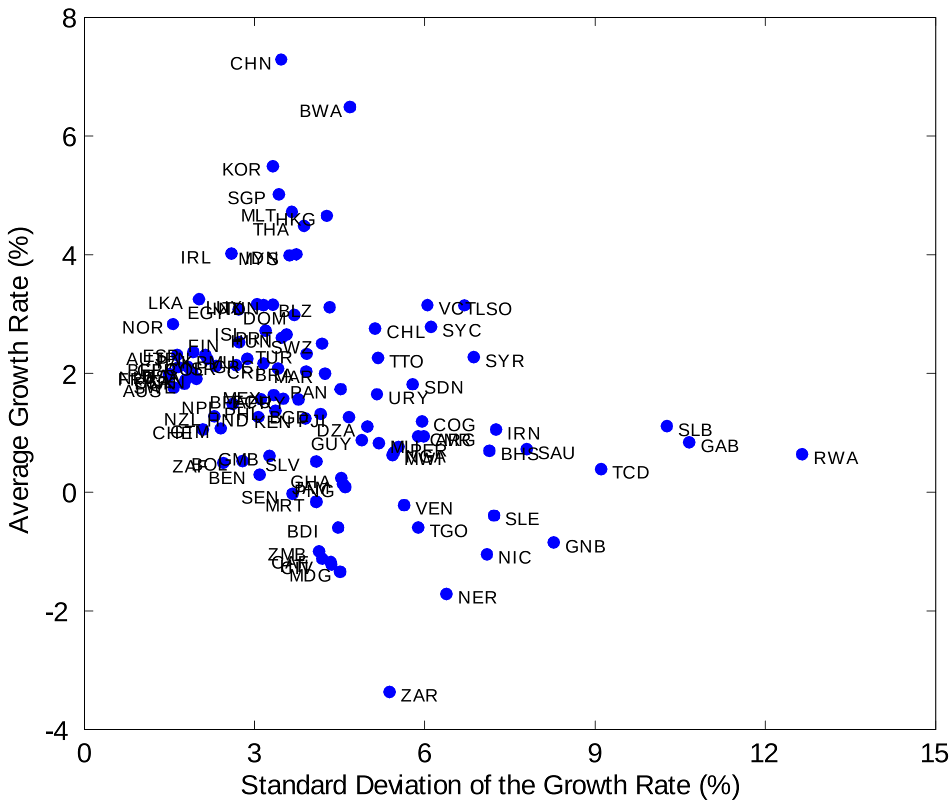
Notes: We present the results of estimating cross-sectional regressions of the form, $g_i = \lambda_0 + \hat{\beta}_i'\lambda + u_i$, $i = 1, \ldots, n$, where n is either 104, when g_i represents the growth rate of an individual country, or 26, when g_i represents the average growth rate of four countries in a portfolio. Portfolios are constructed by sorting countries on the basis of initial income. In the case of "static sorting" countries are sorted on the basis of their per capita income in 1970. In the case of "dynamic sorting" countries are sorted in each year, on the basis of their per capita income in the previous year. The right-hand side variable in the regressions is $\hat{\beta}_i$ which is the slope coefficient in a time series regression of g_{it} on a risk factor, f_t. We consider three risk factors: $\hat{m}$, the measure of risk defined in section 5.1 (assuming $\rho = 0$), the SHL factor (the average growth rate of high-income countries minus the average growth rate of low-income countries, with high and low-income defined in terms of a sort on the basis of 1970 per capita income), the DHL factor (the average growth rate of high income countries minus the average growth rate of low income countries, with high and low income defined in terms of a sort that evolves continuously within the sample). Standard errors that correct for estimation of the betas are presented below the point estimates: Shanken (1992) standard errors are in parentheses; Jagannathan and Wang (1998) standard errors are in brackets.

TABLE 8: Bivariate Cross-Sectional Regressions of Growth Rates on Multivariate Betas with respect to Our Measure of Risk and Income-Sorted Factors

	104 countries		26 portfolios static	26 portfolios dynamic
Factors:	$\hat{m}$ & SHL	$\hat{m}$ and DHL	$\hat{m}$ & SHL	$\hat{m}$ & DHL
$\lambda_{\hat{m}}$	0.62	0.60	0.93	0.57
	(0.32)	(0.32)	(0.47)	(0.28)
	[0.28]	[0.27]	[0.51]	[0.29]
λ_{SHL}	0.85		0.68	
	(0.30)		(0.24)	
	[0.25]		[0.22]	
λ_{DHL}		0.78		1.00
		(0.28)		(0.30)
		[0.24]		[0.23]
R^2	0.23	0.24	0.33	0.78

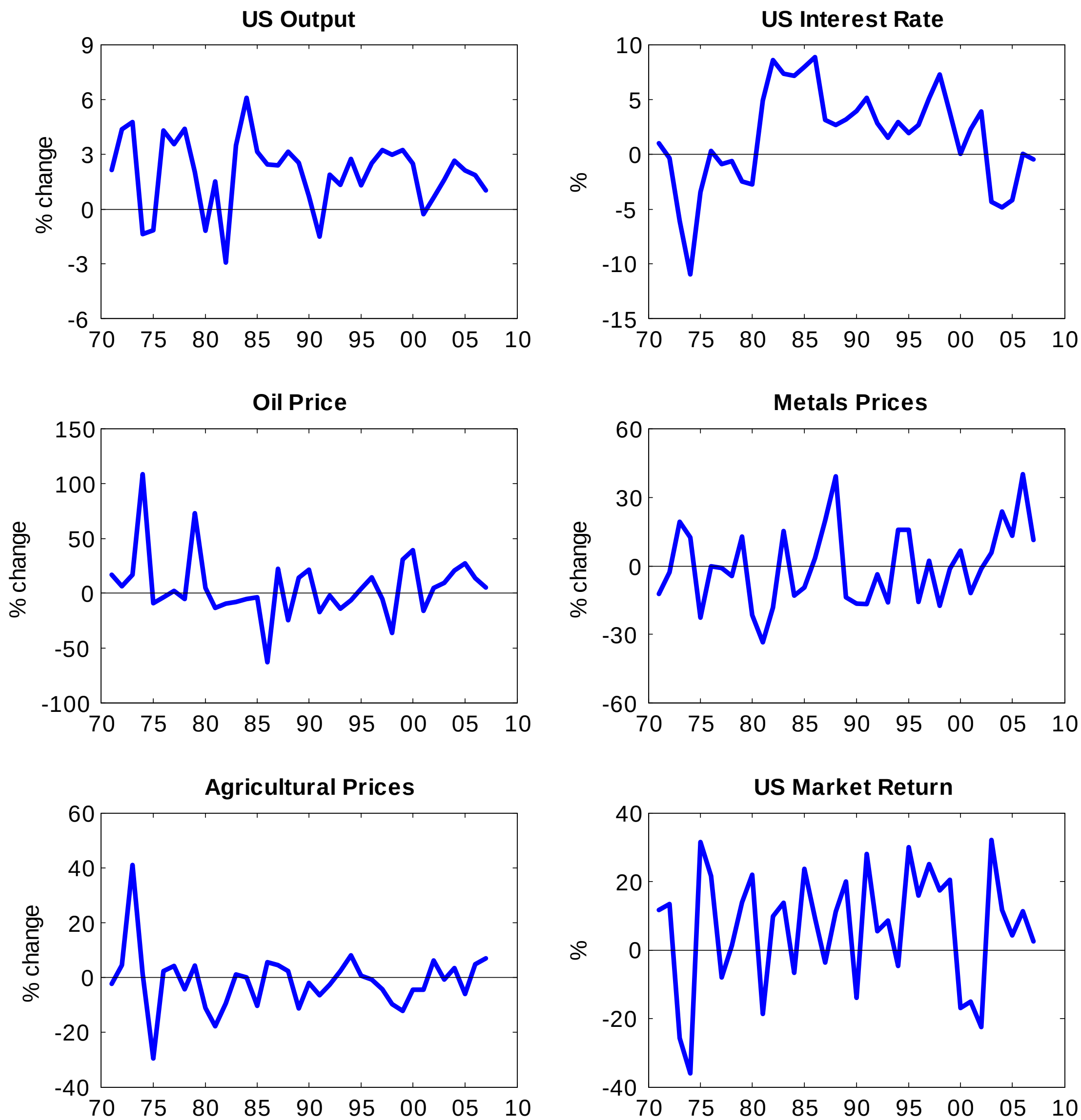
Notes: We present the results of estimating cross-sectional regressions of the form, $g_i = \lambda_0 + \hat{\boldsymbol{\beta}}_i' \boldsymbol{\lambda} + u_i$, $i = 1, \ldots, n$, where n is either 104, when g_i represents the growth rate of an individual country, or 26, when g_i represents the average growth rate of four countries in a portfolio. See the note to Table 7 for details of the sorting. The right-hand side variable in the regressions is $\hat{\boldsymbol{\beta}}_i$ which is the vector of slope coefficients in a time series regression of g_{it} on a pair of risk factors, $\mathbf{f}_t$. We consider the three risk factors described in the note to Table 7: $\hat{m}$, the SHL factor, and the DHL factor. Standard errors that correct for estimation of the betas are presented below the point estimates: Shanken (1992) standard errors are in parentheses; Jagannathan and Wang (1998) standard errors are in brackets.

FIGURE 1: Growth versus Volatility, 1971–2007



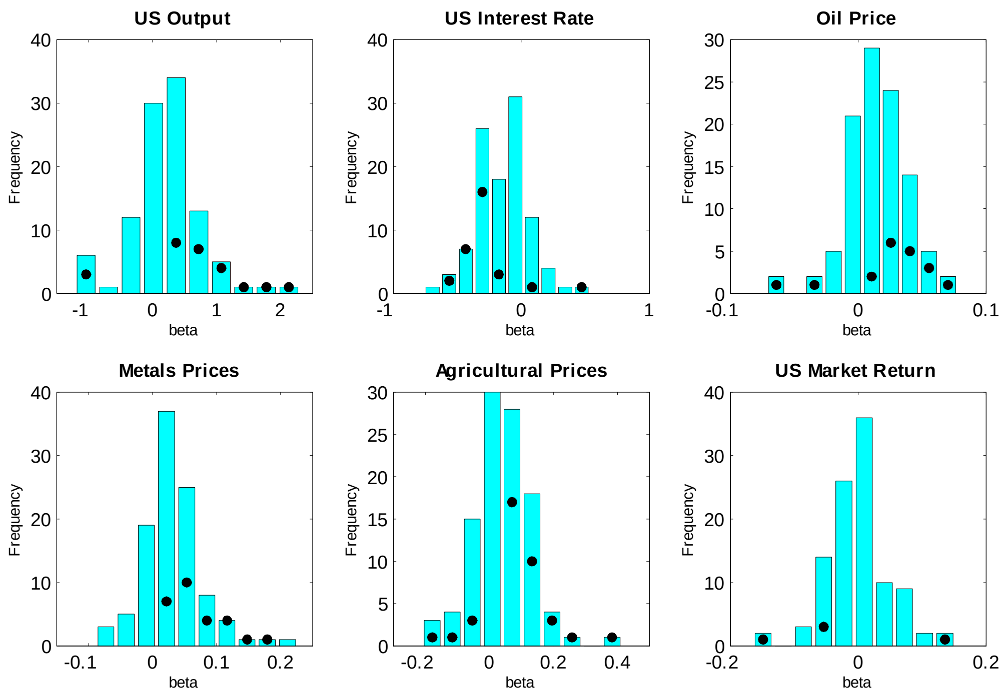
Note: The graph shows a scatter plot of the mean growth rate, g_i, against the standard deviation of the growth rate, σ_i using annual data over the period 1971–2007. Data sources, series definitions, and country labels are described in the Appendix.

FIGURE 2: Measures of Global Risk Factors



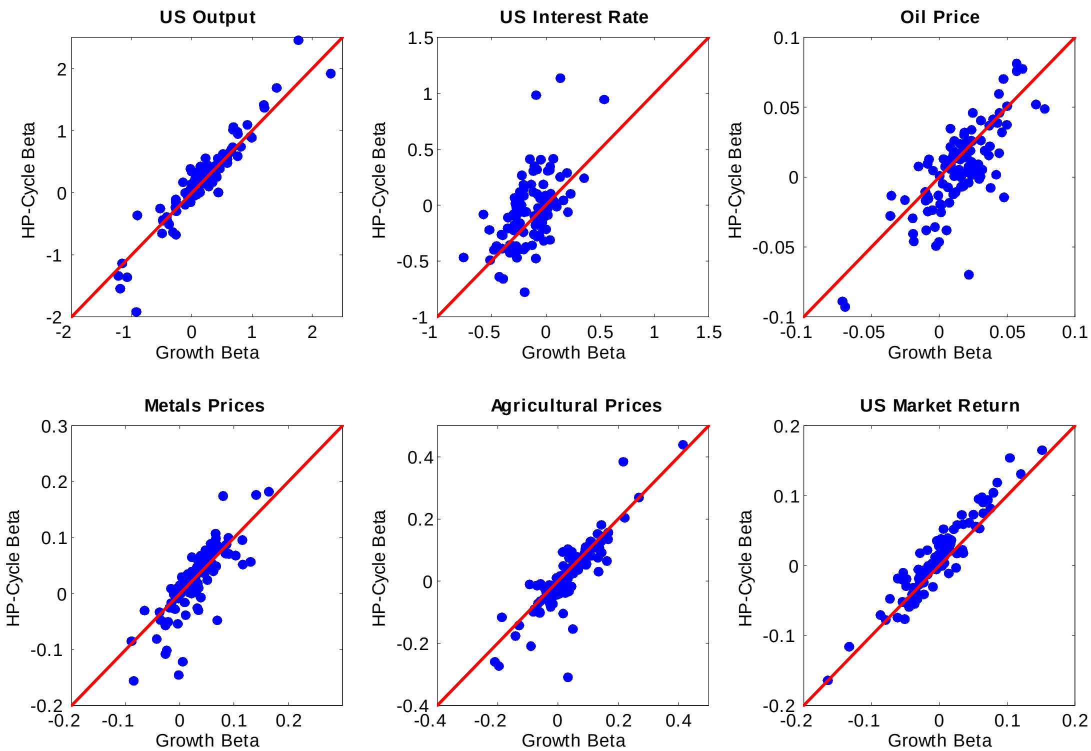
Note: Annual data, 1971-2007. The graphs provide show time series data for the six risk factors described in more detail in the main text: US GDP growth, the US real interest rate, the rates of change of the relative prices of oil, metals, and agricultural products, and the excess return to the US stock market.

FIGURE 3: Estimates of the Betas for Individual Risk Factors



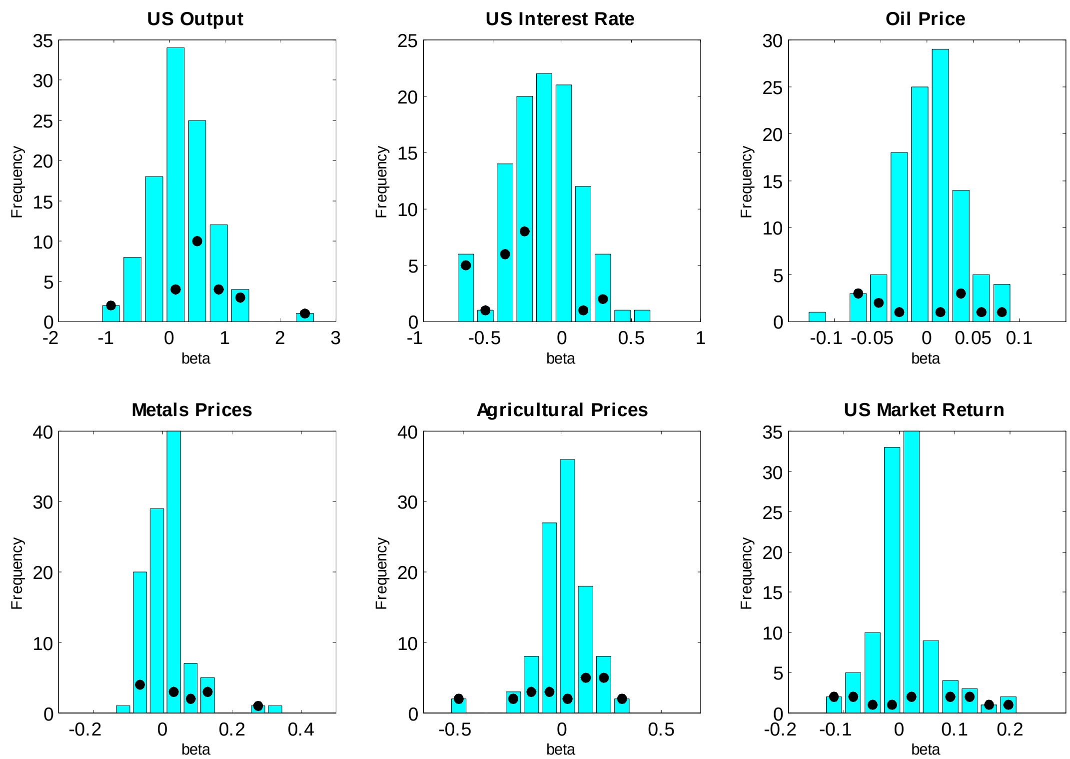
Note: The graphs summarize information obtained from time series regressions of each country's real growth rate, g_{it}, on individual risk factors, f_t, using annual data over the period 1971–2007. Each regression takes the form $g_{it} = a_i + f_t'\beta_i + \epsilon_{it}$. The risk factors are US real GDP growth, the ex-post short term real interest rate in the US, the change in the relative prices of oil, metals and agricultural products, and the US stock market excess return. The countries, series definitions and data sources are described in detail in the Appendix.

FIGURE 4: Growth Rate Based and HP-Filter Based Betas for Individual Risk Factors



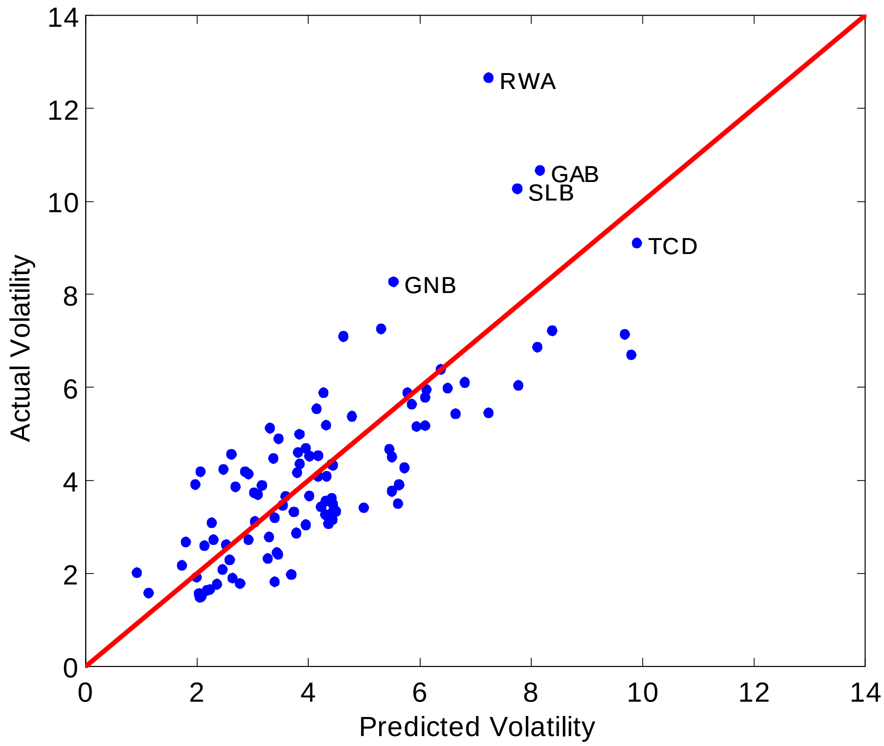
Note: The graphs are scatter plots of estimates of the "growth rate beta," β_i, described in the note to Figure 3, against estimates of the "HP Filter-based beta," β_i^H, described in the main text, which is the slope coefficient from a time series regression of each country's HP-filtered log level of per capital real GDP, y_{it}^H, on HP-filtered log levels of the individual risk factors, f_t^H, using annual data over the period 1971–2007. The data are described in more detail in the main text. Each regression takes the form $y_{it}^H = a_i^H + f_t^{H\prime}\beta_i^H + \epsilon_{it}^H$. The data are described in more detail in the note to Figure 3.

FIGURE 5: Estimates of the Betas for the Vector of Risk Factors



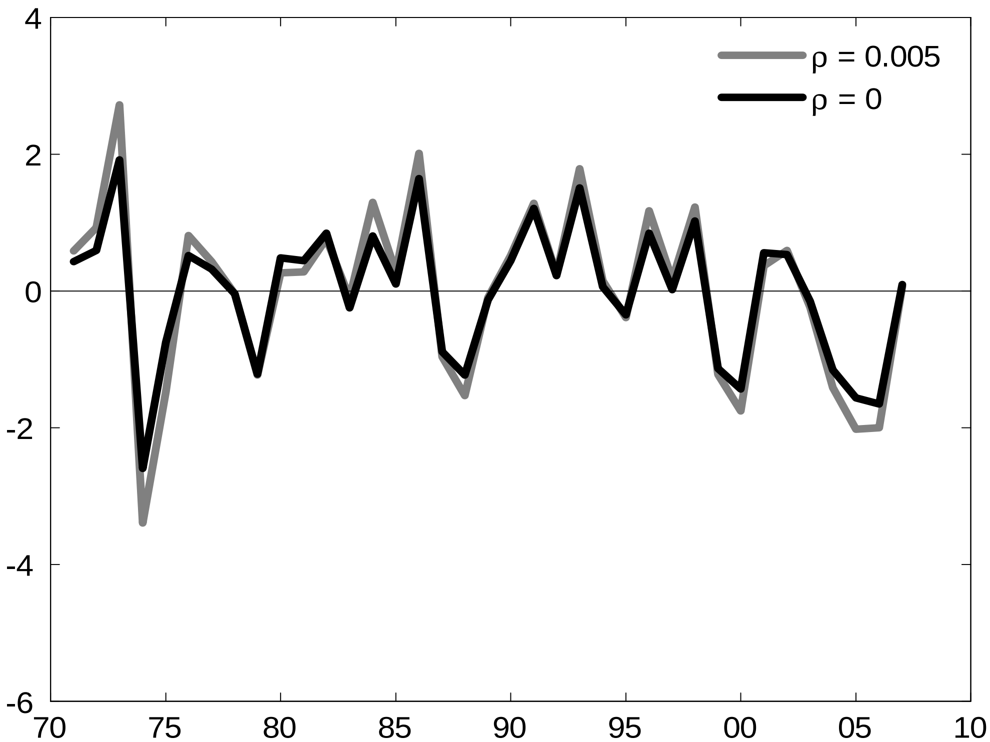
Note: The graphs summarize information obtained from time series regressions of each country's real growth rate, g_{it}, on a 6×1 vector of risk factors, $\mathbf{f}_t$, using annual data over the period 1971–2007. Each regression takes the form $g_{it} = a_i + \mathbf{f}_t'\beta_i + \epsilon_{it}$. The risk factors are US real GDP growth, the ex-post short term real interest rate in the US, the change in the relative prices of oil, metals and agricultural products, and the US stock market excess return. The countries, series definitions and data sources are described in detail in the Appendix.

FIGURE 6: Overall Volatility and Volatility Predicted by Exposure to Risk



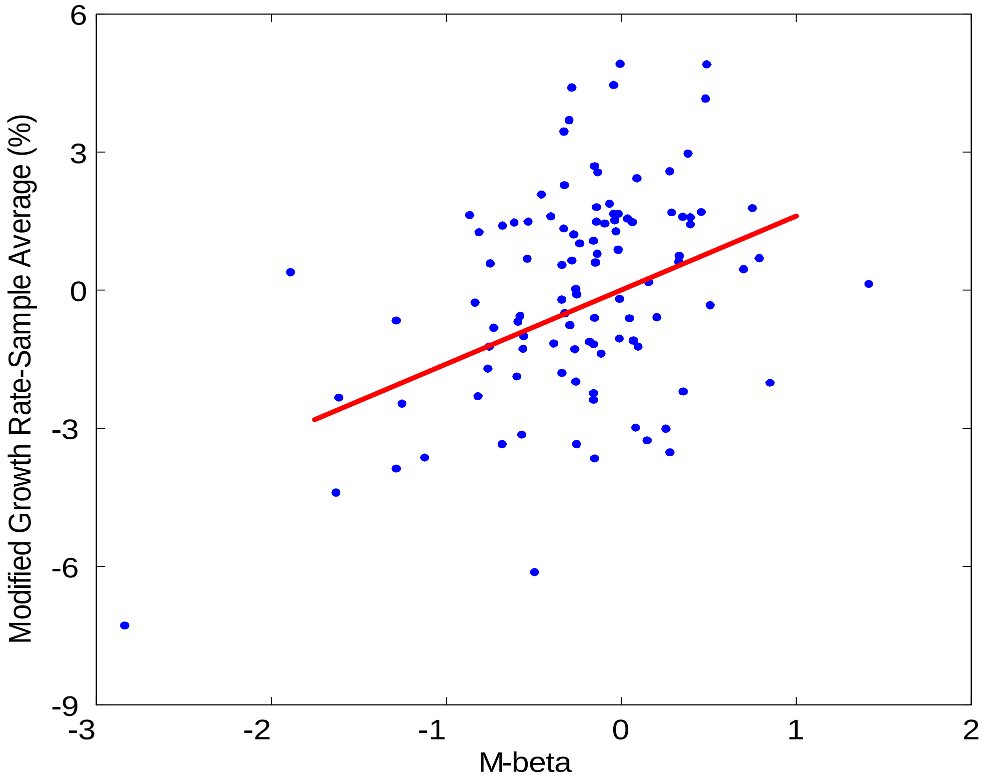
Note: The graph is a scatter plot of the standard deviation of each country's growth rate (overall volatility), against the degree of volatility predicted by its exposure to external shocks. The latter is computed from the regression of "overall volatility", σ_i, on volatility due to external factors, γ_i, described in the text. Sample: 1971–2007. Sources are described in the Appendix.

FIGURE 7: Our Measure of the Proxy for the International Investor's Level of Risk



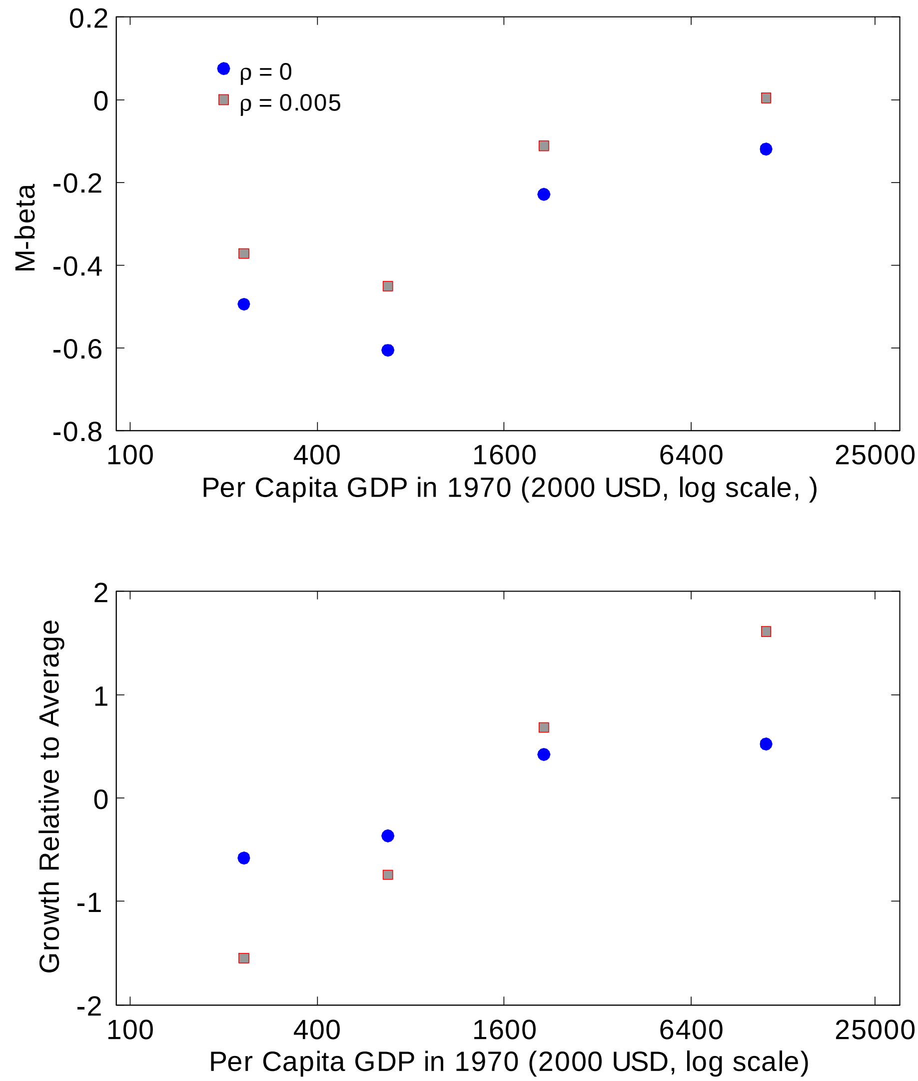
Note: Our measure of risk is $\hat{m}_t = \left(\mathbf{f}_t - \overline{\mathbf{f}}\right)' \hat{\boldsymbol{\Sigma}}_{\mathbf{f}}^{-1} \hat{\boldsymbol{\lambda}}$ where $\mathbf{f}_t$ is the vector of risk factors described in the note to Figure 5, $\overline{\mathbf{f}}$ is the mean of that vector, $\hat{\boldsymbol{\Sigma}}_{\mathbf{f}}$ is its sample covariance matrix and $\hat{\boldsymbol{\lambda}}$ is an estimate of the slope coefficients in the cross-sectional regression described in the note to Table 6. The sample period is 1971–2007. The parameter ρ determines the size of the correction made to the growth rate data to take into account transition dynamics.

FIGURE 8: Average Modified Growth Rates against M-Betas



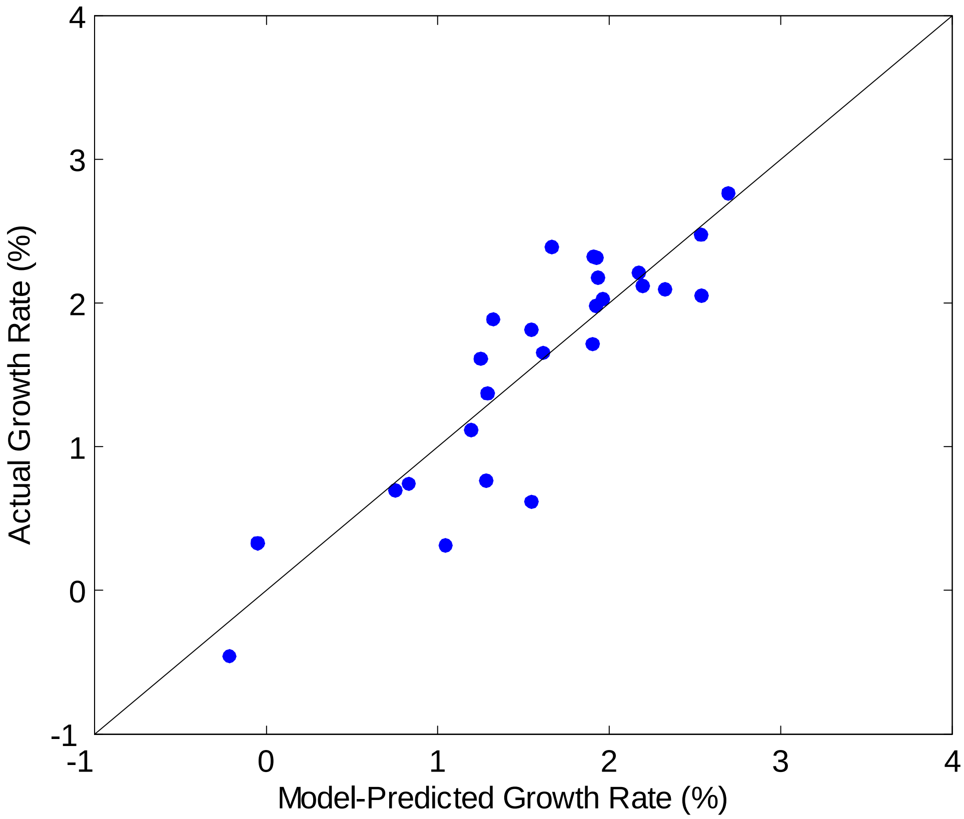
Note: For each country, the M-beta is the slope coefficient in a regression of its modified growth rate, $\hat{g}_{it}$, on the estimated measure of risk, $\hat{m}_t = \left(\mathbf{f}_t - \bar{\mathbf{f}}\right)' \hat{\mathbf{\Sigma}}_{\mathbf{f}}^{-1} \hat{\boldsymbol{\lambda}}$, described in the note to Figure 7. The modified growth rates are measured using $\rho = 0.005$ and the correction described in the main text. Average growth rates for each country are expressed relative to the cross-sectional average of all countries' growth rates.

FIGURE 9: M-Betas and Growth Rates versus Income



Note: For each country, the M-beta is the slope coefficient in a regression of its modified growth rate, $\hat{g}_{it}$, on the estimated measure of risk, $\hat{m}_t = \left(\mathbf{f}_t - \overline{\mathbf{f}}\right)' \hat{\mathbf{\Sigma}}_{\mathbf{f}}^{-1} \hat{\boldsymbol{\lambda}}$, described in the note to Figure 7. The modified growth rates are measured using $\rho = 0$ and $\rho = 0.005$ and the correction described in the main text. Average growth rates for each country are expressed relative to the cross-sectional average of all countries' growth rates. Countries are sorted by per capita real GDP in 1970 and grouped into quartiles. The x-axis in each graph shows the average initial income level of each quartile, while the vertical axis shows either the average M-beta or the average growth rate within that income quartile.

FIGURE 10: Actual Average Growth Rates and Model-Predicted Growth Rates for the 26 Dynamically Sorted Portfolios



Notes: The diagram shows average growth rates plotted against model-predicated growth rates for the dynamically sorted portfolios describes in the text and the note to Table 7. The model uses $\hat{m}$ and DHL as risk factors. These factors are also described in the note to Table 7.