Diversification and Development

Miklós Koren and Silvana Tenreyro*

March 3, 2004

* *Koren*: Harvard University, Department of Economics and Institute of Economics, Hungarian Academy of Sciences. Budaörsi út 45, 1112 Budapest, Hungary, Fax: +36 1 319 3136, E-mail: koren@fas.harvard.edu. *Tenreyro (corresponding author)*: Federal Reserve Bank of Boston, Research Department. 600 Atlantic Avenue, Boston MA 02106. Fax: 617 973 3957, E-mail: silvana.tenreyro@bos.frb.org. We are grateful to Robert Barro, Christian Broda, John Campbell, Francesco Caselli, Gary Chamberlain, Don Davis, Marco Del Negro, Jon Faust, Jean Imbs, David Laibson, Jane Little, Jaume Ventura, and seminar participants at the Boston Fed, the Central European University, Harvard, and Rochester for comments and suggestions. Jiaying Huang provided excellent research assistance. Koren acknowledges financial support from CERGE-EI under a program of the Global Development Network. The views expressed herein are ours and have not been endorsed by the Federal Reserve Bank, CERGE-EI or the GDN.

Diversification and Development

Abstract

This paper explores the relationship between output volatility and economic development. We develop a methodology to assess countries' extent of sectoral diversification. The productive structure of a country tends to be risky when the country (i) specializes in highly volatile sectors, (ii) has high sectoral concentration, and/or (iii) specializes in sectors highly affected by country-specific fluctuations. Within the context of a portfolio choice model, we derive the implied mean-variance frontiers both for individual countries and for the world, and compute countries' distances to each. We find that as countries develop, they move from riskier sectors to safer ones. In addition, sectoral concentration declines with development at early stages, whereas at later stages the relation flattens out and tends to reverse slowly. The concentration index we construct is robust to the arbitrariness of sectoral classification. Finally, poor countries are typically inside their mean-variance frontier, that is, they could achieve the same level of productivity at lower risk by modifying their sectoral composition. Existing theories linking volatility and development are not consistent with all of our findings. We propose new directions for future theoretical work. (O11, O14, E32, G10)

An important theme in the growth and development literature is the relationship between risk, diversification, and economic development. In a seminal paper, Lucas (1988) observes that developed countries tend to exhibit stable growth rates over long periods of time, whereas poorer countries are prone to experience sharp fluctuations in growth rates. This relationship is illustrated in Figure 1, which plots the standard deviation of annual growth rates against the level of real GDP per capita for a large cross section of countries.

Understanding the sources of volatility is a first-order issue for less developed countries, for not only are income fluctuations larger and more abrupt in these economies, but also their ability to hedge against fluctuations is particularly limited by the weakness of their financial infrastructure. Furthermore, identifying the sources of volatility allows to empirically assess existing theories linking risk and development, and may help discern the relevant institutions and policies to mitigate volatility.

In a highly stimulating paper, Burns (1960) points to the choice of technology and the sectoral composition of the economy as the key determinants of volatility. On the one hand, some activities tend to be riskier than others (e.g., agriculture is more volatile than services). On the other hand, sectoral concentration affects the extent of exposure to sector-specific fluctuations (e.g., high concentration in one sector increases the exposure to sector-specific risk).

In this paper, we explore the links between economic development and risk diversification. We investigate how the sectoral structure affects the riskiness of economic activity. This yields direct evidence on the sources of economic fluctuations. More specifically, we distinguish between four dimensions of the overall riskiness of an economy's output mix. The first dimension relates to the degree of specialization in the economy (e.g., typically, an economy that is highly concentrated will tend to be more risk prone). The second dimension relates to the volatility of sectoral shocks (e.g., an economy that specializes in sectors that exhibit high intrinsic volatility will tend to be riskier). The third dimension relates to country-specific risks (e.g. some countries are subject to higher policy and political instability). And the fourth relates to the propensity of different sectors within the economy to be exposed to domestic marcroeconomic fluctuations (e.g., some sectors are more exposed to political, fiscal, or monetary shocks).

We examine the extent of diversification and its evolution over time, borrowing two insights from the finance literature. First, we view the economy as a portfolio of sectors with different intrinsic risk. The portfolio composition of a country is determined by the patterns of sectoral specialization. Second, we derive the *mean-variance frontier* for each country, that is, we compute the minimum variance a country can achieve, for each level of average productivity, by changing its sectoral composition. We compute the countries' distance to their frontier, as well as their distance to the world frontier.

The following findings stand out in our exploration of the diversification dynamics: First, as countries develop, they tend to move towards less risky sectors. Therefore, sectoral risk decreases with the level of development. Second, sectoral concentration sharply declines with development at early stages, whereas at later stages the relation flattens out and tends to reverse slowly. This suggests that there is no monotonic relationship between sectoral riskiness and concentration. We show that our measure of concentration differs from standard ones, in that it is immune to classification issues. Third, country-specific risk falls with development. This result could be the outcome of higher political stability and sounder macroeconomic policies in more developed economies. As for the covariance between country and sectoral shocks, we find that, while there is a high variation across countries, it does not systematically relate to development.

The mean-variance analysis reveals that most countries, particularly developing ones, are inside their own mean-variance frontier and, consequently, inside the world frontier. This means that they could achieve the same average level of labor productivity with lower variance, by changing the sectoral composition of output. Moreover, the distance to the mean-variance frontier decreases with the level of development, which means that the high economic volatility at early stages of development reflects inefficient diversification, rather than the result of some risk-return optimization.

Our analysis is based on industry-level data from UNIDO for a broad sample of developing and developed countries from 1963 to 1998. The findings are robust to the addition of agriculture and services, despite the loss of observations imposed by data constraints. We provide extensive robustness checks with different specifications.

Our study relates to a vast theoretical literature that yields direct predictions on the relationship between risk, diversification, and development. In particular, the finding that countries tend to exhibit high sectoral concentration at early stages of development seems to be in line with Acemoglu and Zilibotti (1997)'s theory: Early in the development process diversification opportunities are limited, owing to the scarcity of capital and the indivisibility of investment projects. However, the finding that this early sectoral concentration falls mainly on highly risky sectors is harder to reconcile with existing theoretical models. These models, most notably, Acemoglu and Zilibotti (1997), Obstfeld (1994), Saint-Paul (1992), and Greenwood and Jovanovic (1990) describe the technology choice of countries as a portfolio decision: In order to reap the benefits of high productivity and high growth, an economy has to bear more risk. The risk tolerance typically relates to the level of development and the financial structure of the economy. These models predict that at early stages of development countries will seek insurance by investing in safer (even if less productive) assets. According to our findings, however, not only are poorer countries highly concentrated in a few sectors, but also those sectors carry particularly high sector-specific risk. Furthermore, and as previously mentioned, we find that most developing countries are inside the mean-variance frontier, being highly prone to invest in high-variance, low-mean sectors. Clearly, important constraints must be at play, preventing developing countries from investing in safer and, at the same time, more productive assets.

Our findings seem to be closer to the predictions of Kraay and Ventura (2001)'s model of comparative advantage, where developed countries specialize in industries intensive in high skills. The key assumption is that high-skill sectors can cope better with external shocks. Their model can then be used to explain the decrease in sectoral risk, together with the decrease in sectoral concentration, provided that more developed countries produce a wider range of varieties. Yet, the model would counterfactually predict a decreasing covariance between sectoral and country risks as countries develop (if it is true that skill-sectors are better able to respond to macro shocks). However, their theory could be extended so that higher levels of human capital decrease country risk (through better macroeconomic policies, for example) and firms take into account the macro risk when deciding their degree of exposure. This will lead to higher covariance between sectoral and country risk together with the decrease in country risk.

Recent empirical studies in this area have focused on indices of concentration of employment or production as indicators of specialization (See, for example, Imbs and Wacziarg (2003) and Kalemli-Ozcan, Sørensen and Yosha (2003).) These measures of specialization do not capture the riskiness embodied in a particular sectoral structure, which is at the heart of theories linking specialization to development. In addition, these indices are highly sensitive to classification schemes. Our study, instead, focuses on the riskiness of the productive structure, allowing us to test the predictions of existing theories.[1]

The remainder of the paper is organized as follows. In Section 1, we introduce the methodology to study the different components of volatility and the mean-variance frontier. In Section 2, we introduce the data set. Section 3 presents and discusses the results. Section 4 performs a set of robustness tests. Section 5 presents our conclusions and directions for future research.

1 Methodology

We view the output of a country as a portfolio of different sectors, which are subject to fluctuations in labor productivity.[2] The portfolio composition of a country is determined by the share of resources allocated to each of the sectors. Consider a world with J countries, each with S sectors. We denote by y_{js} the random variable describing the log-difference of value added per worker in country j and sector s, and by $\mathbf{y}_j$ the $S \times 1$ vector of elements y_{j1} through y_{jS}. Assume that the shocks have been demeaned so that $\mathrm{E}(\mathbf{y}_j) = 0$, and denote

[1] Studies on aggregate volatility, most notably Kose, Otrok and Whiteman (2003) do not study sectoral shocks, which is the critical element that allows us to discriminate among existing theories.

[2] These fluctuations may be driven by demand or technology shocks.

the covariance matrix by $\text{Var}(\mathbf{y}_j) = \Omega_j$. The sectoral structure of country j is summarized by the vector $\mathbf{a}_j$, with elements a_{js} denoting the share of employment in sector s. Value added per worker (in log-differences) in this economy is then

$$q_j = \sum_{s=1}^{S} a_{js} y_{js} = \mathbf{a}_j' \mathbf{y}_j,$$

and the variance of labor productivity (in log differences) is given by:

$$\text{Var}(q_j) = \mathbf{a}_j' \Omega_j \mathbf{a}_j. \tag{1}$$

This last expression is our key measure of a country's riskiness. While sectoral shares can be directly measured, we need to estimate the variance-covariance structure of shocks. In what follows, we propose a factor model to estimate the variance-covariance matrix Ω_j, and its components.[3]

1.1 A factor model of economic fluctuations

In order to decompose fluctuations into different sources, we estimate the following factor model:

$$y_{js} = f_{1s} + f_{2j} + \varepsilon_{js} \tag{2}$$

Labor productivity y_{js} (in log differences) in sector s of country j is the sum of a sector-specific shock (f_{1s}) common to all countries, a country-specific shock (f_{2j}) common to all sectors within a country, and a purely idiosyncratic shock, uncorrelated with the other factors (ε_{js}). Each of these shocks has zero mean. Formally, we impose the following

[3]Note that we can obtain estimates of Ω_j as the sample second moment matrix: $\hat{\Omega}_j = \frac{1}{T_j} \sum_{t=1}^{T_j} \mathbf{y}_{jt} \mathbf{y}_{jt}'$. However, we would like to investigate the *sources* of economic fluctuations (e.g., global shocks to the sector or local shocks to the country), since countries may respond differently to shocks coming from different sources. Hence, we impose some restrictions on the variance-covariance matrix in order to identify the sources. Incidentally, for countries with a short time span, imposing more restrictions allows us to obtain more precise estimate of Ω_j.

restrictions:

$$\mathrm{Cov}(\varepsilon_{js}, \varepsilon_{j's'}) = 0 \text{ if either } j' \neq j \text{ or } s' \neq s,$$

$$\mathrm{Cov}(\mathbf{f}_1, \varepsilon_{js}) = 0, \quad \mathrm{Cov}(\mathbf{f}_2, \varepsilon_{js}) = 0.$$

We do not make further restrictions on the covariance matrix of factors. In particular, country-specific shocks may be correlated with sector-specific shocks and sector-specific shocks can be correlated with each other. We also allow for the idiosyncratic variance, σ^2_{js}, to vary with countries and sectors. This is a flexible way of capturing any heterogeneity that is not explained by the factors. Hence, the only restriction on idiosyncratic shocks is that they are uncorrelated with each other and with the factors.[4]

With vector notations, the variance-covariance matrix of sectoral shocks, their covariance with the factor of country j, the variance of country j, and the variance of idiosyncratic shocks can be written as follows.

$$\begin{aligned} \mathrm{E}(\mathbf{f}_1\mathbf{f}_1') &= \Sigma, \\ \mathrm{E}(\mathbf{f}_1 f_{2j}) &= \Sigma_{0j}, \\ \mathrm{E}(f_{2j}^2) &= \tau_j^2, \\ \mathrm{E}(\varepsilon_j\varepsilon_j') &= \mathbf{D}_j, \end{aligned}$$

where $\mathbf{D}_j$ is an $S \times S$ diagonal matrix containing the idiosyncratic variances, σ^2_{js}, in the diagonal. Since sectoral shocks are common to all countries, we also make the identifying assumption that the sum of country shocks is zero[5]:

$$\sum_{j=1}^{J} f_{2j} = 0.$$

This means that country shocks should be interpreted relative to an average of the world.

Equation (2) can then be written in vector form,

$$\mathbf{y}_j = \mathbf{f}_1 + f_{2j}\mathbf{1} + \varepsilon_j,$$

[4]The estimation also allows for country shocks to be correlated with each other.

[5]In other words, the global component is already embedded in sectoral shocks.

where $\mathbf{1}$ denotes the $S \times 1$ vector of ones. This implies the variance-covariance matrix[6]

$$\Omega_j = \Sigma + \tau_j^2 \mathbf{1}\mathbf{1}' + (\Sigma_{0j}\mathbf{1}' + \mathbf{1}\Sigma_{0j}') + \mathbf{D}_j. \tag{3}$$

The overall riskiness of the economy can be expressed as the sum of four components:

$$\mathrm{Var}(\mathbf{a}_j'\mathbf{y}_j) = \mathbf{a}_j'\Omega_j\mathbf{a}_j = \mathbf{a}_j'\Sigma\mathbf{a}_j + \tau_j^2 + 2(\mathbf{a}_j'\Sigma_{0j}) + \mathbf{a}_j'\mathbf{D}_j\mathbf{a}_j. \tag{4}$$

Hence, production in country j is risky

1. if the country specializes in *risky* sectors ($\mathbf{a}_j'\Sigma\mathbf{a}_j$ is big);
2. if country risk (τ_j^2) is big;
3. if specialization is *tilted* towards sectors positively correlated with country risks ($\mathbf{a}_j'\Sigma_{0j}$ is big);
4. and if it is highly *concentrated* in the (weighted) Herfindahl sense ($\mathbf{a}_j'\mathbf{D}_j\mathbf{a}_j = \sum_s \sigma_{js}^2 a_{js}^2$ is big).

These four components of risk have fundamentally different meanings. Empirical studies usually concentrate on the last source, using, for example, the unweighted Herfindahl formula $\mathbf{a}_j'\mathbf{a}_j = \sum_s a_{js}^2$. This indicator does not weight sectors by their volatility. Such a measure would only capture the riskiness of the sectoral structure under the assumption that sectors are symmetric (homoscedastic) and uncorrelated. In this case, efficient diversification would clearly dictate an even distribution of sectors ($a_{js} = 1/S$ for all s), and any deviation from this can be coined as "lack of diversification."

An additional caveat of the unweighted Herfindahl index as a measure of lack of diversification is that it suffers from a *classification bias*: high-tech sectors are more finely classified than agriculture and low-tech sectors. Our weighted Herfindahl index is not

[6]Note that, since the factors are not orthogonal, we have to keep track of the covariance of sectoral shocks with country shocks, Σ_{0j}.

sensitive to the arbitrariness of classification because broadly defined sectors tend to have lower idiosyncratic risk, hence lower weight in the index. Appendix A proves this property.

Once we measure the covariance matrix of factors, including Σ, Σ_{0j}, τ_j^2, and σ_{js}^2, we can calculate the four measures of risk exposure and total risk as follows:

$$\mathrm{SECT}_{jt} = \mathbf{a}'_{jt}\Sigma\mathbf{a}_{jt} \tag{5}$$

$$\mathrm{HERF}_{jt} = \mathbf{a}'_{jt}\mathbf{D}_j\mathbf{a}_{jt} \tag{6}$$

$$\mathrm{CNT}_j = \tau_j^2 \tag{7}$$

$$\mathrm{COV}_{jt} = 2\mathbf{a}'_{jt}\Sigma_{0j} \tag{8}$$

$$\mathrm{RISK}_{jt} = \mathbf{a}'_{jt}\Omega_j\mathbf{a}_{jt} \tag{9}$$

where SECT_{jt} is the variance of output fluctuations in country j at time t due to sectoral shocks that are common to all countries; HERF_{jt} is a weighted measure of sectoral concentration of country j at time t; CNT_j is the variance due to country shocks (which, by construction, does not depend on time); COV_{jt} is the covariance of sectoral fluctuation at time t with the jth country shock; and RISK_{jt} is the sum of all the risk components. If macro policies successfully stabilize sectoral fluctuations, this would imply a negative COV. At the extreme, $\mathrm{COV}_{jt} = -\mathrm{SECT}_{jt}$ means that sectoral shocks are fully stabilized.

To illustrate the restrictions of our factor model, we provide some examples of particular economic shocks and demonstrate how they fit in our formulation.

Example 1 (Technology Shock). Consider a general improvement in information technology that becomes available in all countries over the course of at most five years. This improves the productivity of sectors that are IT intensive uniformly across all countries, hence it is a global sectoral shock.

Example 2 (Monetary Policy Shock). Suppose there is a monetary tightening in country j. This deteriorates the productivity of each of sectors in country j, given that all need some amount of liquidity to produce. We would thus observe a negative shock.

However, some sectors may be more sensitive to the liquidity squeeze and have a deeper fall in productivity. These sectors exhibit a positive covariance with the country shock.

Example 3 (Spillovers Across Sectors). Suppose an idiosyncratic negative shock hits the steel industry in country j. As steel productivity declines and steel prices rise, other sectors may be affected, too. For example, the value added per worker in the car industry will fall, as an important input has become more expensive. Hence, even though the underlying shock was idiosyncratic, all local sectors will respond to that to some extent. That is, in our factor model, we will observe this shock in part as a local macro shock and in part as an idiosyncratic shock.

Example 4 (Large Idiosyncratic Shocks). Last, consider an idiosyncratic shock in a large, highly specialized country. Suppose, for example, that a draught severely affects coffee crops in Brazil. This raises the world price of coffee, which acts as a positive global shock for all other producers of coffee but is a negative shock for Brazil. Hence our assumption that idiosyncratic shocks are uncorrelated with global sectoral shocks is violated in the case of large idiosyncratic shocks in large specialized countries. Empirically, however, the restrictions of our factor model perform well (as we demonstrate in Section 5), suggesting that such shocks do not play a substantial role.

1.2 Estimating the factor model

We measure sector-specific factors as the cross-country average of labor productivity growth in each of the sectors. Country factors are then identified as the within-country average of labor productivity growth, using only the portion not explained by sector-specific factors. Formally,

$$\hat{f}_{1st} \equiv \frac{1}{J}\sum_{i=1}^{J} y_{ist},$$

$$\hat{f}_{2jt} \equiv \frac{1}{S}\sum_{s=1}^{S} (y_{jst} - \hat{f}_{1st})$$

for each time period t. Note that this yields the same factor estimates as running a cross-sectional regression on country and sector dummies for period t, with the identification restriction that the sum of country coefficients is zero.

A similar procedure to decompose risk is adopted by Stockman (1988), who decomposes the growth of industrial output in seven European countries.Ghosh and Wolf (1997) carry out this exercise for U.S. states. (Methodologically related is a study by Heston and Rouwenhorst (1995), who use this decomposition for stock market fluctuations.) These studies focus on the qualitative distinction of country shocks and industry shocks, but not on the quantitative risk measures, which is the object we pursue in our analysis.

Alternatively, one can estimate the factor model by maximum likelihood, treating only the covariance matrix of fluctuations as observed but not the realizations of factors themselves. (See finance applications in Connor and Korajczyk, (1986) and (1988); Lehmann and Modest, (1985a) and (1985b); and Brooks and Del Negro (2002).) In this approach, the estimation assumes a joint distribution of factors (typically orthogonal standard normals) in order to estimate the factor loadings. We discuss potential differences arising from our restriction that factor loadings are unity in the robustness section. Del Negro (2002) uses this methodology to analyze economic fluctuations of U.S. states. Recently, Kose et al. (2003) have applied a latent factor model to detect common fluctuations of output, consumption and investment across countries. They focus on identifying the world business cycle, captured by a common world factor. Our factor model is more general in the sense that we allow for as many global factors as the number of sectors.

We have to note, however, that maximum likelihood procedures make strict distributional assumptions. We hence use the "cross-sectional regression" methodology because it makes minimal assumptions on the way factors can covary. A potential problem with this method arises in the case of large measurement errors, which could raise the variability of cross-sectional means relative to the variability of the true factors. In Appendix B, we show that the potential biases associated with this are small because of the large number of countries and sectors, and the relatively small idiosyncratic error.

The contribution of our paper is twofold. First, we study how volatility and its components vary with development, using sector-level data from a broad sample of developing and developed countries. This allows us to quantify the contribution of specialization to aggregate volatility at different stages of development. Previous studies did not carry out this exercise, as they have focused either on aggregate fluctuations (e.g., Kose et al. (2003)) or on developed countries (e.g., Stockman (1988)). Second, we address the question of whether countries diversify efficiently, and if not, how much they could gain by moving towards a safer sectoral structure. In order to do this, we derive the mean-variance frontier of the economy.

1.3 The mean-variance frontier

So far we have neglected the potential benefits of having an undiversified production structure. Obviously, some sectors are more productive than others. (Scale economies and potential gains from trade may also dictate a highly risky sectoral structure.) Taking the "portfolio approach" seriously, we study the trade-off between average performance of the various sectors and their riskiness. We derive the mean-variance frontier of countries and that of the world and measure the countries' distance to each.[7,8]

More specifically, the first question we ask in this section is: What is the lowest possible risk attainable holding average labor productivity constant? The answer is given by the country's mean-variance frontier, $V_j(m)$:

$$V_j(m) \equiv \min_{\mathbf{a}_j} \mathrm{Var}(\mathbf{a}_j'\mathbf{y}_j) \text{ s.t. } \mathbf{a}_j'\mathbf{m}_j = m, \mathbf{a}_j'\mathbf{1} = 1, \tag{10}$$

[7] In Appendix C we develop a simple model to motivate our focus on the trade-off between (log of) mean income and the variance of (log) income in the construction of the frontier.

[8] The notion of a *frontier* for individual countries and for the world has been recently used by Caselli and Coleman (2000) in the context of technology choice. Their analysis focuses on the choice of the appropriate technology given the economy's relative endowment of factors; it abstracts from risk considerations.

where m_j is the vector of mean labor productivities of country j's sectors. This frontier plots, for each average productivity level, the lowest variance that can be achieved by changing the sectoral composition of output. Appendix D shows the technicalities for constructing this frontier function.

We can similarly calculate the world mean-variance frontier as the lowest envelope of all the frontiers,[9]

$$V_{\text{world}}(m) \equiv \min_j V_j(m). \tag{11}$$

We illustrate these concepts in Figure D1, in Appendix D. The horizontal axis indicates the variance of labor productivity and the vertical axis measures the mean of labor productivity. The figure considers the cases of two countries: P (poor), with (actual) mean productivity m_p and variance v_p, and R (rich), with (actual) mean productivity m_r and variance v_r. The two curves display the value functions $V_p(m)$ and $V_r(m)$ corresponding to each country, which indicate the minimum variance the countries can achieve for each possible level of average productivity by reshuffling the composition of output. (Only the upper branch of the parabola is relevant.) In particular, for existing levels of productivity in each country, m_p and m_r, the corresponding minimum variances the countries can achieve, are, correspondingly, $V_p(m_p)$ and $V_r(m_r)$, as indicated in the horizontal axis. The minimum variance the world could achieve, for the average labor productivity of country P, m_p, is $V_{\text{world}}(m_p)$, which is also indicated in the horizontal axis. In this example, the minimum variance of the rich country coincides with that of the world, so $V_{\text{world}}(m_r) = V_r(m_r)$.

The second question we address in this section is: How far are countries from their mean-variance frontier and from the world's? To gauge the extent to which countries differ

[9]Note that if consumers could invest in foreign industries, international diversification could bring the minimum variance even below that of the least risky country. We are neglecting this possibility mainly because international diversification is very limited.

from the mean-variance efficient outcome, we compute the following measures of distance:

$$\mathrm{DIST}_{1jt} = \mathrm{RISK}_{jt} - V_j(m_{jt}), \tag{12}$$

$$\mathrm{DIST}_{2jt} = V_j(m_{jt}) - V_{\mathrm{world}}(m_{jt}). \tag{13}$$

The first concept, DIST_{1jt}, measures the distance of country j's risk to its own frontier, i.e., the distance to the minimum variance it could achieve, given its mean labor productivity. In Figure D1, this is given by the difference $v_p - V_p(m_p)$ for the poor country, and by $v_r - V_r(m_r)$ for the rich.[10] The second concept, DIST_{2jt}, measures the distance of country j's minimum variance to the world's minimum variance. In Figure D1, this is given by $v_p - V_{world}(m_p)$ for the poor country and is equal to zero for the rich country. The first measure is aimed at capturing the country's performance relative to its own potential, while the second one reflects the inherent differences in countries' riskiness.

2 Data

To compute the different dimensions of risk in our benchmark exercise, we employ annual data from the United Nations Industrial Development Organization (UNIDO, 2002). The UNIDO data set covers all manufacturing at the 3-digit level of disaggregation from 1963 to 1998 for a broad sample of countries, providing information on labor, value added, and output, which we use to construct various measures of labor productivity shocks. The list of countries included in the analysis is displayed in Table 1.

The original data set contains 28 sectors. However, several countries aggregate value added, employment, and/or output for two or more sectors into one larger sector. For example, various countries group "food products" and "beverages" together. To make the

[10] In the (few) cases in which the vertex of the parabolic frontier of a country or (the world) is above the mean labor productivity of the country, we take the variance at the vertex as the minimum variance of the country (world). This is because the lower part of the parabola is not efficient (one can achieve the same risk with higher mean return) and we would like to measure distance to the efficient frontier.

data comparable, we aggregate sectors so as to obtain a consistent classification across countries. This aggregation leaves us with 19 sectors, which are listed in Table 2. As we show in Appendix A, our results are not sensitive to the specific classification of sectors.

Data on value added and output are expressed both in domestic currencies and U.S. dollars. In the benchmark analysis, we use real value added (per capita) in U.S. dollars.[11] It is worth noting that we do not find significant differences in our results when looking at the output series. We discuss this issue in the Robustness Section. We convert the dollar measures into international dollars using the PPP figures from the *Penn World Tables 6.1*.

Our benchmark analysis focuses on a broad set of countries using detailed Manufacturing data. As a robustness check, we perform a similar exercise using data on value added and labor in Agriculture, Manufacturing, and Services. The information comes from the OECD's *STAN Industrial Structure Analysis.* A drawback of this data set is that it provides information on a smaller set of countries, particularly developed ones. However, the quality of this data, is probably higher. As we comment later in the Robustness Section, applying the factor model to this subsample confirms the empirical regularities dictated by the UNIDO industry data. We offer a rationale for the robustness of our findings to the addition of Agriculture and Services.

We can look at several measures of economic fluctuations, such as value added growth, output growth, employment growth, and labor productivity growth. We focus on the growth of labor productivity (value added per worker) over a five-year interval. Since we are interested in the sources of fluctuations and not on the short-term response of the economy to shocks, we look at a *productivity* measure instead of an activity measure (such as output or employment). In the robustness section, we discuss the results obtained using fluctuations in output per worker as a measure of productivity. We take five-year moving averages because we believe that the relevant fluctuations that may influence the choice

[11]We use the CPI to convert figures into constant dollars.

of sectoral structure of a country occur over the medium to long horizon. This way we can also reduce high frequency noise due to measurement error or demand fluctuations. We also did our exercise using one-year labor productivity growth, obtaining the same patterns of diversification. The only difference is the bigger role of idiosyncratic noise in this last case.

As a measure of development, we use PPP adjusted real GDP per capita from the *Penn World Tables 6.1.*

3 Results

This section is split into three subsections. The first (4.1) summarizes the main features of the variance-covariance structure that we obtain from the factor model. The second (4.2) investigates the relationship between the various measures of risk and economic development. The third subsection (4.3) derives the mean-variance frontiers for individual countries and for the world, and computes countries' distances to their own frontier and to the world's. The results reported in this section are based on the benchmark UNIDO data set, using value added per capita as the productivity measure.

3.1 Decomposition of risk

We begin in Table 3 by showing the decomposition of risk, by country. We report the figures for 1980 (the mid point in the sample 1963-1998).[12] The first column shows our measure of sectoral risk, as gauged by expression (5): $\mathrm{SECT}_{jt} = \mathbf{a}'_{jt}\Sigma\mathbf{a}_{jt}$. This takes into account the riskiness of the different sectors and the comovement across sectors. The top five countries according to this dimension of risk are Bangladesh, Pakistan, Egypt, Ghana, and India, whereas Singapore, Hong Kong, Denmark, Israel and the Netherlands exhibit the lowest levels of sectoral risk.

[12]The figures for the remaining years are available at request from the authors.

The second column shows the weighted Herfindahl index of sectoral concentration resulting from expression (18): $\mathbf{a}_j'\mathbf{D}_j\mathbf{a}_j = \sum_s \sigma_{js}^2 a_{js}^2$. The top five Herfindahl indices correspond to Bolivia, Egypt, Ghana, Pakistan, and Bangladesh. The United States, France, Japan, Australia and the United Kingdom are the countries with the lowest (weighted) Herfindahl indices.

The third column displays the country-specific risk, τ_j^2. Iran, Ghana, Nicaragua and Bangladesh appear to be the riskiest countries, whereas Finland, South Africa, the United States, Denmark and Austria qualify as the least risky.

The fourth column indicates the sector-country covariance that is, the covariance between sector and country specific shocks: $\text{COV}_{jt} = \mathbf{a}_{jt}'\Sigma_{0j}$. Ghana, Nicaragua, and Greece show the highest covariance. Bangladesh, Australia, and Singapore, in contrast, exhibit the lowest covariances. Unlike other dimensions of risk, the covariance does not seem to relate systematically with the level of income. Negative covariances may suggest that countries implement output-stabilizing macroeconomic policies, or that investment is directed to sectors whose shocks are negatively correlated with country specific shocks in order to reduce total risk.

The last column displays the overall riskiness of the economy, as indicated by expression (20): $\text{RISK}_{jt} = \mathbf{a}_{jt}'\Omega_j\mathbf{a}_{jt}$. Iran, Ghana, and Nicaragua ranks first in the level of overall riskiness, whereas the United States, Finland, and Canada rank last.

Table 4 presents the relative importance of the different dimensions of risk, that is, every dimension of risk is expressed relatively to the overall risk of the economy.[13] As the table shows, there is enormous variance across countries regarding the relative importance of the different dimensions of risk. For example, in Iran, the (weighted) sectoral concentration and the sectoral risk contribute little to the extremely high risk of the economy. Most of the risk is country specific. For France, instead, a significant part of the risk

[13]In cases in which the covariance term is negative, it is harder to interpret this numbers as "shares." Still, the numbers are indicative of the relative contribution of the different sources of risk.

(40 percent) is explained by the high covariance between country- and sector-specific risk. The United States, in contrast, have a relatively large negative sector-country covariance, which contributes to lower overall risk.

Even though Kose et al. (2003) do not address specialization and its impact on volatility, we can compare the aggregate behavior of our factor model to theirs by looking at the broad patterns in both variance decomposition exercises. Despite the differences in methodology discussed above, the aggregate patterns are remarkably close. For the median country in their sample, global shocks account for 14.7 percent of the total volatility in output. We estimate that, for the median country, 16.4 percent of overall risk is attributable to global sectoral shocks. Our median share of country shocks (including here the covariance with sectors) is 67.4 percent, compared to their 65.0 (Kose et al. (2003), Table 4). By separating sectoral fluctuations, however, we can focus on the differences across sectors and sectoral diversification as two key determinants behind volatility patterns. This is what we turn to next.

In Table 5 we present the summary statistics by sector for the each of the 19 sectors in the benchmark analysis. The first column presents the standard deviations of productivity shocks, and the second displays the average correlations of each sector with the rest. The range of standard deviations goes from 5 percent to 13 percent. Note that the sectoral shocks exhibit high correlations with each other, the average correlation coefficient running from 0.52 to 0.71.

3.2 Diversification along the development process

3.2.1 A note on the methodology

In order to characterize the evolution of the various dimensions of risk in the development process, we use both non-parametric and parametric techniques.

The non-parametric methodology we use, known as "lowess," elicits the shape of the relationship between two variables imposing practically no structure on the functional form. More specifically, lowess provides a locally weighted smoothing, based on the following method: Consider two variables, z_i and x_i, and assume that the data are ordered so that $x_i \leq x_{i+1}$ for $i = 1, ..., N-1$. For each value z_i, the method calculates a smoothed value, z_i^s. The smoothed values are obtained by running a regression of z_i on x_i using a small number of data points near this point. In particular, the regression is weighted so that the central point (x_i, z_i) receives the highest weight and points farther away get less weight.[14] The smoothed value z_i^s is then the weighted regression prediction at x_i. The procedure is carried out for each observation—the number of regressions is equal to the number of observations—and the fitted curve is the set of all (x_i, z_i^s).

We look at risk patterns both across countries and across time within countries. The within-country variation shows how our risk measures change with development over time after controlling for heterogeneous initial conditions of countries. Formally, we express the different risk measures as an arbitrary function of GDP per capita, shifted by a country-specific intercept, $y_{it} = f(x_{it}) + u_i$. We estimate the country fixed effect, u_i, by running a panel regression of y_{it} on a fourth-order polynomial of log GDP per capita. We then take $y_{it} - u_i$ as the within-country component.

We employ these non-parametric methods to uncover the relationship between each dimension of risk and the level of development (real per capita GDP). We also use standard parametric techniques to complement the analysis. The results are presented in the next subsection.

3.2.2 Different dimensions of risk in the development process

Non-parametric Results We start the analysis by documenting the relationship between the various dimensions of risk and (the log of) real GDP per capita, using the lowess

[14]The subset of data used in the calculation of z_i^s corresponds to the interval $[x_{i-k}, x_{i+k}]$, where k determines the width of the intervals and the weights for each of the observations between the interval, x_j, with $j = i-k, ..., i+k$ are: $w_j = \left[1 - \left(\frac{|x_j - x_i|}{D}\right)^3\right]^3$, and $D = 1.0001 \max(x_{i+k} - x_i, x_i - x_{i-k})$

method described before.

We first study the relationship between sectoral risk and real GDP per capita. Figure 2 displays the estimated cross-country relationship, and Figure 3 displays the estimated within-country relationship. Both plots uncover a negative correlation, which is remarkably strong in the within-country evidence. The within-country evidence is perhaps more relevant in our context, as it shows the evolution of sectoral concentration for the typical country along its development path. (Or, in other words, it controls for country-specific effects, which in a simple cross section might blur the evolution of specialization by shifting the curve.)

Figure 4 displays the cross-country estimated relationship between the weighted Herfindahl index and development, and Figure 5 shows the corresponding within-country estimated relationship. The cross-country and the within-country estimations show a declining curve, which flattens out at latter stages of development, showing tenuous signs of reversal at very late stages. The relationship between the Herfindahl index and development has been recently studied by Imbs and Wacziarg (2003), who reported a U-shape relationship. We display the unweighted Herfindahl indices in Figures 6 (cross section) and 7 (within). For the reasons we discussed in the methodology section, we find the weighted measure more meaningful, as it takes proper account of the asymmetry of the sectors and better captures the extent of (lack of) diversification. Equally important, the weighted Herfindahl index is immune to classification biases.

While both the weighted and unweighted Herfindahl indices point to a decrease in sectoral concentration at early stages, they differ in their behavior at later stages: The weighted index flattens out after a critical point. It shows some (weak) evidence of reversal, but the reversal is attenuated by the significantly lower levels of idiosyncratic risk at later stages, which lead to the flattening of the curve. The unweighted index, in contrast, shows an increasing part at later stages. It is remarkable, however, that the critical points for both the weighted and unweighted concentration measures occur at very similar levels of development.

Evidence on the unweighted Herfindahl-GDP relationship has led to the conclusion that countries "diversify" first, until they reach a critical point at which they start specializing again. However, we have argued that Herfindahl indices (weighted or unweighted) do not take into account the full riskiness embedded in the economy's sectoral composition. Indeed, our sector-risk measure exhibits a declining pattern, as shown in Figures 2 and 3.

Putting the two pieces together, one can infer that at early stages of development, countries tend to concentrate heavily on relatively high-risk sectors. As countries grow, they shift production towards lower-risk sectors, experiencing a decrease in sectoral risk together with a decrease in concentration. Later in the development process, while sectoral risk continues to decline, concentration tends to flatten out and even reverses to higher levels at sufficiently large values of per capita GDP.

A closer look into the change in sectoral composition reinforces the claim that more developed countries move resources from riskier to less risky sectors. As illustrations, Figures 8 to 11 plot the employment shares in the textile industry (a highly risky industry with a standard deviation of shocks of 8 percent) and the electric machinery industry (the safest industry, with a standard deviation of 4 percent) against the level of GDP per capita. The plots present both the cross country and the within-country relations. As anticipated, the electric machinery industry expands with development while textile rapidly shrinks.

The relationship between country-specific risk and the level of development is displayed in Figure 12. Remember that, by construction, there is no within-country variation over time for this dimension of risk, hence we only plot the data corresponding to 1980 for each country, and omit the within-country figure. The evidence points to a negative relationship. This suggests that countries at higher levels of development enjoy higher macroeconomic stability, which could be the result of lower political risks and better conduct of fiscal and monetary policies, among other factors.

As noted before, we are also interested in the behavior of the covariance between country risk and sectoral risk. The evolution of the covariance along the development process is shown in Figures 13 and 14, both in the cross-country and the within-country estimations. While there is a high variability in the covariances, the cross-sectional evidence indicates no particular relationship with the level of development development. The within-country evidence reveals a slightly increasing relationship at early stages of development. As we later comment in the Robustness section, this increasing pattern becomes more relevant when using output per capita (instead of value added per capita) as a measure of productivity.

Parametric Results In this section, we examine the relationship between the different dimensions of risk and the level of development, using standard regression analysis. Based on the non-parametric findings, we explore the fit of first and second-order polynomials. (We also explore cubic forms, but they turn out to be insignificant.) The results are summarized in Table 6.

As already suggested by the graphs, sectoral risk decreases during the development process. Moreover, the coefficient on the squared GDP term is positive, confirming that the curve flattens out at later stages. The estimated critical point at which the curve starts flattening out occurs at very high values (out of sample).

It is worth noting that for most of the remaining measures of risk, the cross-section regressions show only weakly significant relationships with per capita GDP. In contrast, the within-country regressions reflect the interesting patterns hinted at by the graphs. This is indeed the case for the weighted Herfindahl index. The within variation indicates that the weighted Herfindahl first decreases with (the log of per capita) GDP, until GDP reaches the critical point of US $\$8,040$ (with US \$585 standard error). From this point on, the weighted Herfindahl index remains constant with respect to development. Note that this point corresponds, approximately, to the 62nd percentile value in our sample, that is, the kink point of the weighted Herfindahl index occurs at an advanced stage in the development process.[15]

Country risk decreases along the development path. (The coefficient on the (log) GDP in this last case is -0.031, with a 0.01 robust standard error.) Including the quadratic term does not improve the fit of the relationship.

The sector-country covariances do not show any clear pattern in the cross-section. However, the within variation suggests that the sector-country covariances tend to increase over the development path, although significance is not high. Including second terms in the regression, as shown in the bottom part of Table 6, depicts that the increasing relationship occurs early on, and then the relationship flattens out at levels of GDP above $9,576 (with US $1,984 standard error)

The result of all these dimensions of risk is that the overall riskiness of the economy's output mix first decreases until it reaches the critical point of US $10,892 (with US $1,352 standard error), after which the curve tends to flatten out. Note that this occurs later than the critical point of the weighted Herfindahl index, because both sectoral and country risk continue to decline at higher stages of development (counteracting the flattening out of the weighted Herfindahl index).

3.3 Empirical mean-variance frontier

In Table 7, we display the derived risk-return frontier, by country. The table shows the figures for 1980.[16] The first column indicates the mean average productivity *per worker* of all sectors, in thousand international dollars. Note that some developing countries show high labor productivity (in PPP). Such is the case of Chile and Venezuela, for example. This is greatly due to the relatively low consumption prices in developing countries[17] (see

[15]Population weights were used to compute the percentiles. The unweighted percentile is 50.

[16]The figures for the remaining years are available at request from the authors.

[17]This might also be due to the fact that a relatively low number of workers work in the key sectors of the economy, leading to high average productivity.

Hsieh and Klenow (2003) for a thorough discussion of relative prices). The second column displays the overall risk (repeated here for expositional ease).

The third column displays the countries' distance to its own minimum variance frontier,

$$\mathrm{RISK}_j - V_j(m)$$

that is, the decline in variance the country can achieve by changing the sectoral composition, keeping constant the average level of productivity.

The fourth column shows the distance between the country and the world frontier. In effect, columns three and four decompose the total difference between a country's overall risk and the world's minimum risk into two measures: the distance to the country individual frontier (column 3), and the distance between the country frontier and the world frontier (column 4).

The numbers in column 3 indicate that Ghana, Iran, and Egypt are the countries that are farthest away from their own frontier. That is, for the same productivity level, they could achieve lower levels of risk by modifying their sectoral composition. In the other extreme, Finland and Canada are practically operating on their own frontier.

The figures in column 4 show, for example, that Ghana, Hungary, and the Philippines exhibit the largest difference between their own minimum variances and the world's minimum, given their average level of per worker productivity. Whereas the United States and Sweden exhibit the smallest difference. In fact, the United States have the safest productive structure for a productivity level of $43,000$ international dollars per worker. This measure of distance reflects mainly the effect of country risk.

In Figures 15 to 17, we plot the two distance measures against the countries' level of development, gauged, as before, as real per capita GDP. Figure 15 shows the cross sectional relationship between the difference between overall riskiness and the country's minimum variance. Figure 16 shows the corresponding within-country variation. Both figures suggest that, as countries develop, they tend to move closer to their own minimum variance frontier. The relation flattens out at high levels of development. In other words, for given levels of productivity, developed countries can achieve lower volatility.

Figure 17 plots the difference between countries' minimum variance and the world minimum variance against the level of development. The numbers correspond to 1980, as there is little within-country variation. The plot suggests a negative relationship with development, which, as anticipated earlier, mimics the behavior of country risk.[18]

The relationships are summarized in Table 6, which shows the linear and quadratic regressions of the two measures of distance on the level of development. Overall, the regressions indicate a significantly negative association, confirming that, as countries develop they tend to close the gap between their level of volatility and the minimum volatility they could achieve through efficient diversification.

Putting the findings of this section together, we conclude that developing countries tend to be farther away from the world's frontier. The main component of the difference is the distance between a country's minimum variance and that of the world. More surprisingly, however, we also find that countries move closer to *their own* minimum variance frontier as they develop. This means that the high economic volatility at early stages of development is not the result of some risk-return optimization but is due to inefficient diversification.

4 Robustness

We perform several robustness checks. For space considerations, we do not present the corresponding tables and figures in the paper. They are available at request from the authors. We comment below on each sensitivity exercise.

[18]Since both the overall variance and the minimum variance have negligible within-country variation, we do not report the usual within graph.

4.1 Alternative measures of productivity

Our first robustness check consists of computing economic shocks from data on output per capita, rather than value added per capita. It can be argued that output per capita carry less measurement error than value added. However, the main results obtained using value added per capita remain mostly unaltered. The only change is in the within-country behavior of sector-country covariances. In contrast with the tenuous increase observed in Figure 14, when shocks are calculated using output per capita, sector-country covariances increase very decisively with the level of development. This supports the conjecture that as countries develop, they are willing to take higher exposure to country risk by specializing in sectors that correlate more with country-specific macroeconomic fluctuations.

Second, we check whether the UNIDO data in US dollars lead to different findings than the data in domestic currency. We redo our exercise both for value added and output per capita in both US dollars and domestic currency. As before, the patterns we document remain unaltered. The only difference lies on a smaller average correlation of shocks among sectors when using domestic currencies.

4.2 Accounting for agriculture and services

Up to now, our analysis has focused on manufacturing. In this section, we extend the analysis to agriculture and services. One limitation, however, is that we have a consistent data set on value added and labor for agriculture, manufacturing, and services for OECD countries only. Hence, when performing this exercise, developed countries are overrepresented in the sample. Interestingly, the empirical regularities we document, that is, the relationship between different measures of risk and development, are exacerbated by the inclusion of these two sectors. The interpretation of this result is that agriculture, a relatively important sector for developing countries, behaves like the highest risk industries, whereas Services, an important sector in developed countries, mimics the behavior of less volatile industries. Applying the same factor-model methodology to the OECD sample, based on these three-sector classification of output, we find that the standard deviations of shocks are 8.1 percent in agriculture, 5.4 percent in manufacturing, and 4.6 percent in services. This leads to a marked decline in sectoral risk, as countries develop, shifting the composition of output from agriculture to manufacturing to services. This pattern is illustrated in Figures 18 and 19, which show, respectively, the cross section and within-country estimated relationships between sectoral risk and real GDP per capita.

For the relationship between sectoral concentration and GDP per capita, similar robustness to the inclusion of Agriculture and Services has been noted by Imbs and Wacziarg (2003). Our weighted Herfindahl index also shares this feature. The patterns of covariances and country risk are also similar to those described for the broader sample.

4.3 Allowing for different exposure to sectoral shocks

A restriction in the factor model (2) is that global sectoral shocks have the same impact in each country. In this subsection, we also estimate our factor model without enforcing this restriction.

As the trade and financial openness of countries varies remarkably, it may be important to allow for a country-specific spillover of global shocks. In a similar fashion, we can allow for differential impact of country shocks on different sectors, as some sectors may be more sensitive to macroeconomic conditions than others. However, we already addressed this latter issue in our benchmark estimation by letting sectoral shocks covary with country shocks.

The formal treatment of the differences in exposure changes the factor model as follows.

$$y_{js} = B_j f_{1s} + b_s f_{2j} + \varepsilon_{js}, \tag{14}$$

where B_j is the exposure of country j to worldwide sectoral shock s (potentially related to overall openness), and b_s is the sensitivity of sector s to country j shock (related to the cyclicality of the sector).

This approach is very similar to the one applied by Del Negro (2002) and Kose et al. (2003), who allow the impact of global shocks to vary by country (or by states in Del Negro (2002)). This makes the results of this exercise more directly comparable to theirs. The key distinction is that we use sectoral data, whereas Del Negro (2002) and Kose et al. (2003) use macroeconomic aggregates. This has two important implications.

First, since the benchmark factor model lets global shocks vary sector by sector, we already incorporated some heterogeneity in the global exposure of countries, the sensitivity to global shocks being determined by the sectoral structure of the economy. As we have documented in the previous section, differences in sectoral composition imply substantial variation in the riskiness of the economy. Factor models working with aggregates can only capture this variation if they *assume* differential global exposure of countries. Second, by looking at sectoral data, we can investigate how a country can endogenously shield itself from global fluctuations. Studies based on aggregate fluctuations cannot address this choice of specialization.

Nonetheless, we look at different exposures to the global shocks as a test of robustness of our benchmark factor model. Writing the modified factor model in vector notations,

$$\mathbf{y}_j = B_j \mathbf{f}_1 + f_{2j}\mathbf{b} + \varepsilon_j. \tag{15}$$

Since we already allow for a differential impact of country shocks on different sectors and global sectoral shocks in different countries, we no longer need to allow for the correlation of the two sources of shocks. This implies the following variance decomposition,

$$\widetilde{\Omega}_j = B_j^2 \Sigma + \tau_j^2 \mathbf{b}\mathbf{b}' + \mathbf{D}_j. \tag{16}$$

Our modified risk measures are defined as follows.

$$\widetilde{\mathrm{SECT}}_{jt} = B_j^2 \mathbf{a}'_{jt} \Sigma \mathbf{a}_{jt} \tag{17}$$

$$\widetilde{\mathrm{HERF}}_{jt} = \mathbf{a}'_{jt} \mathbf{D}_j \mathbf{a}_{jt} \tag{18}$$

$$\widetilde{\mathrm{CNT}}_{j} = \tau_j^2 (\mathbf{a}'_{jt} \mathbf{b})^2 \tag{19}$$

$$\widetilde{\mathrm{RISK}}_{jt} = \mathbf{a}'_{jt} \widetilde{\Omega}_j \mathbf{a}_{jt} \tag{20}$$

We estimate the exposures to factors by running time-series OLS regressions of labor productivity on the predicted factor realizations. Note that, because factor realizations are predicted with error, the loading estimates will be somewhat biased towards one. The bias decreases with the number of countries and sectors and increases with the magnitude of idiosyncratic risk.

We find that all the risk measures exhibit the same patterns as in the benchmark case, both across countries and within countries. The main reason for this is that the estimated exposures are very close to one, which is our benchmark assumption. Exposure to country shocks ranges from 0.82 (Paper and products) to 1.10 (Furniture), whereas exposure to global shocks is never significantly different from one (ranging from 0.89 to 1.09). This suggests that the sectoral structure already captures the bulk of exposure to global shocks.

4.4 Allowing for time-varying measures of risk

Recent studies have documented a sharp decline in volatility for the United States, around the early 1980s (see Stock and Watson (2002) and the references therein). This consideration led us to allow for time varying measures of risk. To explore this possibility, we split the sample into two periods, before and after 1980, and apply the factor-model procedure to the two subsamples.

We find that there has been, on average, a decline in both sectoral and country volatility. Surprisingly, the qualitative patterns do not change. The decline in volatility occurred broadly across all sectors, and the volatility ranking of sectors shows only minor changes.

The correlation between the sectoral standard deviations based on the pre-1980 sample and the standard deviations obtained with the pooled sample (i.e., the measures described before) is 0.75. The corresponding correlation based on the post-1980 sample and the pooled sample is 0.81. These changes can be seen in Figure 20, which shows the relationship between sectoral risk and development, based on the pre- and post-1980 samples. The graph shows that while on average sectoral volatility is lower in the post-1980 period, it still the case that as countries develop, they tend to move to less risky sectors. Figure 21 shows a similar relationship based on within-country variation. Pooling together the results obtained from the two subsamples, we find that the sectoral risk decreases sharply with development.

Country-specific risk has also changed over time, but the declining relationship with respect to development is preserved in the two subsamples, and also preserved if the subsamples are pooled together. Finally, the weighted Herfindahl index does not show significant changes across the two subsamples, whereas the covariances tend, on average, to be higher in the second half.

We conclude from this exercise that while there have been changes in the underlying measures of risk, they lead to a consistent decline in both sectoral and country risk.

4.5 Allowing for differences between developing and developed countries

In our analysis, global shocks to a given sector are assumed to be identical across countries. One concern, however, is that shocks to industries in developing countries might be different from the corresponding ones in developed ones. In this section, we relax this restriction, by allowing sectoral shocks to be different between developing and developed countries. In order to do so, we split the sample into two parts: (i) The subsample of countries whose real GDP per capita was below the median in 1980 and (ii) the subsample of countries with real GDP per capita above the median in 1980.

After controlling for country-effects, we estimate the sector-specific factors in each of the two subsamples. As before, they are estimated as the cross-country average of labor productivity growth in each of the sectors. We then compute the standard deviations of each sector in each subsample. The surprising and reassuring finding is that the standard deviations are extremely similar, and the ranking of sectors by standard deviations across the two subsamples is virtually identical. The correlation between the standard deviations is 0.75. This suggests that our initial estimates capture the global shocks to the sector well, and were not an artifact of our model restrictions.

Going one step deeper, one can compare the estimated *realizations* of factors (or shocks), sector by sector. We find that, as can be guessed for the high correlation between standard deviations, for most sectors, the correlation of shocks between the low-income and high-income subsamples is extremely high. There are two exceptions: One is "Professional and scientific equipment" (the correlation of shocks here is only 0.17). The other is "Industrial chemicals and petroleum" (with a correlation across subsamples of 0.27.) Regarding the first, it is a minor sector even within developed countries, and it is perhaps not well represented in developing economies. As for the second, one interpretation is that "supply shocks" in the oil sector of developing countries have large (and opposite) effects on the terms of trade in these economies (as discussed in Example 4 above). The resulting impact in labor productivity is hence different for developed economies.

This exercise suggests that our benchmark model is a reasonable description of sectoral shocks, and little is gained by allowing for differences between developing and developed countries. In other words, the benchmark model captures global sectoral shocks almost as well as the more permissive extension.

4.6 Allowing for differences between low-trade and high-trade, financially open and closed countries, small and large

One natural concern with our factor model is whether global sectoral shocks have the same impact regardless of the level of openness of the country. This may not be a good representation of reality. For example, one may think that more open countries will tend to have different exposure to sectoral shocks than relatively closed countries. We test this hypothesis (and therefore the validity of our restriction) by following a procedure similar to the one described before. That is, we split the sample into two groups, according to some measure of openness, and compute the sector-specific factors for each of the two subsamples, after controlling for country effects.

More specifically, we consider three dimensions that relate to the openness of a country. First, we calculate openness as exports plus imports divided by GDP from Penn World Tables (`openc`). The correlation of the sectoral standard deviations between low-trade and high-trade countries was remarkably high: 0.82. The ranking of sectors according to standard deviations is very similar for the two subsamples. The split between low-trade and high-trade countries, hence, does not lead to any significant departure from the findings based on the benchmark model.

Second, we look at whether financial openness significantly affects the exposure to global shocks. Using data on financial liberalization dates, we classify countries as financially open or close and estimate the sector-specific factors in the resulting two subsamples.[19] The ranking of sectors by standard deviation, is, as in our previous exercises, remarkably similar. The correlation of standard deviations of sectoral shocks between the two subsamples is 0.77. While portfolio-view theories would predict different exposures depending on the degree of financial development, this exercise does not reveal significant differences. The high correlation of risk between the subsamples (0.77) lends support to the simpler specification of the benchmark model.

[19] The data come.from Kaminsky and Schmukler (1999).

Finally, we test whether global shocks hit small and large countries differently. We hence split the sample into small and large countries using the median population in 1980 as the dividing line. The ranking of sectors by standard deviation of shocks is again almost identical, and the corresponding correlation of standard deviations between the two subsamples is 0.61. The split between small and large countries, therefore, does not point to any significant departure from the benchmark specification.

5 Conclusions and Directions for Future Research

Several interesting patterns emerge in our study of the evolution of risk in the development path: First, sectoral risk decreases monotonically with the level of development. Second, sectoral concentration first decreases with respect to development until it reaches a point at which the relation flattens out, starting a slow reversal. That is, the high concentration at early stages of development typically falls in high risk sectors, which compounds the exposure to risk at early stages. As countries develop, they tend to shift their production towards less risky sectors. Third, country risk tends to decrease with the level of development. Fourth, the covariance between sectoral risk and country risk does not vary systematically with the level of development. Fifth, many countries, particularly low income ones, are inside the world's mean-variance frontier. Finally, countries move closer to *their own* minimum variance frontier as they develop, suggesting that the high economic volatility at early stages of development is not the result of some risk-return optimization but is due to inefficient diversification.

The paper's findings are at odds with portfolio choice models such as Obstfeld (1994). These models would predict that countries pick different combinations of risk and productivity at the efficient minimum-variance frontier. Development would simply mean a move along this frontier. In contrast, we find that countries are far inside their minimum-variance frontier and development brings about both higher productivity and lower risk.

Our findings seem to be in line with a theory based on comparative advantage, where either low-risk sectors are high-skill intensive or, alternatively, high-skill sectors are better able to cope with shocks. This last possibility is embedded in Kraay and Ventura (2001)'s model, who show that high-skill sectors work with higher markups and hence less elastic product demand. High markups can then serve as a buffer against productivity shocks, reducing the volatility of high-skill sectors. Given this assumption, and provided that the degree of exposure to macro risk is endogenous, all our findings follow. Sectoral risk will decline with development as countries accumulate human capital. Sectoral concentration will also decline, provided that higher skills lead to a wider range of varieties. Country risk will decrease, if higher skills improve macroeconomic policies. And, finally, the covariance between sector- and country-specific shocks will increase, as country risk becomes less important.

In the future we plan to go one step further and explore the hypothesis that low-risk sectors are high-skill intensive. This could be the case if there is scope for technology diversification: a sector using a larger variety of inputs can mitigate the fluctuations affecting the productivity of the individual inputs. This makes the productivity of low-tech sectors volatile whereas sectors employing sophisticated technology are less risky. For instance, growing wheat with only land and labor as inputs, renders the yield vulnerable to idiosyncratic shocks (e.g., weather). In contrast, using land and labor together with artificial irrigation, fertilizers, pesticides, etc., makes wheat-growing not only more productive but also less risky. We then need a theory of what prevents countries from moving to more complex technologies. Such a theory would also relate technological sophistication of production to capital and skill abundance, since developing and operating new methods of production are capital and skill-intensive activities.

We also plan to study the connection between the different dimensions of diversification and financial development, as financial development has been the main suspected channel in linking the two phenomena. In particular, Kalemli-Ozcan et al. (2003) empirically document that countries (and regions) with more risk-sharing opportunities tend to have more specialized industrial structures. We plan to revisit their finding with our specialization measures in the context of a consumption CAPM framework.

Also in our research agenda is the study of the relationship between diversification and globalization, or, more concretely, the link with financial openness and trade. Koren (2003) provides a theoretical framework for how financial openness leads to more trade. We believe that our measures of sector-specific fluctuations could be used to test for the trade consequences of development.

References

Acemoglu, D and F Zilibotti, "Was Prometheus Unbound by Chance? Risk, Diversification, and Growth," *Journal of Political Economy*, 1997, *105* (4), 709–751.

Brooks, Robin and Marco Del Negro, "International Diversification Strategies," Nov 2002. Working Paper 2002-23. Federal Reserve Bank of Atlanta.

Burns, Arthur, "Progress Towards Economic Stability," *American Economic Review*, March 1960, *50* (1), 1–19.

Caselli, Francesco and John Coleman, "The World Technology Frontier," *NBER Working Paper*, 2000, *7904*.

Connor, G. and R. Korajczyk, "Performance Measurement with the Arbitrage Pricing Theory: A New Framework for Analysis," *Journal of Financial Economics*, 1986, *15*, 373–394.

– **and** – , "Risk and Return in an Equilibrium APT: Application of a New Test Methodology," *Journal of Financial Economics*, 1988, *21*, 255–290.

Del Negro, Marco, "Asymmetric Shocks among U.S. States," *Journal of International Economics*, March 2002, *56* (2), 273–297.

Ghosh, Atish R. and Holger C. Wolf, "Geographical and sectoral shocks in the U.S. business cycle," *NBER Working Paper*, 1997, *6180.*

Greenwood, Jeremy and Boyan Jovanovic, "Financial Development, Growth, and the Distribution of Income," *Journal of Political Economy*, 1990, *98* (5), 1076–1107.

Heston, A., R. Summers, and B. Aten, *Penn World Table Version 6.1*, Center for International Comparisons at the University of Pennsylvania (CICUP), October 2002.

Heston, Steven L and K Geert Rouwenhorst, "Industry and Country Effects in International Stock Returns," *Journal of Portfolio Management*, Spring 1995, *21* (3), 53–58.

Hsieh, C. and P. Klenow, "Relative Prices and Relative Prosperity," *NBER Working Paper*, May 2003, *9701.*

Imbs, J. and R. Wacziarg, "Stages of Diversification," *American Economic Review*, March 2003, *93* (1), 63–86.

International Labor Office, *Yearbook of Labor Statistics*, Geneva: International Labor Office Press, 1998.

Kalemli-Ozcan, S., B Sørensen, and O Yosha, "Risk sharing and industrial specialization: Regional and international evidence," *American Economic Review*, June 2003, *93* (3), 903–918.

Kaminsky, Graciela and Sergio Schmukler, "On Booms and Crashes: Stock Market Cycles," 1999. The World Bank Working Paper, December 1999.

Koren, Miklós, "Financial Globalization, Portfolio Diversification, and the Pattern of International Trade," 2003. IMF Working Paper 03/233.

Kose, M. Ayhan, Christopher Otrok, and Charles H. Whiteman, "International Business Cycles: World, Region, and Country- Specific Factors," *American Economic Review*, September 2003, *93* (4), 1216–1239.

Kraay, A. and J. Ventura, "Comparative Advantage and the Cross-Section of Business Cycles," *NBER Working Paper*, January 2001, *8104.*

Lehmann, Bruce N and David M Modest, "The Empirical Foundations of Arbitrage Pricing Theory I: The Empirical Tests," *NBER Working Paper*, October 1985, *1725.*

— **and** — , "The Empirical Foundations of Arbitrage Pricing Theory II: The Optimal Construction of Basis Portfolios," *NBER Working Paper*, October 1985, *1726.*

Lucas, Robert E Jr., "On the Mechanics of Economic Development," *Journal of Monetary Economics*, July 1988, *22* (1), 3–42.

Obstfeld, M., "Risk Taking, Global Diversification, and Growth," *American Economic Review*, 1994, *84* (5), 1310–1329.

Organization for Economic Cooperation and Development, *Labor Market Statistics*, Paris: Organization for Economic Cooperation and Development Press, 2003.

— , *STAN Industrial Structure Analysis*, Paris: Organization for Economic Cooperation and Development, 2003.

Saint-Paul, Gilles, "Technological Choice, Financial Markets and Economic Development," *European Economic Review*, May 1992, *36*, 763–781.

Stock, James and Mark Watson, *Has the Business Cycle Changed and Why?*, Cambridge, MA: NBER Macroeconomics Annual, 2002.

Stockman, A C, "Sectoral and national aggregate disturbances to industrial output in seven European countries," *Journal of Monetary Economics*, 1988, *21*, 387–409.

United Nations Industrial Development Organization, *Industrial Statistics Database, 3-digit ISIC*, Vienna: United Nations Industrial Development Organization, 2002.

World Bank, The, *World Development Indicators CD-ROM*, Washington, DC: The World Bank, 2002.

Appendix

A The Classification Problem

This appendix proves that a reclassification of sectors does not alter the weighted Herfindahl index. Suppose there are S sectors, with labor shares $a_1, a_2, ..., a_S$ and idiosyncratic variance $\sigma_1^2, \sigma_2^2, ..., \sigma_S^2$. The weighted Herfindahl index is then $\sum_{s=1}^{S} \sigma_s^2 a_s^2$. Let us carry out the following thought experiment. We aggregate the first two sectors into one and see how the Herfindahl index changes. The unweighted index becomes

$$(a_1 + a_2)^2 + \sum_{s=3}^{S} a_s^2 = 2a_1 a_2 + \sum_{s=1}^{S} a_s^2,$$

indeed bigger than the previous one. However, the weights change, too. Under the null hypothesis that our factor model holds, the idiosyncratic variance of the new sector is

$$\sigma_{1+2}^2 = \left(\frac{a_1}{a_1 + a_2}\right)^2 \sigma_1^2 + \left(\frac{a_2}{a_1 + a_2}\right)^2 \sigma_2^2.$$

Labor share in the new sector is $(a_1 + a_2)$, so the weighted Herfindahl index is

$$(a_1 + a_2)^2 \left[\left(\frac{a_1}{a_1 + a_2}\right)^2 \sigma_1^2 + \left(\frac{a_2}{a_1 + a_2}\right)^2 \sigma_2^2\right] + \sum_{s=3}^{S} \sigma_s^2 a_s^2 = \sum_{s=1}^{S} \sigma_s^2 a_s^2,$$

identical to the old index. It follows that the weighted Herfindahl index is robust to any reclassification.

When we estimate the empirical counterparts of σ_s^2 from a finite sample, the idiosyncratic variance of the aggregated sector (and hence the weighted Herfindahl) may be different from the formula above in any given sample. However, as the number of years grows without bound, the sample Herfindahl converges in probability to the theoretical (and hence robust) Herfindahl.

B Bias of the Estimated Factor Covariance Matrix

Assume for simplicity that idiosyncratic variance is the same across sectors and across countries, $\sigma_{js}^2 = \sigma^2$ for all j and s. If the factor model exactly holds, then our estimated factors relate to the true factors as follows.

$$\hat{\mathbf{f}}_1 = \mathbf{f}_1 + \frac{1}{J}\sum_{i=1}^{J}\varepsilon_i, \tag{21}$$

$$\hat{f}_{2j} = f_{2j} + \frac{1}{S}\left[\frac{J-1}{J}\sum_{s=1}^{S}\varepsilon_{js} - \frac{1}{J}\sum_{s=1}^{S}\sum_{i\neq j}\varepsilon_{is}\right] \tag{22}$$

Then the second moments of these estimated factors are

$$\begin{aligned}
\mathrm{E}(\hat{\mathbf{f}}_1\hat{\mathbf{f}}_1') &= \Sigma + \frac{\sigma^2}{J}\mathbf{I}, \\
\mathrm{E}(\hat{\mathbf{f}}_1\hat{f}_{2j}) &= \Sigma_{0j} \\
\mathrm{E}(\hat{f}_{2j}^2) &= \tau_j^2 + \frac{J-1}{SJ}\sigma^2.
\end{aligned} \tag{23}$$

The magnitude of the bias depends on the variance of idiosyncratic shocks (σ^2), the number of countries (J) and the number of sectors (S). Since there are 48 countries countries and 19 sectors in the data, the estimated factors are close the the true factors.

To assess the bias more precisely, take the average idiosyncratic variance, $\sigma^2 = 0.05$. The bias in the sectoral covariance matrix ($\hat{\Sigma}$) is of the order $0.05/48 \approx 0.001$. Our sectoral risk measure would then increase by $0.001 \cdot \mathbf{a}_j'\mathbf{a}_j$, approximately 0.00011. This is a tiny fraction of the average sectoral risk. For country risk, the bias would be of order $0.05 \cdot 47/(19 \cdot 48) \approx 0.0026$. This is about 5 percent of the average country risk. Note that there is no bias in the covariance term.

C Consumer's Trade-Off Between Mean and Variance

Consumers are risk averse and hence they care about the variability of output. We posit a representative agent in every country, neglecting the distributional effects of fluctuations.[20]

Consumers derive utility from consuming a bundle of goods and they have homothetic preferences over these goods. This implies that their indirect utility function depends on

[20]This may be valid as long as there are sufficient opportunities to share risk within countries. For less developed countries, however, this assumption might not hold because of financial underdevelopment and the presence of specific factors.

their real income only, where the nominal income is deflated by an appropriate utility-based price index. We assume that indirect utility exhibits constant relative risk aversion over real income,

$$u(C_j) = \frac{C_j^{1-\gamma}}{1-\gamma} \tag{24}$$

$$C_j = I_j/P_j \tag{25}$$

where C_j denotes consumption by agent j, γ is the coefficient of relative risk aversion, I_j is nominal income and P_j is the price index.

For simplicity, suppose that real income, I_j/P_j is lognormally distributed. Then utility is also lognormal, so we can use the formula for the mean of lognormal variables ($\mathrm{E}\, z = \mathrm{E}\ln z + \frac{1}{2}\operatorname{Var}\ln z$) to express expected utility.

$$\max \mathrm{E}\left[\frac{(I_j/P_j)^{1-\gamma}}{1-\gamma}\right] \tag{26}$$

$$\max\left\{\ln \mathrm{E}(I_j/P_j) - \frac{\gamma}{2}\operatorname{Var}\ln(I_j/P_j)\right\}. \tag{27}$$

That is, the representative agent is a mean-variance optimizer, where variance is calculated over log income. The higher the coefficient of risk aversion, γ, the bigger weight the consumer gives to the riskiness of income.

D Constructing the Minimum Variance Frontier

Suppose that sectoral labor productivities in country j have a covariance matrix $\mathbf{\Omega}_j$ and the mean productivites are listed in the $S \times 1$ vector $\mathbf{m}_j$. The minimum variance frontier answers the following question. What is the lowest possible variance attainable by reallocating sectors in such a way as to keep mean productivity constant? We will then express the minimal variance as a function of the mean productivity. Intuitively, this function will be quadratic, since it is the value of the following quadratic problem. The investor minimizes risk subject to the resource constraint (the employment shares add up to one) and the constraint that average productivity be held constant at m:

$$
\begin{aligned}
V_j(m) &\equiv \min_{\mathbf{a}} \mathbf{a}'\boldsymbol{\Omega}_j\mathbf{a} \\
\text{s.t. } 2\mathbf{a}'\mathbf{m}_j &= 2m \\
2\mathbf{a}'\mathbf{1} &= 2
\end{aligned}
$$

We have multiplied both sides of the constraints by two to economize on notation later. Let μ and λ be the Langrange multipliers corresponding to the first and second constraints respectively. Then the first-order conditions for minimum are

$$
\begin{aligned}
\boldsymbol{\Omega}_j\mathbf{a} &= \mu\mathbf{m}_j + \lambda\mathbf{1}, \\
\mathbf{a}'\mathbf{m}_j &= m, \\
\mathbf{a}'\mathbf{1} &= 1,
\end{aligned}
$$

which, if $\boldsymbol{\Omega}_j$ is invertible,[21] becomes a system of two linear equations in the two Lagrange multipliers, μ and λ,

$$
\begin{aligned}
\mu\mathbf{m}_j'\boldsymbol{\Omega}_j^{-1}\mathbf{m}_j + \lambda\mathbf{m}_j'\boldsymbol{\Omega}_j^{-1}\mathbf{1} &= m, \\
\mu\mathbf{1}'\boldsymbol{\Omega}_j^{-1}\mathbf{m}_j + \lambda\mathbf{1}'\boldsymbol{\Omega}_j^{-1}\mathbf{1} &= 1. \\
\begin{pmatrix} \mu \\ \lambda \end{pmatrix} &= \mathbf{A}_j^{-1}\begin{pmatrix} m \\ 1 \end{pmatrix} \\
\mathbf{A}_j &= \begin{bmatrix} \mathbf{m}_j'\boldsymbol{\Omega}_j^{-1}\mathbf{m}_j & \mathbf{m}_j'\boldsymbol{\Omega}_j^{-1}\mathbf{1} \\ \mathbf{1}'\boldsymbol{\Omega}_j^{-1}\mathbf{m}_j & \mathbf{1}'\boldsymbol{\Omega}_j^{-1}\mathbf{1} \end{bmatrix}
\end{aligned}
$$

The minimum variance is then

$$
V_j(m) = \mu^2\mathbf{m}_j'\boldsymbol{\Omega}_j^{-1}\mathbf{m}_j + 2\mu\lambda\mathbf{1}'\boldsymbol{\Omega}_j^{-1}\mathbf{m}_j + \lambda^2\mathbf{1}'\boldsymbol{\Omega}_j^{-1}\mathbf{1},
$$

[21] Here it is important to have some restrictions on the covariance matrix, such as the factor model in Section 1.1, because otherwise the empirical estimate of $\boldsymbol{\Omega}_j$ may be nonsingular.

which is a quadratic function of λ and μ and hence a quadratic function of m. In quadratic form,

$$V_j(m) = \begin{pmatrix} \mu & \lambda \end{pmatrix} \mathbf{A}_j \begin{pmatrix} \mu \\ \lambda \end{pmatrix} = \begin{pmatrix} m & 1 \end{pmatrix} \mathbf{A}_j^{-1} \begin{pmatrix} m \\ 1 \end{pmatrix} = b_{0j} + b_{1j}m + b_{2j}m^2,$$

where the coefficients b_{0j}, b_{1j} and b_{2j} can be obtained from the elements of $\mathbf{A}_j^{-1}$.

Table 1. List of Countries

Australia	Greece	Norway
Austria	Guatemala	Pakistan
Bangladesh	Hungary	Philippines
Belgium	India	Poland
Canada	Indonesia	Portugal
Chile	Iran	Singapore
China, Hong Kong	Ireland	South Africa
China, Taiwan	Israel	Spain
Colombia	Italy	Sri Lanka
Czechoslovakia	Japan	Sweden
Denmark	Kenya	Turkey
Ecuador	Korea, Republic of	United Kingdom
Egypt	Malaysia	United States of America
El Salvador	Netherlands	Venezuela
Finland	New Zealand	Yugoslavia
France	Nicaragua	Zimbabwe

Table 2. List of Sectors

1	Food products; Beverages; Tobacco
2	Textiles
3	Wearing apparel, except footwear
4	Leather products
5	Footwear, except rubber or plastic
6	Wood products, except furniture
7	Furniture, except metal
8	Paper and products
9	Printing and publishing
10	Industrial chemicals; Petroleum refineries; Petroleum and coal products
11	Rubber products
12	Plastic products
13	Pottery, china, earthenware; Glass; Other non-metallic mineral prod.
14	Iron and steel; Non-ferrous metals
15	Fabricated metal products; Machinery, except electrical
16	Machinery, electric
17	Transport equipment
18	Professional & scientific equipment
19	Other manufactured products

Table 3. Different Dimensions of Risk, by Country, 1980.

Country	Sectoral Risk (1)	Weighted Herfindah Index (2)	Country Risk (3)	Sector-Country Covariance (4)	Overall Risk (5)
Australia	0.0037	0.0006	0.0132	-0.0088	0.0088
Austria	0.0036	0.0008	0.0051	0.0006	0.0101
Bangladesh	0.0059	0.0158	0.1625	-0.0187	0.1655
Bolivia	0.0041	0.0327	0.0704	-0.0061	0.1011
Canada	0.0037	0.0007	0.0065	-0.0059	0.0052
Chile	0.0041	0.0035	0.0176	0.0010	0.0263
Colombia	0.0036	0.0019	0.0133	-0.0056	0.0132
Denmark	0.0031	0.0009	0.0047	-0.0012	0.0075
Ecuador	0.0037	0.0117	0.0222	0.0025	0.0401
Egypt, Arab Rep.	0.0048	0.0254	0.0719	0.0001	0.1022
El Salvador	0.0040	0.0119	0.0164	0.0061	0.0383
Finland	0.0036	0.0012	0.0030	-0.0042	0.0035
France	0.0035	0.0005	0.0069	0.0073	0.0182
Ghana	0.0045	0.0184	0.2499	0.0434	0.3162
Greece	0.0038	0.0013	0.0170	0.0114	0.0334
Hong Kong, China	0.0029	0.0014	0.0098	-0.0028	0.0113
Hungary	0.0035	0.0079	0.1238	0.0020	0.1371
India	0.0044	0.0054	0.0197	-0.0071	0.0224
Indonesia	0.0042	0.0157	0.0124	-0.0006	0.0317
Iran, Islamic Rep.	0.0040	0.0096	0.5356	0.0031	0.5524
Ireland	0.0032	0.0017	0.0063	-0.0027	0.0085
Israel	0.0032	0.0013	0.0330	0.0045	0.0420
Italy	0.0038	0.0010	0.0180	-0.0011	0.0218
Japan	0.0034	0.0005	0.0130	0.0088	0.0257
Korea, Rep.	0.0038	0.0021	0.0195	-0.0078	0.0176
Malaysia	0.0037	0.0032	0.0073	-0.0026	0.0116
Netherlands	0.0032	0.0009	0.0088	0.0003	0.0132
New Zealand	0.0034	0.0019	0.0168	-0.0075	0.0147
Nicaragua	0.0039	0.0120	0.2081	0.0306	0.2546
Norway	0.0037	0.0014	0.0052	-0.0008	0.0096
Pakistan	0.0050	0.0171	0.0200	-0.0046	0.0374
Philippines	0.0037	0.0086	0.0710	-0.0067	0.0766
Portugal	0.0040	0.0041	0.0206	-0.0030	0.0257
Singapore	0.0029	0.0055	0.0131	-0.0082	0.0133
South Africa	0.0038	0.0017	0.0034	-0.0026	0.0063
Spain	0.0037	0.0016	0.0097	0.0036	0.0186
Sri Lanka	0.0039	0.0110	0.0240	-0.0048	0.0342
Sweden	0.0037	0.0009	0.0138	0.0019	0.0203
Turkey	0.0044	0.0039	0.0243	-0.0040	0.0285
United Kingdom	0.0035	0.0007	0.0095	0.0024	0.0161
United States	0.0033	0.0004	0.0045	-0.0046	0.0035
Uruguay	0.0037	0.0096	0.0573	0.0013	0.0719
Venezuela, RB	0.0037	0.0051	0.0406	-0.0021	0.0474
Zimbabwe	0.0039	0.0044	0.0202	0.0029	0.0314
Median	0.0037	0.0026	0.0169	-0.0011	0.0240
Standard Deviation	0.0015	0.0073	0.0924	0.0098	0.0995

Table 4. Different Dimensions of Risk Relative to Overall Risk, by Country, 1980.

Country	Sectoral Risk (1)	Weighted Herfindah Index (2)	Country Risk (3)	Sector-Country Covariance (4)	Overall Risk (5)
Australia	0.4175	0.0725	1.5084	-0.9983	1.0000
Austria	0.3579	0.0794	0.5000	0.0626	1.0000
Bangladesh	0.0354	0.0955	0.9818	-0.1128	1.0000
Bolivia	0.0402	0.3237	0.6961	-0.0600	1.0000
Canada	0.7227	0.1449	1.2693	-1.1369	1.0000
Chile	0.1558	0.1338	0.6711	0.0394	1.0000
Colombia	0.2710	0.1416	1.0079	-0.4204	1.0000
Denmark	0.4108	0.1146	0.6310	-0.1563	1.0000
Ecuador	0.0919	0.2914	0.5536	0.0630	1.0000
Egypt, Arab Rep.	0.0472	0.2484	0.7034	0.0010	1.0000
El Salvador	0.1035	0.3107	0.4273	0.1586	1.0000
Finland	1.0054	0.3434	0.8474	-1.1962	1.0000
France	0.1933	0.0260	0.3790	0.4017	1.0000
Ghana	0.0144	0.0581	0.7904	0.1372	1.0000
Greece	0.1126	0.0378	0.5090	0.3406	1.0000
Hong Kong, China	0.2582	0.1243	0.8668	-0.2493	1.0000
Hungary	0.0254	0.0573	0.9026	0.0147	1.0000
India	0.1955	0.2427	0.8797	-0.3179	1.0000
Indonesia	0.1314	0.4966	0.3906	-0.0186	1.0000
Iran, Islamic Rep.	0.0073	0.0174	0.9696	0.0057	1.0000
Ireland	0.3823	0.1971	0.7404	-0.3199	1.0000
Israel	0.0754	0.0298	0.7871	0.1077	1.0000
Italy	0.1730	0.0479	0.8282	-0.0491	1.0000
Japan	0.1332	0.0187	0.5057	0.3424	1.0000
Korea, Rep.	0.2178	0.1177	1.1105	-0.4461	1.0000
Malaysia	0.3194	0.2749	0.6312	-0.2255	1.0000
Netherlands	0.2412	0.0682	0.6654	0.0251	1.0000
New Zealand	0.2331	0.1296	1.1455	-0.5083	1.0000
Nicaragua	0.0151	0.0473	0.8173	0.1202	1.0000
Norway	0.3906	0.1455	0.5480	-0.0842	1.0000
Pakistan	0.1335	0.4558	0.5342	-0.1234	1.0000
Philippines	0.0477	0.1128	0.9266	-0.0871	1.0000
Portugal	0.1550	0.1607	0.8026	-0.1183	1.0000
Singapore	0.2153	0.4171	0.9835	-0.6159	1.0000
South Africa	0.5944	0.2758	0.5458	-0.4160	1.0000
Spain	0.1987	0.0863	0.5217	0.1934	1.0000
Sri Lanka	0.1144	0.3230	0.7031	-0.1406	1.0000
Sweden	0.1812	0.0466	0.6784	0.0938	1.0000
Turkey	0.1535	0.1350	0.8516	-0.1401	1.0000
United Kingdom	0.2153	0.0446	0.5884	0.1517	1.0000
United States	0.9354	0.1024	1.2819	-1.3197	1.0000
Uruguay	0.0517	0.1333	0.7975	0.0175	1.0000
Venezuela, RB	0.0790	0.1084	0.8579	-0.0453	1.0000
Zimbabwe	0.1253	0.1394	0.6416	0.0937	1.0000
Median	0.1644	0.1270	0.7637	-0.0546	1.0000
Standard Deviation	0.2236	0.1228	0.2465	0.3904	0.0000

Table 5. Variance and Correlations, by Sector

	Sector	Standard Deviation	Average Correlation	Standard Deviation of Idyosincratic Shock
1	Food products; Beverages; Tobacco	0.0723	0.5821	0.2281
2	Textiles	0.0885	0.6752	0.1774
3	Wearing apparel, except footwear	0.0575	0.5905	0.2120
4	Leather products	0.0835	0.6491	0.2709
5	Footwear, except rubber or plastic	0.0904	0.6695	0.2600
6	Wood products, except furniture	0.0881	0.7152	0.2484
7	Furniture, except metal	0.0609	0.5835	0.2383
8	Paper and products	0.1008	0.5339	0.2753
9	Printing and publishing	0.0524	0.7238	0.2043
10	Industrial chemicals; Petroleum refineries; Petroleum and coal products	0.0662	0.6192	0.2927
11	Rubber products	0.0976	0.6440	0.2978
12	Plastic products	0.0760	0.6977	0.2250
13	Pottery, china, earthenware; Glass; Other non-metallic mineral prod.	0.0663	0.6925	0.2096
14	Iron and steel; Non-ferrous metals	0.1310	0.6388	0.3710
15	Fabricated metal products; Machinery, except electrical	0.0510	0.7072	0.1531
16	Machinery, electric	0.0598	0.5746	0.2479
17	Transport equipment	0.0905	0.5320	0.2959
18	Professional & scientific equipment	0.0598	0.5203	0.3448
19	Other manufactured products	0.0749	0.6443	0.3223

Table 6. Different Dimensions of Risk and Economic Development, 1963-1998

Linear Relation	Dependent Variable:								
	Sectoral risk		Weighted Herfindahl Index		Country risk	Sector-country Covariance		Overall risk	
	Overall	Within	Overall	Within	Overall	Overall	Within	Overall	Within
Log GDP per capita	-0.00043**	-0.00049**	-0.00497**	-0.00028*	-0.03094*	-0.00013	0.00013	-0.03646**	-0.00064**
(constant PPP $)	(0.00006)	(0.00001)	(0.00081)	(0.00014)	(0.01151)	(0.00186)	(0.00008)	(0.01279)	(0.00016)
R-squared	0.570	0.460	0.480	0.000	0.050	0.000	0.000	0.060	0.010

Quadratic Relation	Dependent Variable:								
	Sectoral risk		Weighted Herfindahl Index		Country risk	Sector-country Covariance		Overall risk	
	Overall	Within	Overall	Within	Overall	Overall	Within	Overall	Within
Log GDP per capita	-0.00243*	-0.00068**	-0.00927	-0.01604**	0.31883	0.01210	0.00388**	0.33743	-0.01339**
(constant PPP $)	(0.00100)	(0.00017)	(0.01291)	(0.00156)	(0.35344)	(0.03570)	(0.00096)	(0.38025)	(0.00183)
Log GDP per capita	0.00012*	0.00001	0.00025	0.00089**	-0.02031	-0.00071	-0.00021**	-0.02175	0.00072**
squared	(0.00006)	(0.00001)	(0.00073)	(0.00009)	(0.02054)	(0.00199)	(0.00005)	(0.02207)	(0.00010)
R-squared	0.600	0.480	0.480	0.070	0.060	0.000	0.010	0.080	0.050
Critical Point	34118.36	3.96E+13	95369641.00	8040.20	2561.85	4947.38	9576.80	2339.18	10892.42
S.E. of Critical Point	(27544.50)	(7.60e+14)	(2.65e+09)	(585.49)	(2068.19)	(7443.50)	(1984.12)	(2130.34)	(1352.27)

Note: Constants included---not reported. Clustered standard errors in parentheses. * significant at 5%; ** significant at 1%. Number of countries: 46. Standard errors for turning points computed with Delta method. Number of observations=1427.

Table 7. Risk-Return Frontier, 1980

Country	Mean (1)	Overall Risk (2)	Dist to Own Frontier (3)	Dist from Own to World Frontier (4)
Australia	22.9397	0.0088	0.0037	0.0034
Austria	25.6378	0.0101	0.0033	0.0051
Bangladesh	6.3192	0.1655	0.0063	0.0014
Canada	40.7767	0.0052	0.0010	0.0025
Chile	51.2758	0.0263	0.0017	0.0224
Colombia	31.7987	0.0132	0.0011	0.0105
Denmark	21.1585	0.0075	0.0013	0.0045
Ecuador	25.8521	0.0401	0.0049	0.0335
Egypt, Arab Rep.	9.4068	0.1022	0.0212	0.0011
El Salvador	25.1740	0.0383	0.0068	0.0299
Finland	21.1884	0.0035	0.0008	0.0010
France	25.4345	0.0182	0.0082	0.0084
Ghana	8.1426	0.3162	0.0407	0.2739
Greece	22.5571	0.0334	0.0072	0.0245
Hong Kong, China	17.8622	0.0113	0.0021	0.0076
Hungary	15.7853	0.1371	0.0165	0.1189
India	8.4743	0.0224	0.0067	0.0012
Indonesia	14.2262	0.0317	0.0111	0.0007
Iran, Islamic Rep.	12.1252	0.5524	0.0344	0.0009
Ireland	43.9543	0.0085	0.0024	0.0043
Israel	22.1156	0.0420	0.0065	0.0003
Italy	34.4091	0.0218	0.0071	0.0130
Japan	37.7062	0.0257	0.0097	0.0143
Korea, Rep.	34.6033	0.0176	0.0021	0.0138
Malaysia	21.0488	0.0116	0.0027	0.0072
Netherlands	32.3246	0.0132	0.0036	0.0079
New Zealand	16.7913	0.0147	0.0061	0.0070
Norway	23.2408	0.0096	0.0032	0.0047
Pakistan	13.7450	0.0374	0.0150	0.0008
Philippines	20.5728	0.0766	0.0074	0.0675
Portugal	19.3095	0.0257	0.0031	0.0210
Singapore	25.4647	0.0133	0.0041	0.0075
South Africa	24.4271	0.0063	0.0010	0.0037
Spain	26.7758	0.0186	0.0034	0.0001
Sri Lanka	11.7718	0.0342	0.0086	0.0239
Sweden	28.1124	0.0203	0.0053	0.0001
Turkey	38.9237	0.0285	0.0031	0.0237
United Kingdom	29.3940	0.0161	0.0073	0.0071
United States	43.1835	0.0035	0.0017	0.0000
Uruguay	27.1270	0.0719	0.0044	0.0658
Venezuela, RB	35.4876	0.0474	0.0024	0.0433
Zimbabwe	19.7212	0.0314	0.0102	0.0195
Median	22.5571	0.0224	0.0063	0.0072
Standard Deviation	3.2677	0.0082	0.0013	0.0091

Table 8. The Mean Variance Frontier and Economic Development, 1963-1998

Linear Relation	Dependent Variable:		
	Distance to Own Frontier		Distance from Own to World Frontier
	Overall	Within	Overall
Log GDP per capita (constant	-0.00365**	-0.00061**	-0.01596*
	(0.00126)	(0.00014)	(0.00946)
R-squared	0.070	0.011	0.090

Quadratic Relation	Dependent Variable:		
	Distance to Own Frontier		Distance from Own to World Frontier
	Overall	Within	Overall
Log GDP per capita (constant PPP $)	0.00660	-0.01109**	0.05060
	(0.03652)	(0.00170)	(0.18605)
Log GDP per capita squared	-0.00060	0.00059**	-0.00387
	(0.00210)	(0.00010)	(0.01040)
R-squared	0.070	0.040	0.100
Critical Point	252.78	11727.64	688.15
S.E. of Critical Point	(2827.14)	(1723.14)	(4482.75)

Note: Constants included---not reported. Clustered standard errors in parentheses. * significant at 5%; ** significant at 1%. Number of countries: 46. Standard errors for turning points computed with Delta method. Number of observations=1427.

Figure 1: Volatility and Development. Averages from 1960−1998

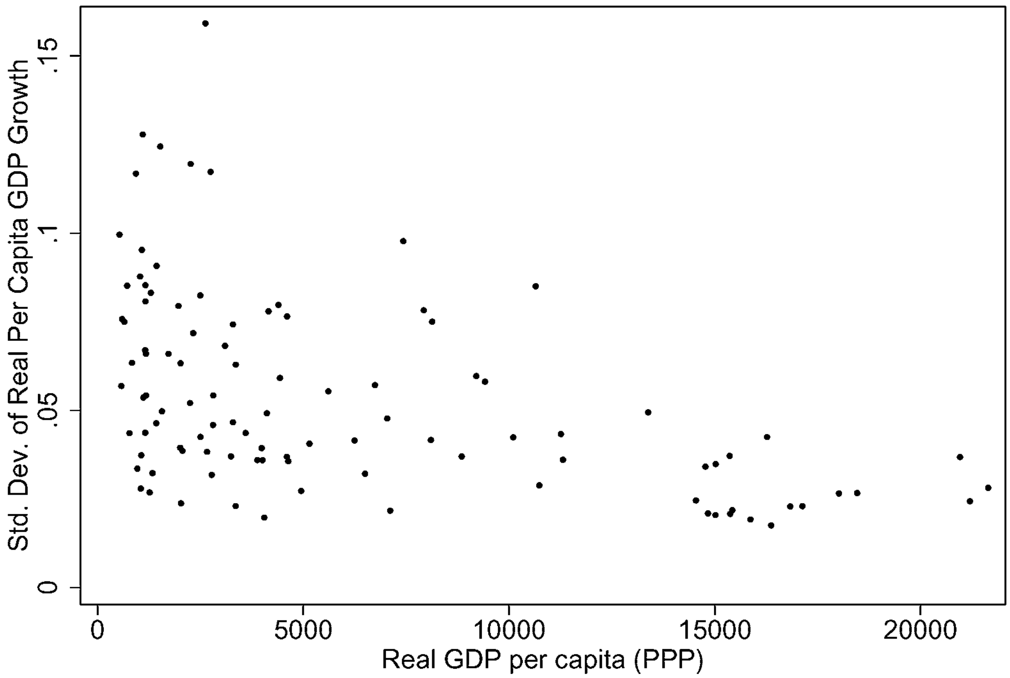


Figure 2: Sectoral_Risk
Mean adjusted smooth

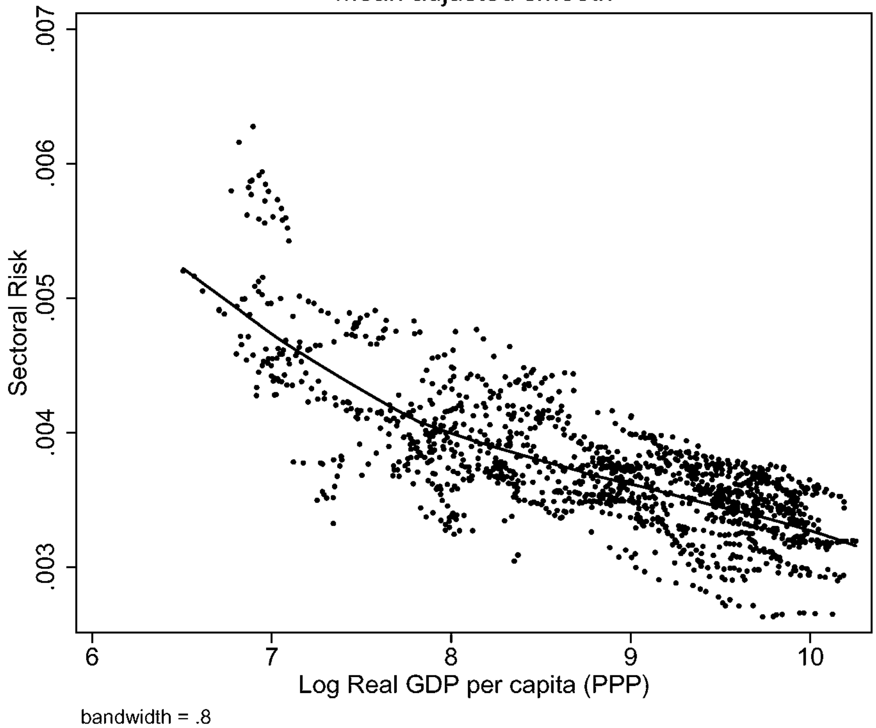


Figure 3: Sectoral_Risk (within)
Mean adjusted smooth

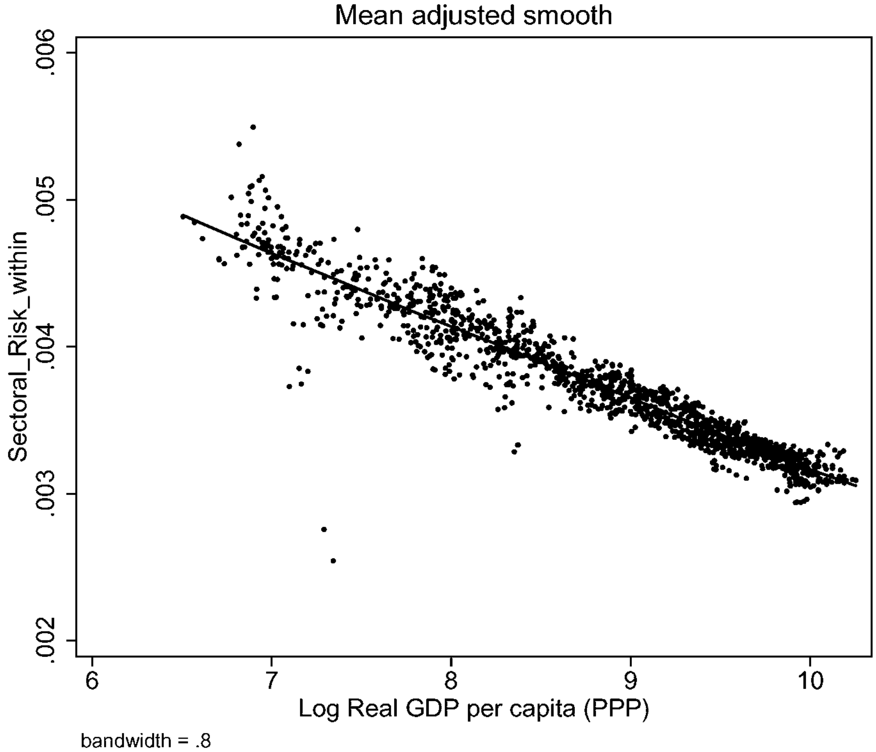


Figure 4: Weighted_Herfindahl
Mean adjusted smooth

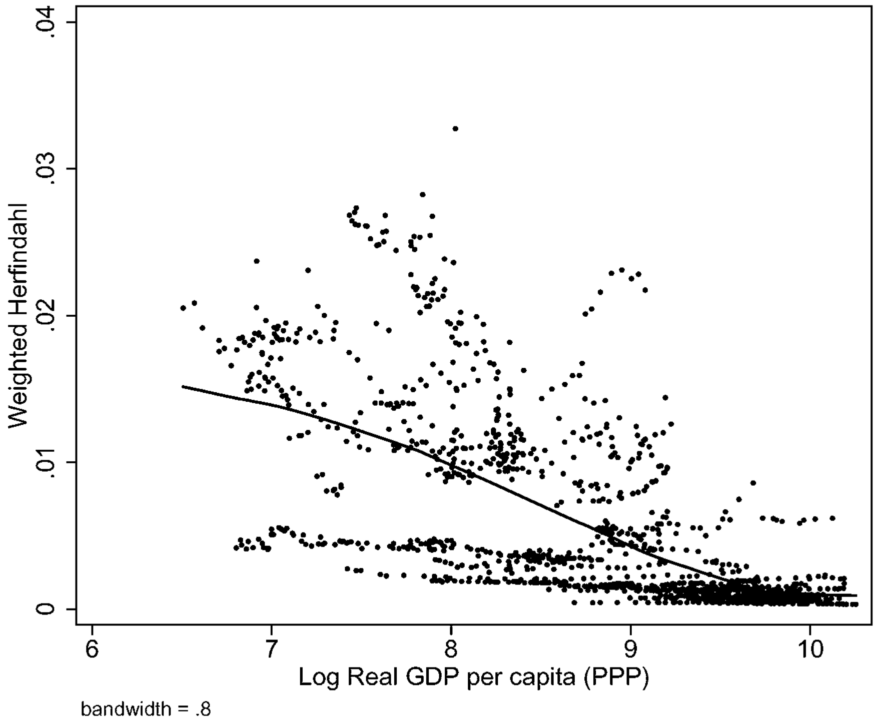


Figure 5: Weighted_Herfindahl (within)
Mean adjusted smooth

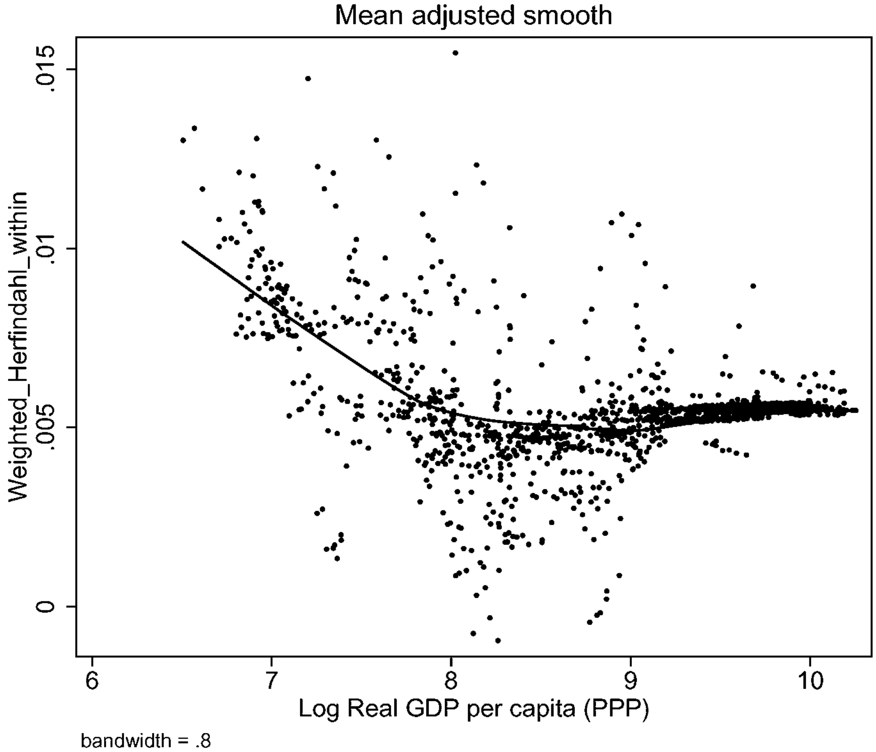


Figure 6: Unweighted_Herfindahl
Mean adjusted smooth

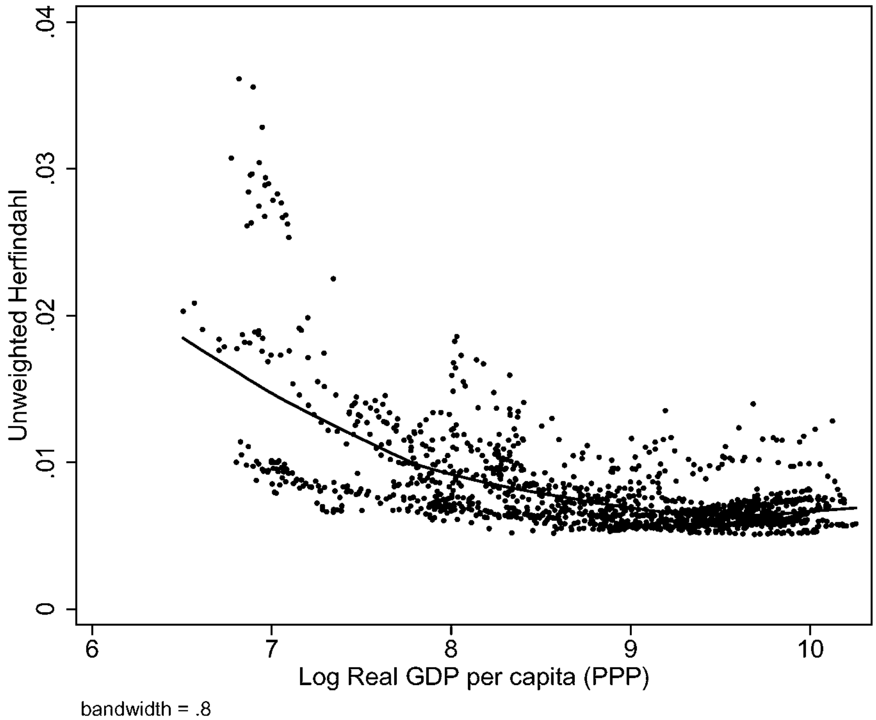


Figure 7: Unweighted_Herfindahl (within)
Mean adjusted smooth

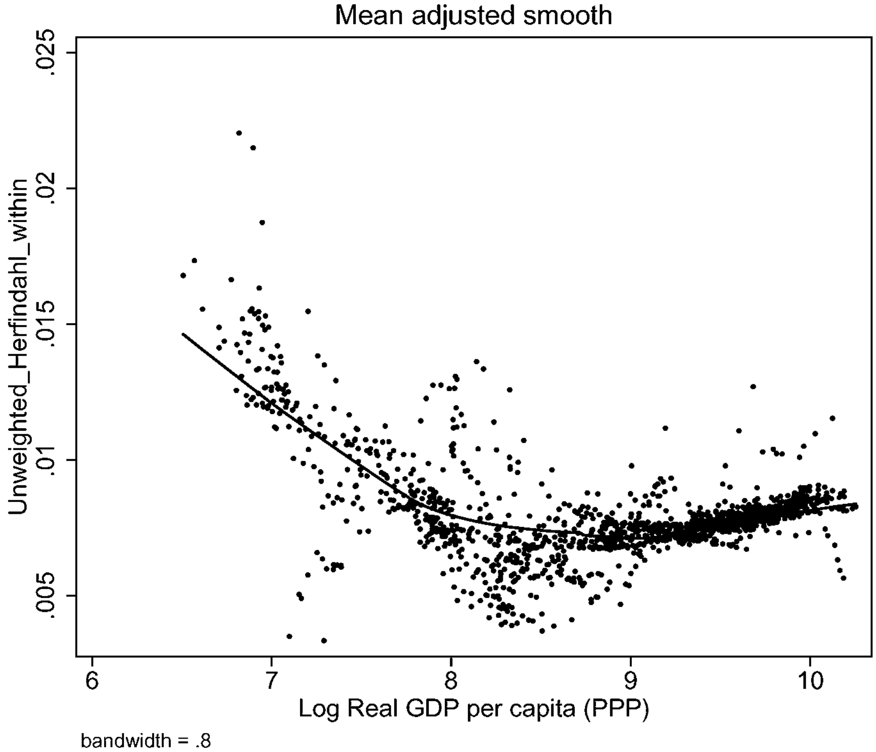


Figure 8: Textiles
Mean adjusted smooth

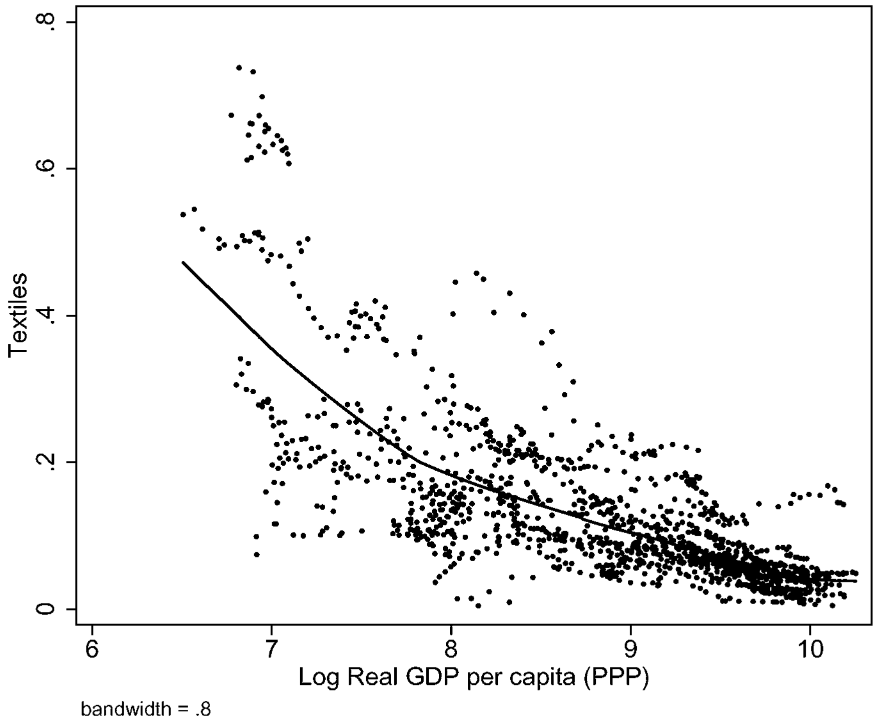


Figure 9: Textiles (within)
Mean adjusted smooth

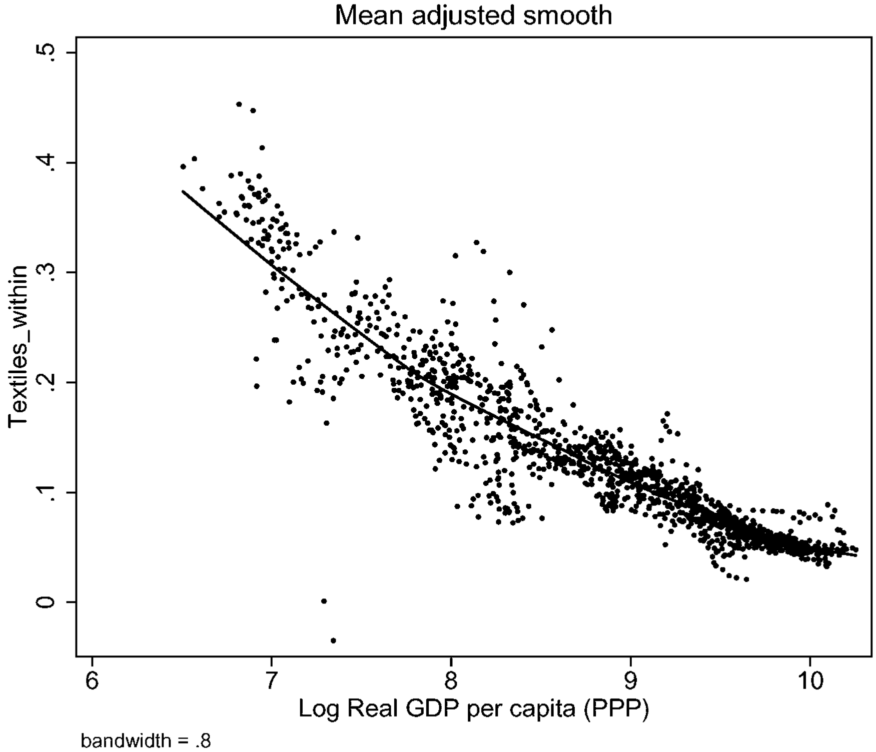


Figure 10: Electric_Machinery
Mean adjusted smooth

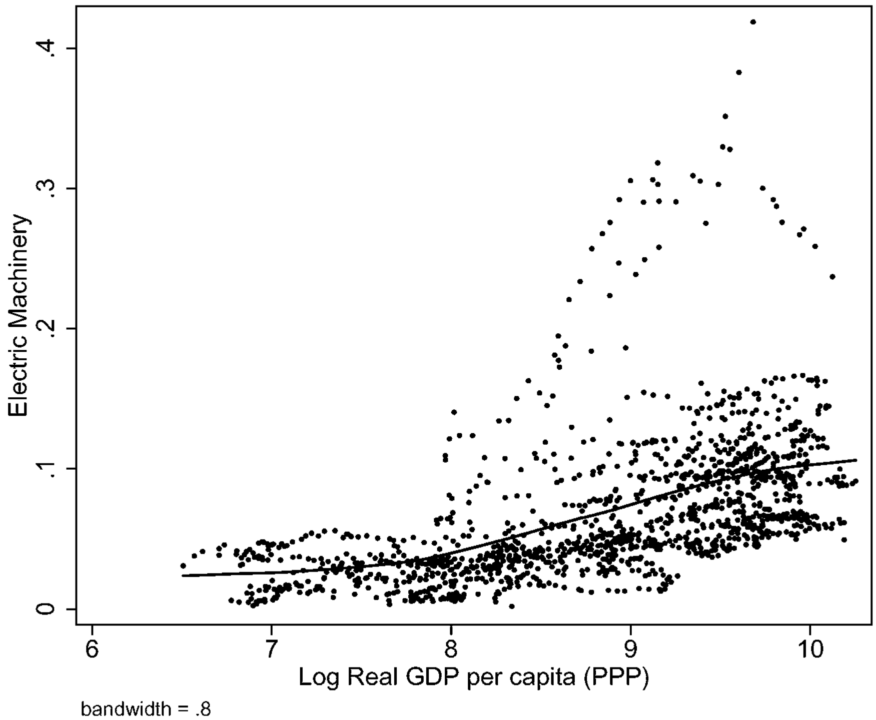


Figure 11: Electric_Machinery (within)
Mean adjusted smooth

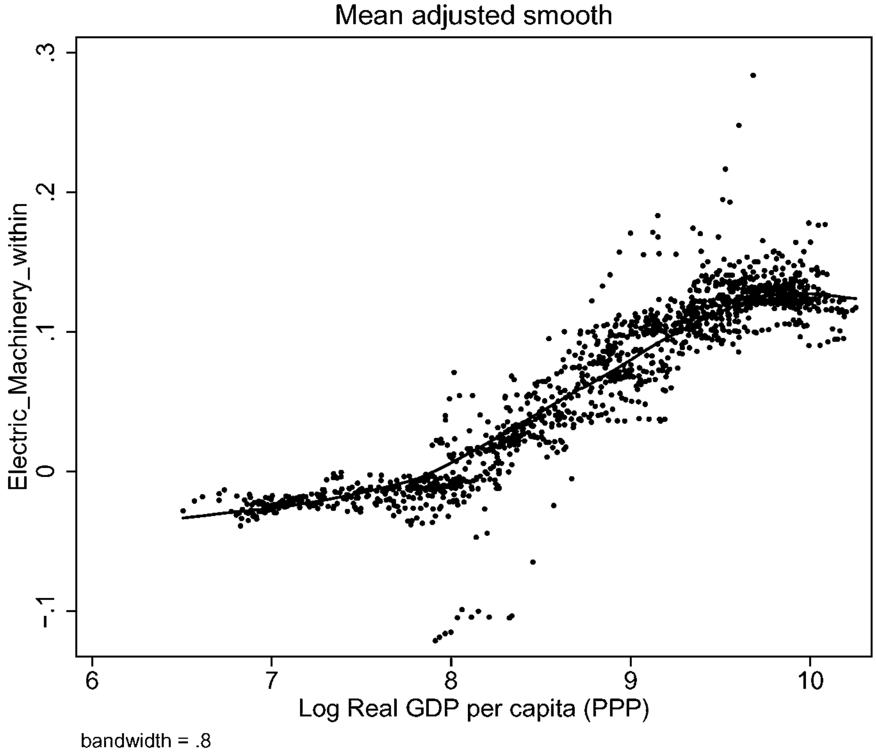


Figure 12: Country_Risk (1980)

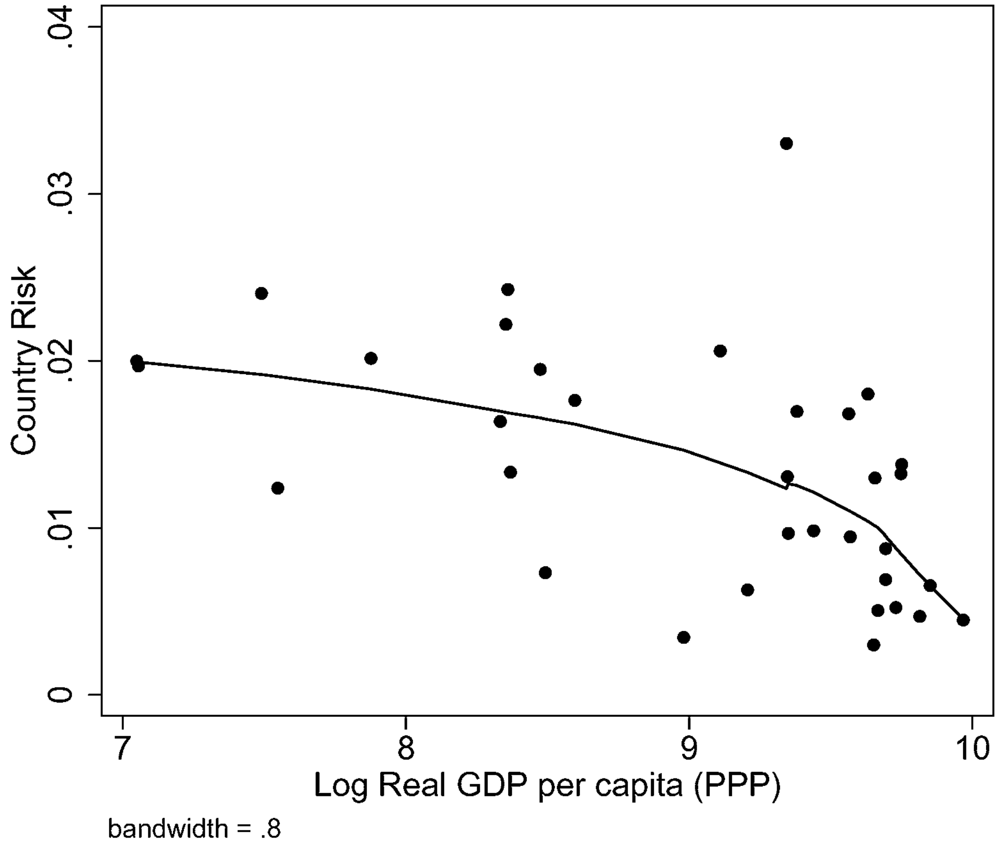


Figure 13: Sector_Country_Covariance
Mean adjusted smooth

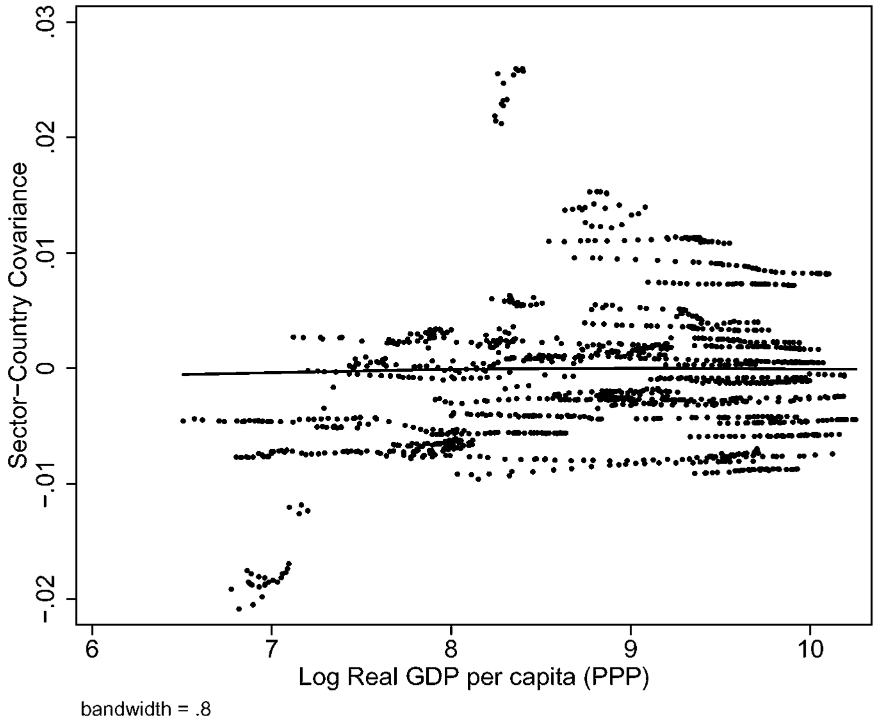


Figure 14: Sector_Country_Covariance (within)
Mean adjusted smooth

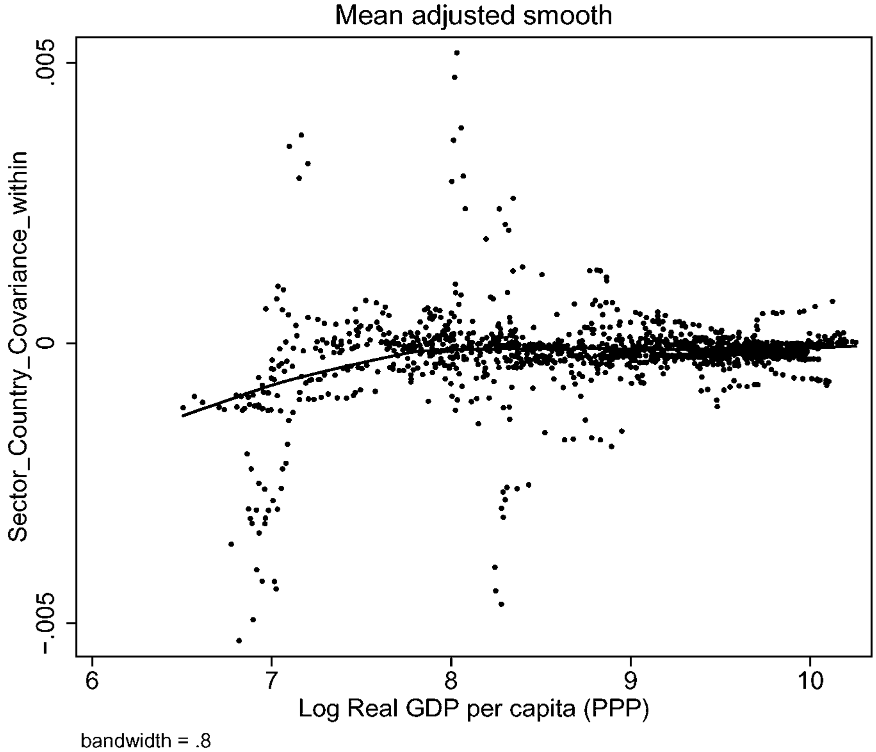
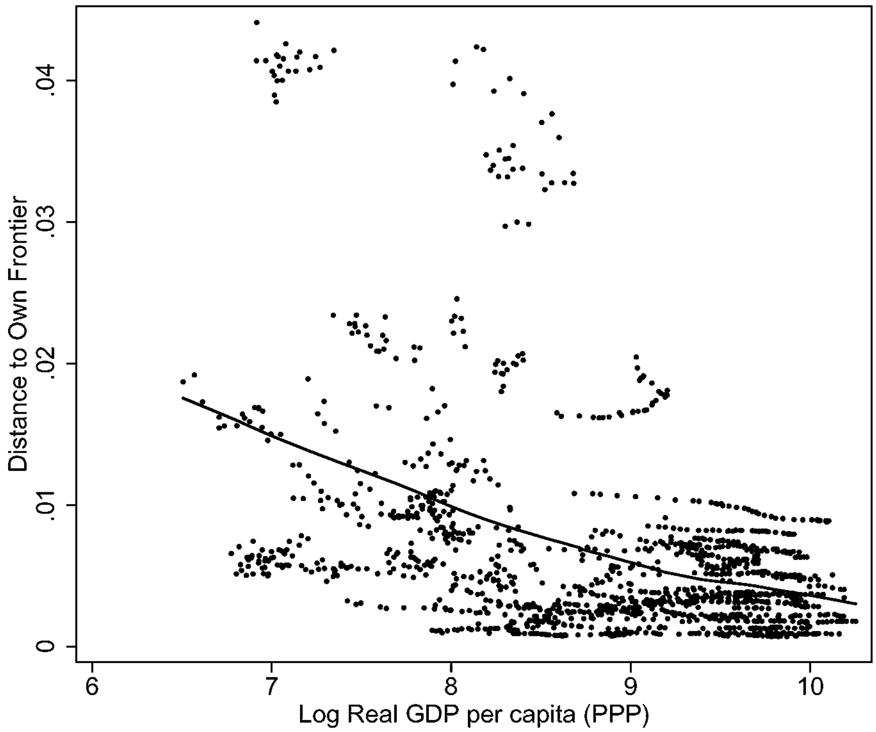
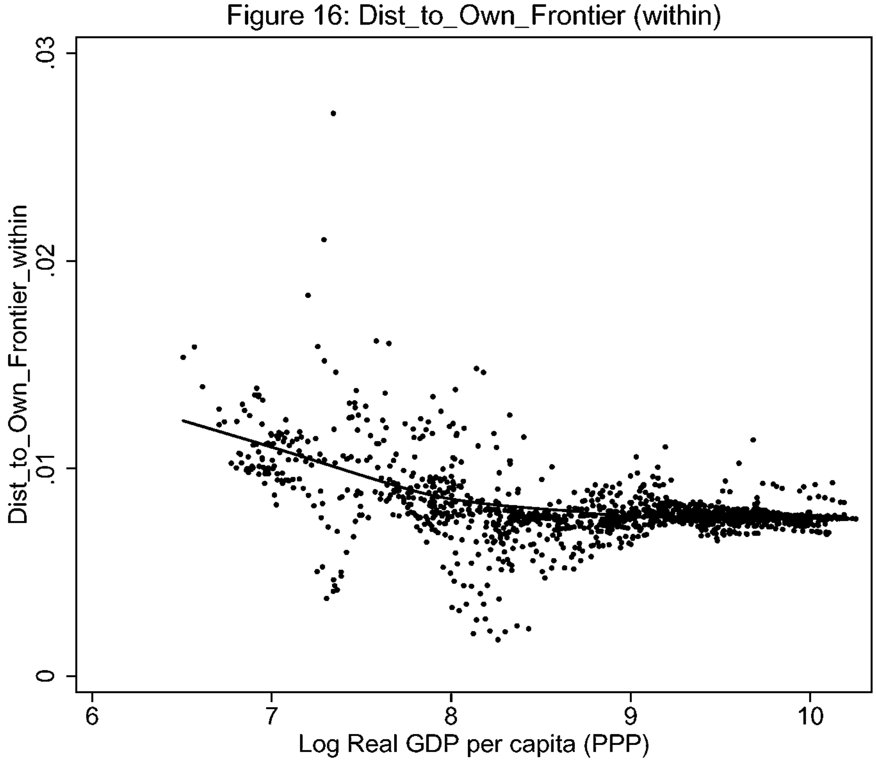


Figure 15: Dist_to_Own_Frontier



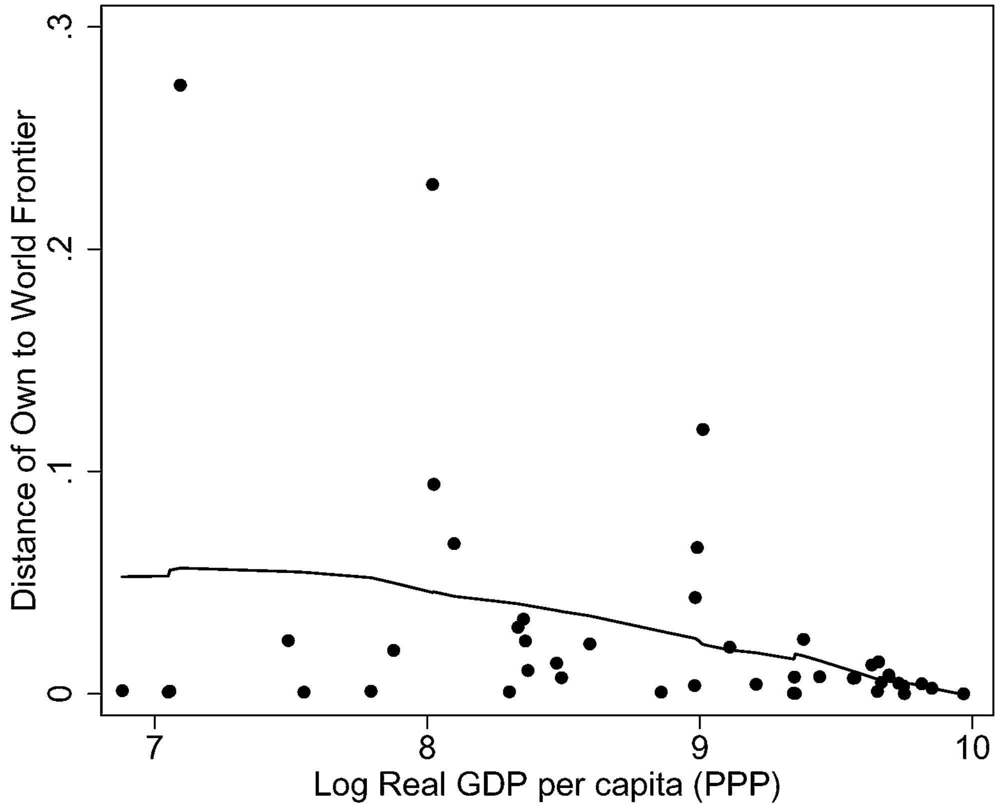
bandwidth = .8

Figure 16: Dist_to_Own_Frontier (within)



bandwidth = .8

Figure 17: Distance of Own to World Frontier (1980)



bandwidth = .8

Figure 18: Sectoral_Risk
Agriculture, Manufacturing, and Services

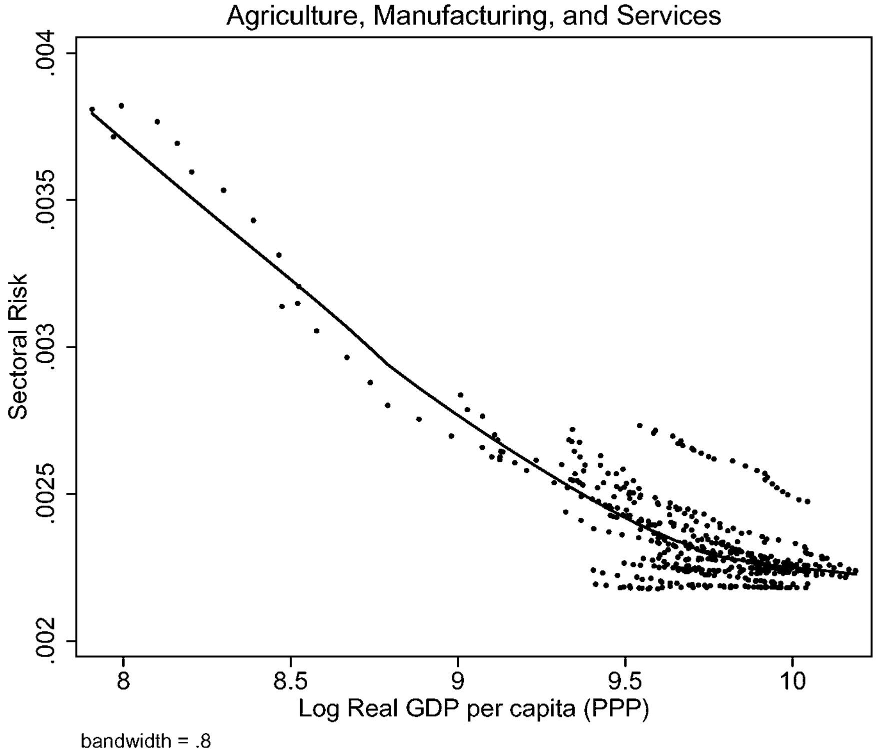


Figure 19: Sectoral_Risk (within)
Agriculture, Manufacturing, and Services

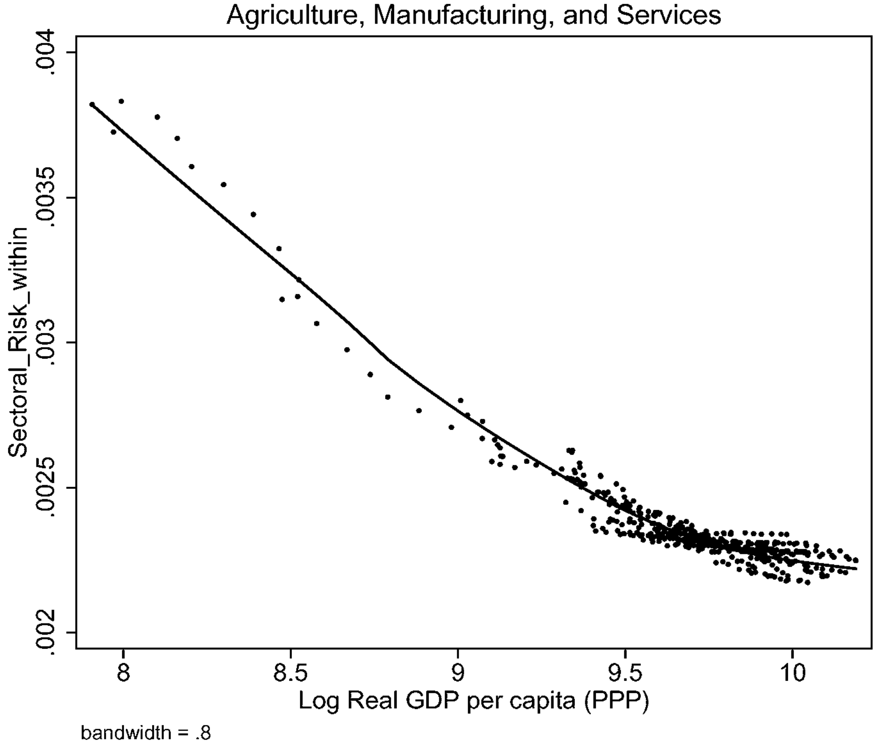


Figure 20. Sectoral Risk Before and After 1980

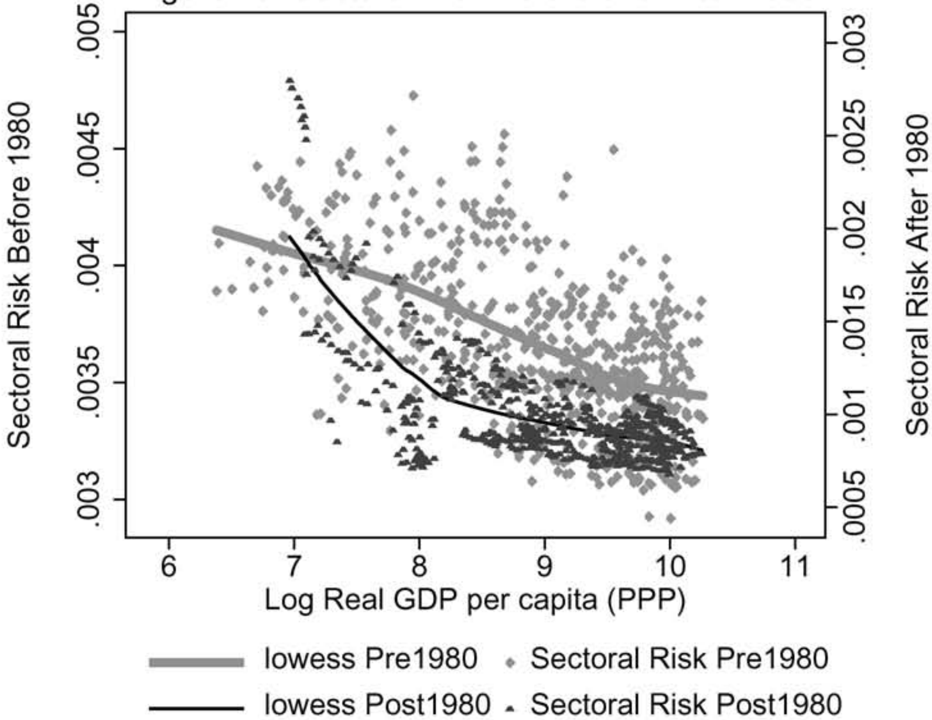


Figure 21. Sectoral Risk Before and After 1980 (within)