VOLATILITY AND DEVELOPMENT*

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Why is GDP growth so much more volatile in poor countries than in rich ones? We identify three possible reasons: (i) poor countries specialize in fewer and more volatile sectors; (ii) poor countries experience more frequent and more severe aggregate shocks (e.g., from macroeconomic policy); and (iii) poor countries' macroeconomic fluctuations are more highly correlated with the shocks affecting the sectors they specialize in. We show how to decompose volatility into the various sources, quantify their contribution to aggregate volatility, and study how they relate to the stage of development. We document the following regularities. First, as countries develop, their productive structure moves from more volatile to less volatile sectors. Second, the volatility of country-specific macroeconomic shocks falls with development. Third, the covariance between sector-specific and country-specific shocks does not vary systematically with the level of development. There is also some evidence that the degree of sectoral concentration declines with development at early stages, and increases at later stages. We argue that many theories linking volatility and development are not consistent with these findings, and suggest new directions for future theoretical work.

I. INTRODUCTION

An important theme in the growth and development literature is the relationship between volatility, 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 sharp fluctuations in growth rates. This relationship is illustrated in Figure I, which plots the standard deviation of annual (per capita) 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

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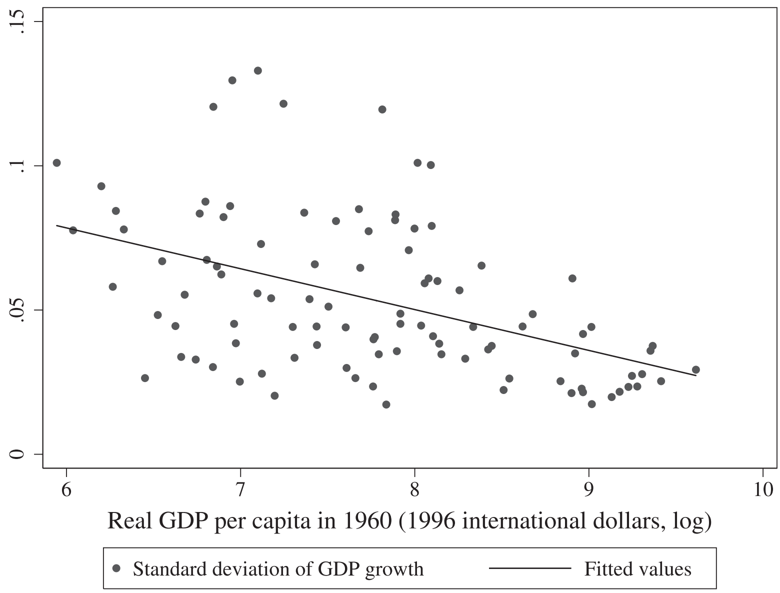

FIGURE I
Aggregate Volatility and Development
The graph shows the standard deviation of GDP growth from 1960 through 1996 against log real GDP per capita in 1960.

to hedge against fluctuations is particularly limited by the weakness of their financial infrastructure.

This paper presents a new approach to identifying and quantifying the sources of volatility. In particular, the analysis identifies three components of the volatility of aggregate GDP growth. The first component relates to the volatility of sectoral shocks: an economy that specializes in sectors that exhibit high intrinsic volatility will tend to experience higher aggregate volatility. The second component relates to aggregate country-specific shocks: some countries are subject to greater policy and political instability. The third component relates to the covariance between country-specific and sector-specific shocks: for example, fiscal or monetary policy innovations in some countries might be correlated with the shocks to particular sectors. We show how to decompose overall volatility into these different components.

This breakdown of volatility is important for at least two reasons. First, it helps to point out the potential areas to which risk management efforts should be directed. If, for example, a large part of a country's volatility is accounted for by high exposure to a few high-risk sectors, then policies aimed at mitigating volatility (or its consequences) should probably focus on the development and strengthening of financial institutions and, perhaps, on the diversification of the economy. If, instead, most of the volatility is due to country-specific shocks, then attention should probably be directed to macroeconomic policy (i.e., high volatility might reflect inadequate aggregate domestic policies). Second, as we discuss below, this breakdown helps to empirically assess existing theoretical models linking volatility and development, and can thus shed more light on the underlying mechanisms generating volatility.

The empirical analysis leads to the following findings. First, as countries develop, they tend to move towards sectors with lower intrinsic volatility.[1] There is also some evidence that sectoral concentration declines with the level of income at early stages of development, whereas at later stages it tends to increase with income. These findings indicate that there is no one-to-one relationship between sectoral riskiness and concentration: The relatively higher concentration observed at later stages of development tends to occur in low-volatility sectors. Third, country-specific volatility falls with development. This result could be the outcome of greater political stability and sounder macroeconomic policies in more developed economies. Finally, the covariance between country- and sector-specific shocks shows no systematic pattern with respect to the level of development.

As the previous qualitative description suggests, poor countries are more volatile because they specialize in fewer and more volatile sectors and because they experience more frequent and more severe aggregate shocks. Quantitatively, roughly 50 percent of the differences in volatility between poor and rich countries can be accounted for by differences in country-specific volatility, whereas the remaining 50 percent is accounted for by differences in the sectoral composition.

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

1. In the analysis we distinguish between global sectoral shocks, which are common to all countries, and idiosyncratic sectoral shocks, which differ across countries.

development is in line with Acemoglu and Zilibotti [1997]: Early in the development process diversification opportunities are limited, owing to the scarcity of capital and the indivisibility of investment projects. However, these authors, as well as Obstfeld [1994], Saint-Paul [1992], and Greenwood and Jovanovic [1990] predict that at early stages of development countries will seek insurance by investing in safer (even if less productive) sectors.[2] According to our findings, instead, not only are poorer countries highly concentrated in few sectors, but also those sectors carry particularly high sector-specific risk, which is hard to reconcile with existing theories. In addition, most models explicitly (e.g., Obstfeld [1994]; Saint-Paul [1992]) or implicitly (e.g., Acemoglu and Zilibotti [1997]; Greenwood and Jovanovic [1990]) take a "portfolio choice" view: high sectoral productivity comes at the cost of higher volatility. This view is inconsistent with the decline in sector-specific volatility as countries develop and thus become more productive.[3]

Our work also relates to a recent contribution by Imbs and Wacziarg [2003], who provide an empirical characterization of the relationship between sectoral concentration and development.[4] Our paper has a broader focus, in that it looks at all of the sources of the volatility-development pattern and not only the degree of sectoral concentration. This allows us to quantitatively assess the relative importance of the various components of volatility as well as to make a closer contact with the theoretical literature linking volatility and development.[5] We should also note that, while indexes of sectoral concentration are sensitive to the aggregation and definition of sectors, as shown later, the quantitative mea-

2. Acemoglu and Zilibotti [1997] refer to projects and sectors interchangeably (p. 711). It is of course possible that sectors are not the relevant empirical counterparts of their theory. However, given that developing countries are subject to the highest sectoral risk, it is unlikely that they choose the safest projects as implied by the model.

3. The results appear to be more in line with Kraay and Ventura [2001]. In their model, rich countries have a comparative advantage in sectors which can cope better with macroeconomic shocks. Their model, however, does not allow for sectoral shocks.

4. Kalemli-Ozcan, Sørensen, and Yosha [2003] study the relationship between specialization and financial openness.

5. Studies on aggregate volatility, most notably Ramey and Ramey [1995]; Kose, Otrok, and Whiteman [2003]; and Kose, Prasad, and Terrones [2005] do not study sectoral shocks, which is the critical element that allows us to discriminate among the theories discussed before. Note that Ramey and Ramey [1995], as well as Imbs [2006] (who studies sectoral patterns), focus on the link between volatility and *growth*, whereas our focus is on the link between volatility (and its components) and the *level* of development. Our contribution can hence be seen as complementary to these studies.

sures of sectoral risk we derive are invariant to the classification scheme.

Finally, our paper is methodologically related to the work of Stockman [1988], who decomposes the variance of industrial output growth in seven European countries. We go beyond the variance-decomposition analysis performed by Stockman [1988] both by deriving quantitative risk measures for the various components of volatility and by linking them to the level of development.

II. Method

Two main ideas underlie the discussion over the determinants of the volatility of GDP growth. The first emphasizes the role of the sectoral composition of the economy as the main culprit for volatility: a high degree of specialization or specialization in high-risk sectors translate into high aggregate volatility.[6] The second idea points to domestic macroeconomic risk, possibly related to policy mismanagement or political instability, among other country-specific factors.[7]

The emphasis on sectoral composition motivates the first breakdown of the value added of a country into the sum of the value added of different sectors, each of which has a potentially different level of intrinsic volatility. Innovations in the growth rate of GDP per worker in country j, ($j = 1, \ldots, J$) denoted by q_j, can then be expressed, as a first-order approximation, as the weighted sum of the innovations in the growth rates of value-added per worker in every sector, y_{js}, with $s = 1, \ldots, S$:

$$q_j = \sum_{s=1}^{S} a_{js} y_{js},$$

where the weights, a_{js}, denote the share of employment in sector s of country j. The object of our study is the variance of q_j, Var (q_j), and its components.

To separate the role of domestic aggregate risk from that of the sectoral composition of the economy, we can further break-

6. See, for example, Burns [1960]; Newbery and Stiglitz [1984]; Greenwood and Jovanovic [1990]; Saint-Paul [1992]; Obstfeld [1994]; Acemoglu and Zilibotti [1997]; and Kraay and Ventura [2001].

7. See, for example, Hopenhayn and Muniagurria [1996]; and Gavin and Hausmann [1998].

down innovations to a sector's growth rate, y_{js}, into three disturbances:

$$y_{js} = \lambda_s + \mu_j + \varepsilon_{js}. \tag{1}$$

The first disturbance (λ_s) is specific to a sector, but common to all countries. This includes, for example, a shock to the price of a major input in production, such as steel, which may affect the productivity of sectors that are steel-intensive. More generally, technology- and price-shocks that affect a sector or group of sectors across countries will fall in this category.

The second disturbance (μ_j) is specific to a country, but common to all sectors within a country. So, for example, a monetary tightening in country j might deteriorate the productivity of all sectors in country j, because all need some amount of liquidity to produce.

The third disturbance (ε_{js}) captures the residual unexplained by the other two. In the previous example, if some sectors are more sensitive to the liquidity squeeze and have a deeper fall in productivity, the difference with respect to the average will be reflected in ε_{js}. Similarly, if some global shocks have different impact on sectoral productivity in different countries, the differential impact will be captured by ε_{js}. Finally, any disturbance specific to both a country and sector will be reflected in ε_{js}.

Of course all three disturbances can potentially be correlated with each other. For example, λ_s and μ_j will tend to be correlated if in some countries macroeconomic policies are more responsive to global sectoral shocks, or, alternatively, if a country is highly influential in a particular sector, in which case an aggregate shock in that country may affect that sector in other countries. Moreover, as pointed out above, certain sectors may be more responsive to country-specific shocks (implying that ε_{js} and μ_j could be correlated) or sectoral productivity in certain countries may be affected differently by global sectoral shocks (implying that ε_{js} and λ_s could be correlated).

Expression (1) provides a convenient way of partitioning the data. Written as such, it is simply an accounting identity, since the residual picks up everything not accounted for by the sector- or country-specific shocks, and since we do not place any restriction on the way the three disturbances covary.[8]

8. In the robustness section we discuss alternative ways of breaking down the data on y_{js}. In particular, we consider the partition $y_{js} = B_j\lambda_s + b_s\mu_j + \varepsilon_{js}$, where

In what follows, we explain how to decompose the variance of q_j into the corresponding variances and covariances of these different disturbances.

II.A. Volatility Decomposition

It is convenient to rewrite innovations to growth of GDP per capita in matrix notation. Denoting by $\mathbf{y}_j$ the vector of sectoral innovations y_{js} and by $\mathbf{a}_j$ the vector of sectoral shares a_{js}, our object of interest, Var (q_j), can be written as

$$\text{Var}\ (q_j) = \mathbf{a}_j' \mathrm{E}(\mathbf{y}_j \mathbf{y}_j') \mathbf{a}_j. \tag{2}$$

Thus, to decompose Var (q_j) we need to decompose the variance–covariance matrix of the innovations to sectoral growth rates, $\mathrm{E}(\mathbf{y}_j \mathbf{y}_j')$.

Given (1), simple matrix algebra shows that the variance–covariance matrix of country j's sectoral shocks can be expressed as[9]

$$\mathrm{E}(\mathbf{y}_j \mathbf{y}_j') = \Omega_\lambda + \Omega_{\varepsilon_j} + \omega_{\mu j}^2 \mathbf{1}\mathbf{1}' + (\Omega_{\lambda_{\mu_j}} \mathbf{1}' + \mathbf{1}\Omega_{\lambda_{\mu_j}}') + \Gamma_j \tag{3}$$

where

$$\begin{aligned}
\Omega_\lambda &= \mathrm{E}(\lambda\lambda'),\\
\Omega_{\varepsilon_j} &= \mathrm{diag}(\sigma_{j1}^2 \ . \ . \ . \ \sigma_{jS}^2),\\
\omega_{\mu_j}^2 &= \mathrm{E}(\mu_j^2),\\
\Omega_{\lambda_{\mu_j}} &= \mathrm{E}(\lambda\mu_j),
\end{aligned}$$

$\mathbf{1}$ denotes the $S \times 1$ vector of ones, and λ and μ denote the vectors of sectoral shocks (λ_s) and country shocks (μ_j), respectively. The matrix Ω_λ is the variance–covariance matrix of sector-specific global shocks; Ω_{ε_j} is the matrix collecting the variances of the sector- and country-specific residuals ε_{js}, $\sigma_{js}^2 = \mathrm{E}(\varepsilon_{js}^2)$; $\omega_{\mu_j}^2$ is the variance of country-specific shocks; $\Omega_{\lambda\mu_j}$ is the covariance between country-specific and global sectoral shocks; and finally, as shown in Appendix I, the matrix Γ_j collects the remaining components of $\mathrm{E}(\mathbf{y}_j \mathbf{y}_j')$, that is, the covariances between the residuals and the sectoral and country-specific shocks, $\mathrm{E}(\varepsilon_{js}\lambda)$ and $\mathrm{E}(\varepsilon_{js}\mu_j)$,

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B_j captures the differential impact of global shocks on sectoral productivity, by country, and b_s captures the differential impact of country-specific shocks, by sector. In specification (1), the differential impact of these shocks is captured by the residual term ε_{js}.

9. Appendix I presents the derivation.

respectively, and the covariance among residuals, $E(\varepsilon_{js},\varepsilon_{js'})$, for $s \neq s'$.[10]

As we show later, it turns out that the term Γ_j plays a quantitatively negligible role in accounting for aggregate volatility. We come back to the quantitative assessment of Γ_j in Section V.[11] In anticipation of that result, the exposition that follows ignores this last component. More specifically, we will maintain the working hypothesis that the residual shocks are idiosyncratic (uncorrelated with each other and with the sector- and country-specific shocks), and hence Γ_j is null. This implies that we can write the variance–covariance matrix as

$$\text{(4)} \qquad E(\mathbf{y}_j\mathbf{y}_j') = \Omega_\lambda + \Omega_{\varepsilon_j} + \omega^2_{\mu j}\mathbf{1}\mathbf{1}' + (\Omega_{\lambda\mu_j}\mathbf{1}' + \mathbf{1}\Omega'_{\lambda\mu_j}).$$

Plugging (4) into (2), aggregate volatility can be written as

$$\text{(5)} \qquad \mathrm{Var}\,(q_j) = \mathbf{a}_j'E(\mathbf{y}_j\mathbf{y}_j')\mathbf{a}_j = \mathbf{a}_j'\Omega_\lambda\mathbf{a}_j + \mathbf{a}_j'\Omega_{\varepsilon_j}\mathbf{a}_j + \omega^2_{\mu_j} + 2(\mathbf{a}_j'\Omega_{\lambda\mu_j}).$$

This formulation clearly shows that GDP growth in country j is more volatile:

1. if the country specializes in *risky* sectors, that is, sectors exposed to large and frequent shocks. This is reflected in the first two terms:
   (a) The first, $\mathbf{a}_j'\Omega_\lambda\mathbf{a}_j$, relates to global sectoral shocks. This term is large when sectors exposed to big and frequent global shocks account for a large share of the country's employment. For example, if the textiles sector is highly volatile in all countries, then countries with high shares of textiles will tend to exhibit a large value for $\mathbf{a}_j'\Omega_\lambda\mathbf{a}_j$.
   (b) The second term, $\mathbf{a}_j'\Omega_{\varepsilon_j}\mathbf{a}_j = \sum_{s=1}^{S} \sigma^2_{js}a^2_{js}$, relates to idiosyncratic sectoral shocks. This term is large when sectors with high idiosyncratic volatility, σ^2_{js}, account for a large share of employment. For example, suppose textiles is particularly volatile in country j: then, if the

10. The model also allows for correlation of country-specific shocks across countries. Hence, we could further decompose the country-specific variance and quantify covariances of country shocks across regions (or group of countries). For simplicity, the exposition ignores these correlations.

11. Note that the term Γ_j will be potentially important in the case of a large idiosyncratic shock in big, highly specialized countries. To see why, suppose, for example, that a drought 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. Thus ε_{js} will be correlated with global sectoral shocks. Empirically, however, as we show later, such shocks do not play a substantial role in our sample.

share a_{js} of textiles in country j is large, the country will exhibit a large value for $\Sigma_{s=1}^{S} \sigma_{js}^2 a_{js}^2$.

2. if country risk ($\omega_{\mu_j}^2$) is big, that is, if aggregate domestic shocks are larger and more frequent.
3. if specialization is *tilted* towards sectors whose shocks are positively correlated with country-specific shocks ($\mathbf{a}_j' \Omega_{\lambda_\mu j}$ is big). This term will tend to be small, for example, if policy innovations are negatively correlated with the shocks to sectors that have a large share in country j's employment. For example, if monetary policy in country j reacts countercyclically to shocks in the textiles sector, and textiles account for a large share of the economy, then this term will tend to be small, and possibly negative.

The second term in (5) can be further decomposed as the product of the average idiosyncratic variance of country j, measured as $\bar{\sigma}_{js}^2 = \Sigma_{s=1}^{S} \sigma_{js}^2 (a_{js}^2 / \Sigma_{s=1}^{S} a_{js}^2)$, and $\mathbf{a}_j'\mathbf{a}_j = \Sigma_{s=1}^{S} a_{js}^2$, the Herfindahl concentration index. That is, $\Sigma_{s=1}^{S} \sigma_{js}^2 a_{js}^2 = (\mathbf{a}_j'\mathbf{a}_j)\bar{\sigma}_{js}^2$. The Herfindahl concentration index $\mathbf{a}_j'\mathbf{a}_j$ is large if the country specializes in *few* sectors, and $\bar{\sigma}_{js}^2$ is large when idiosyncratic shocks are frequent and large.[12]

Thus, the aggregate volatility of the economy can be decomposed as the sum of components with fundamentally different meanings. Empirical papers studying diversification typically focus on the Herfindahl index (or other concentration indexes) as a measure of diversification. This is a convenient measure to capture the riskiness of the sectoral structure (and the lack of diversification) under the assumption that sectors are homoscedastic and uncorrelated. The decomposition we perform indicates that to measure diversification it is important to take into account the riskiness embedded in a particular sectoral structure. Furthermore, we note that, while sectoral indexes of concentration are sensitive to the particular sectoral classification scheme (that is, to the particular way firms are assigned to sectors), as we show in Section V, the global sectoral risk component, $\mathbf{a}_j'\Omega_\lambda \mathbf{a}_j$, and the idiosyncratic risk component, $\mathbf{a}_j'\Omega_{\varepsilon_j}\mathbf{a}_j$, are invariant to changes in

12. The Herfindahl index reaches its maximum when the country is totally concentrated in one sector ($a_{js} = 1$ and $a_{j\bar{s}} = 0$ for $s \neq \bar{s}$) and is lowest for an equal division of sectors, $a_{js} = 1/S$ for all s. The average idiosyncratic variance is highest if the country is concentrated in the sector with the highest idiosyncratic variance and lowest if the country is concentrated in the sector with the lowest variance.

classification. Because of these considerations, we report both the total idiosyncratic risk component (insensitive to classification) and its breakdown into Herfindahl index and average variance (potentially sensitive to classification).

II.B. Estimating the Model

To quantify the various components of volatility in equation (5), we need to estimate the variance–covariance matrices Ω_{λ}, Ω_{ε_j}, $\omega^2_{\mu_j}$, and $\Omega_{\lambda\mu_j}$. Our general strategy is to use data across countries, sectors, and time to back out estimates of the sectoral shocks, λ_s, and the country shocks, μ_j. We then compute the sample variances and covariances of the estimated shocks and treat them as estimates of the corresponding population moments.

Innovations to growth in value-added per worker in country j and sector s, y_{jst}, are computed as the deviation of the growth rate from the average growth rate of country j and sector s over time.

We measure global sector-specific shocks as the cross-country average of y_{jst} in each of the sectors. Country-specific shocks are then identified as the within-country average of y_{jst}, using only the portion not explained by sector-specific shocks. The residual is then the difference between y_{jst} and the two shocks. Formally,

$$
\begin{aligned}
\hat{\lambda}_{st} &\equiv \frac{1}{J}\sum_{j=1}^{J} y_{jst},\\
\hat{\mu}_{jt} &\equiv \frac{1}{S}\sum_{s=1}^{S} (y_{jst} - \hat{\lambda}_{st}), \qquad (6)\\
\hat{\varepsilon}_{jst} &\equiv y_{jst} - \hat{\lambda}_{st} - \hat{\mu}_{jt}.
\end{aligned}
$$

Note that we normalize shocks so that $\Sigma_{j=1}^{J}\ \mu_{jt} = 0$, that is, country shocks are expressed as relative to world shocks.

An equivalent way to formalize this is to frame the analysis as a set of cross-sectional regressions of y_{jst} on country and sector dummies. More specifically, the formulas for $\hat{\lambda}_{st}$, $\hat{\mu}_{jt}$, and $\hat{\varepsilon}_{jst}$ given above will be the result of running a regression, for each time t, of y_{jst}, on a set of sector-specific and country-specific dummies. (See the derivation in Appendix II.) The econometric specification is[13]

$$y_{jst} = \lambda_{1t}d_1 + \ldots + \lambda_{St}d_S + \mu_{1t}h_1 + \ldots + \mu_{Jt}h_J + \varepsilon_{jst} \tag{7}$$

where d_s, $s = 1, \ldots, S$, are dummy variables that take the value 1 for sector s, and 0 otherwise, and h_j, $j = 1, \ldots, J$, are dummy variables taking the value 1 for country j, and 0 otherwise. The estimated coefficients $\hat{\lambda}_{st}$ and $\hat{\mu}_{jt}$, and the residuals $\hat{\varepsilon}_{jst}$ are, respectively, the global sector-s-specific shock, country-j-specific shock, and the (s,j)-country-and-sector-specific shock at time t.

Estimates of the matrices $\Omega_\lambda, \Omega_{\lambda\mu_j}, \omega^2_{\mu_j}$, and Ω_{ε_j} are then computed using the estimated shocks. In particular, $\hat{\Omega}_\lambda = (1/T) \sum_{t=1}^{T} \hat{\lambda}_t \hat{\lambda}'_t$ is the estimated variance–covariance of global-sectoral shocks;[14] $\hat{\omega}^2_{\mu_j} = (1/T) \sum_{t=1}^{T} \hat{\mu}^2_{jt}$ is the estimated variance of country-j-specific shocks; $\hat{\Omega}_{\lambda\mu_j} = (1/T) \sum_{t=1}^{T} \hat{\lambda}_t \hat{\mu}_{jt}$ is the estimate of the covariance between sectoral shocks and country-j-shocks; and $\hat{\sigma}^2_{js} = (1/T) \sum_{t=1}^{T} \hat{\varepsilon}^2_{jst}$, with $s = 1, \ldots, S$ are the estimated variances of the sectoral idiosyncratic shocks.[15]

Given the estimates of the variance–covariance matrix of factors, we use data on sectoral labor shares, a_{sjt}, to compute the various measures of risk exposure:

$$\mathrm{GSECT}_{jt} = \mathbf{a}'_{jt} \hat{\Omega}_\lambda \mathbf{a}_{jt} \tag{8}$$

$$\mathrm{ISECT}_{jt} = \sum_{s=1}^{S} \hat{\sigma}^2_{js} a^2_{jst} \tag{9}$$

$$\mathrm{CNT}_j = \hat{\omega}^2_{\mu_j} \tag{10}$$

$$\mathrm{COV}_{jt} = 2\mathbf{a}'_{jt} \hat{\Omega}_{\lambda\mu_j} \tag{11}$$

where GSECT_{jt} is the part of the volatility of country j at time t due to sectoral shocks that are common to all countries; ISECT_{jt} is the part of volatility due to sectoral shocks idiosyncratic to

13. For each cross section of data, the number of observations is $J \cdot S$, and the number of regressors is $J + S$.

14. The vector of estimated sectoral shocks, $\hat{\lambda}_t$ has elements $\hat{\lambda}_{st}$.

15. A fast reading might lead some to mistakenly think that, by construction, the regressions impose orthogonality conditions between $\hat{\varepsilon}_{jst}$ and $\hat{\lambda}_{st}$ (and between $\hat{\varepsilon}_{jst}$ and $\hat{\mu}_{jt}$). Note that this is not the case. The specification in (7) implies that the residuals $\hat{\varepsilon}_{jst}$ are uncorrelated with the sectoral and country dummies, but not necessarily with the shocks $\hat{\lambda}_{st}$ and $\hat{\mu}_{jt}$. In fact, as we later discuss, these correlations are nonzero, though they are quantitatively small and this is why we opt to ignore them. This is a result, not an assumption.

country j; CNT_j is the part of volatility due to country shocks (which, by construction, does not depend on time); and COV_{jt} is twice the covariance of global sectoral shocks with the jth country shock at time t. Total volatility can be hence expressed as the sum of these four components.

We shall further decompose the idiosyncratic sectoral risk component into the product of the sectoral concentration index, HERF_{jt}, and the average idiosyncratic variance, AVAR_{jt}:

$$\mathrm{ISECT}_{jt} = \mathrm{HERF}_{jt} \cdot \mathrm{AVAR}_{jt},$$
$$\mathrm{HERF}_{jt} = \mathbf{a}'_{jt}\mathbf{a}_{jt},$$
$$\mathrm{AVAR}_{jt} = \sum_{s=1}^{S} \sigma_{js}^2 \frac{a_{js}^2}{\sum_{s=1}^{S} a_{js}^2}.$$

II.C. Related Empirical Applications

The econometric model specified in (7), known as a factor model, is popular in finance applications, where it is used to decompose volatility of asset returns. A similar procedure to study shocks 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 [1994], who use this decomposition for stock market fluctuations. These studies focus on the qualitative distinction between country shocks and industry shocks, but not on the quantitative risk measures, which is the object we pursue in our analysis.

An alternative specification for the factor model allows for shocks to have a differential impact in each country and sector (different factor loadings), while treating factors as orthogonal to each other. (See finance applications in Connor and Korajczyk [1986] and [1988]; Lehmann and Modest [1985a] and [1985b]; and Brooks and Del Negro [2004].) This methodology can also be used to analyze the comovement of economic fluctuations across countries (Forni and Reichlin [1986], Lumsdaine and Prasad [1999], and Kose, Otrok, and Whiteman [2003]) or regions (Del Negro [2002]).

The cross-sectional regression method we use is convenient because it makes minimal assumptions on the way factors 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 III, we show that the potential biases associated with this are very small given the number of countries and sectors, and the relative size of the variances σ_{js}^2.

III. Data

We apply the decomposition previously described to two data sets. The first data set comes from the United Nations Industrial Development Organization [UNIDO, 2002]. UNIDO reports annual employment and value added data for all manufacturing sectors at the 3-digit level of disaggregation from 1963 to 1998 for a broad sample of countries. According to the World Bank's *World Development Indicators,* the share of manufacturing in total GDP for the countries in the UNIDO sample was on average 36 percent in 1980 (the mid point of our sample), ranging from 12 percent in Ghana to 48 percent in South Africa. (The list of countries with their corresponding manufacturing shares is displayed in Table I.) Although manufacturing is only part of the economy, we think it is important to study its patterns of volatility, since, as we shall argue, the patterns we document are likely to be accentuated when agriculture and services are considered in the analysis.

The original UNIDO data set contains 28 sectors. However, several countries aggregate value added or employment for two or more sectors into one larger sector. For example, various countries group "food products" and "beverages" together. To make the data comparable, we aggregate sectors into 19 categories and thus obtain a consistent classification across countries; the list of sectors is displayed in Table II.

The second data set is the OECD's *STAN Industrial Structure Analysis* [2003], which reports annual GDP data, disaggregated in sectors, including agriculture, mining, and services, from 1978 through 1999. As before, we have to aggregate some sectors to make the data comparable across countries, which results in 18 sectors.[16] A limitation of this data set is that it provides information on a smaller set of countries than UNIDO, typically more developed ones. On the positive side, however, this data set covers all sectors in the economy and the quality of these data is likely higher. (The countries included in the sample are marked with an

16. Section V discusses the robustness of the exercise to the degree of sectoral aggregation.

TABLE I
LIST OF COUNTRIES IN UNIDO SAMPLE AND MANUFACTURING SHARES IN GDP

Country	Share of manufacturing in GDP 1980
Australia*	37.03
Austria*	38.10
Bangladesh	20.63
Belgium*	36.84
Canada*	37.62
Chile	37.44
Colombia	32.49
Denmark*	28.23
Ecuador	42.01
Egypt	36.78
Finland*	39.19
France*	36.03
Ghana	11.87
Greece	32.94
Guatemala	21.99
Hong Kong	31.87
Hungary	47.06
India	24.50
Indonesia	41.72
Ireland	35.94
Israel	n.a.
Italy*	40.38
Japan*	41.00
Kenya	20.85
Korea*	n.a.
Malaysia	41.04
Netherlands*	34.52
New Zealand	32.19
Nicaragua	31.42
Norway*	40.39
Pakistan	24.92
Philippines	38.79
Poland	n.a.
Portugal	32.88
Singapore	n.a.
South Africa	48.21
Spain*	38.57
Sri Lanka	29.64
Sweden*	33.02
Turkey	22.17
United Kingdom*	42.35
United States*	33.51
Uruguay	33.69
Venezuela	46.41
Zimbabwe	n.a.

Note: Countries with an asterisk (*) are also included in the STAN-OECD sample. Manufacturing shares in GDP come from the WDI. n.a., Not available.

TABLE II
LIST OF SECTORS (UNIDO sample)

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

asterisk in Table I and the list of sectors is shown in Table III.)

We focus the analysis on the variance of the 1-year growth rate of real value added per worker.[17] As a measure of development, we use PPP adjusted real GDP per capita from the *Penn World Tables 6.1* (Heston et al. [2002]).

IV. RESULTS

This section is split into three subsections. The first (IV.A.) briefly introduces the reader to the estimates of the various components of volatility. The second (IV.B.) investigates the relationship between the various measures of risk and economic development. The third (IV.C.) presents the results of a volatility accounting exercise. As indicated below, we report the results based on the UNIDO sample first and on the STAN-OECD sample second.

17. In both data sets, value added is expressed in U.S. dollars. We use the U.S. CPI to convert figures into constant dollars.

TABLE III
LIST OF SECTORS (STAN-OECD sample)

1	Agriculture, hunting, forestry, and fishing
2	Mining and quarrying
3	Food products, beverages, and tobacco
4	Textiles, textile products, leather, and footwear
5	Wood and cork
6	Pulp, paper, paper products
7	Chemical, rubber, plastic, and fuel products
8	Other nonmetallic mineral products
9	Basic metals and fabricated metal products
10	Machinery and equipment
11	Transport equipment
12	Manufacturing not elsewhere classified
13	Electricity, gas and water supply
14	Construction
15	Wholesale and retail trade; restaurants and hotels
16	Transport and storage and communication
17	Finance, insurance, real estate, and business services
18	Community social and personal services

IV.A. Decomposition of Risk

UNIDO sample. We begin in Table IV by illustrating the decomposition of risk, by country, in 1980 for the UNIDO sample. (The Figures in the next Section will display the corresponding numbers for all years.) The numbers are expressed as variance components (not standard deviations).[18]

The first column shows the global sectoral risk component, $\mathrm{GSECT}_j = \mathbf{a}_j'\Omega_\lambda\mathbf{a}_j$. The key element of this component is the variance–covariance of global sectoral shocks, Ω_λ, which measures the intrinsic riskiness of the various sectors that is common to all countries. In 1980 the top five countries according to this dimension of risk are Pakistan, Bangladesh, Egypt, Ghana, and Turkey, whereas Denmark, Singapore, the Netherlands, and Ireland exhibit the lowest levels of global sectoral risk.

Column (2) shows the idiosyncratic sectoral risk component, $\mathrm{ISECT}_j = \sum_{s=1}^{S} \hat{\sigma}_{js}^2 a_{js}^2$. The highest levels of idiosyncratic sectoral risk are observed in Egypt, Bangladesh, Ghana, and Ecuador. In contrast, the United States, Japan, and France display the lowest

18. We express them in terms of variance components so as to emphasize the additive contribution to total variance.

levels. As mentioned, we can further decompose this term into the product of the Herfindahl index of sectoral concentration, $\Sigma_{s=1}^{S}\ a_{js}^2$, and the average idiosyncratic variances of sectoral shocks, $\Sigma_{s=1,js}^{S}\ \hat{\sigma}_{js}^2(a_{js}^2/\Sigma_{s=1}^{S}\ a_{js}^2)$; these terms are displayed in columns (2a) and (2b). The countries with highest concentration levels are Bangladesh, Nicaragua, Pakistan, and Guatemala. The ones with lowest concentration are Canada, Spain, Italy, and South Africa. The largest average idiosyncratic variance is displayed by Egypt, Ghana, and Ecuador, whereas the United States, Japan, and France show the smallest variance.

Column (3) displays the country-specific risk, $\omega_{\mu_j}^2$. Ghana, Nicaragua, Egypt, Bangladesh, Philippines, and Israel are the countries with highest country-specific risk, whereas the United States, Belgium, France, Ireland, and Austria qualify as the safest.

Column (4) indicates the sector-country covariance: $\mathrm{COV}_j = 2\mathbf{a}_j'\Omega_{\lambda\mu_j}$. Nicaragua, Hungary, Philippines, Bangladesh, and Sweden show the highest covariance, whereas Egypt, Indonesia, Colombia, Zimbabwe, Italy, and Australia exhibit the lowest covariances.

Column (5) presents the sum of the four components.

In Table V we present the summary statistics for the global shocks, by sector, for each of the 19 sectors in the UNIDO sample. The first column presents the standard deviations of the global sector-specific shocks, and the second displays the average correlations of each sector-specific global shock with the sector-specific global shocks of the remaining 18 sectors. Note that there is considerable variation in standard deviations (the range goes from 2.5 percent in "printing and publishing" to 7.2 percent in "iron and steel") as well as in average correlations (the range goes from 0.14 in "professional and scientific equipment" to 0.53 in "furniture").

STAN-OECD sample. Table VI presents the decomposition using the STAN database for OECD countries in 1980.[19] South Korea, the lowest-income country in this sample, ranks first in all dimensions of risk. The United States displays very low levels of sectoral and idiosyncratic volatility together with relatively high levels of sectoral concentration (which illustrates the point that

19. For later years, see figures in the next Section.

TABLE IV
DIFFERENT DIMENSIONS OF RISK, BY COUNTRY, 1980 (UNIDO sample)

Country	Global sectoral risk $a'\Omega_\lambda a$ (1)	Idiosyncratic sectoral risk $\Sigma\sigma_{ij}^2 a_{ij}^2$: Total $\Sigma\sigma_{ij}^2 a_{ij}^2$ (2)	Herfindahl Index of Concentration $\Sigma a_{ij}^{(2)}$ (2a)	Average Idiosyncratic Variance $(\Sigma\sigma_{ij}^2 a_{ij})/\Sigma a_{ij}^2$ (2b)	Country specific risk ω_μ (3)	Sector–Country covariance $2a'\Omega_{\lambda\mu}$ (4)	Overall risk (5) = (1) + (2) + (3) + (4)
Australia	0.070	0.023	0.096	0.247	0.168	−0.202	0.060
Austria	0.068	0.030	0.091	0.327	0.119	−0.088	0.129
Bangladesh	0.104	1.023	0.458	2.233	3.027	0.091	4.246
Belgium	0.070	0.036	0.089	0.410	0.089	0.027	0.223
Canada	0.074	0.025	0.080	0.318	0.137	−0.068	0.168
Chile	0.074	0.138	0.109	1.268	0.461	−0.137	0.536
Colombia	0.067	0.077	0.102	0.752	0.342	−0.335	0.150
Denmark	0.058	0.036	0.120	0.300	0.324	0.053	0.472
Ecuador	0.067	0.693	0.151	4.578	0.688	−0.030	1.419
Egypt	0.082	1.539	0.187	8.219	3.286	−0.591	4.318
Finland	0.074	0.063	0.089	0.715	0.175	−0.033	0.280
France	0.067	0.018	0.091	0.202	0.101	−0.060	0.127
Ghana	0.081	0.828	0.143	5.778	5.871	0.079	6.860
Greece	0.070	0.045	0.101	0.450	0.195	−0.009	0.302
Guatemala	0.067	0.437	0.188	2.321	0.514	−0.168	0.852
Hong Kong	0.069	0.064	0.151	0.427	0.533	−0.103	0.564
Hungary	0.062	0.111	0.086	1.294	1.403	0.483	2.061
India	0.079	0.192	0.149	1.284	0.526	−0.002	0.795
Indonesia	0.073	0.346	0.184	1.878	0.902	−0.553	0.769
Ireland	0.061	0.036	0.114	0.317	0.117	−0.071	0.144
Israel	0.063	0.057	0.099	0.574	1.939	−0.015	2.045
Italy	0.070	0.038	0.085	0.454	0.348	−0.220	0.237
Japan	0.066	0.015	0.091	0.172	0.215	−0.098	0.199

TABLE IV
(CONTINUED)

Country	Global sectoral risk $a'\Omega_{\lambda}a$ (1)	Idiosyncratic sectoral risk $\Sigma\sigma_{ij}^2 a_{ij}^2$: Total $\Sigma\sigma_{ij}^2 a_{ij}^2$ (2)	Herfindahl Index of Concentration $\Sigma a_{ij}^{(2)}$ (2a)	Average Idiosyncratic Variance $(\Sigma\sigma_{ij}^2 a_{ij})/\Sigma a_{ij}^2$ (2b)	Country specific risk ω_{μ} (3)	Sector–Country covariance $2a'\Omega_{\lambda\mu}$ (4)	Overall risk (5) = (1) + (2) + (3) + (4)
Kenya	0.073	0.177	0.123	1.439	0.317	−0.144	0.423
Korea	0.071	0.089	0.090	0.984	0.663	−0.127	0.696
Malaysia	0.070	0.090	0.096	0.940	0.227	−0.160	0.227
Netherlands	0.061	0.030	0.109	0.276	0.217	−0.079	0.229
New Zealand	0.066	0.078	0.113	0.692	0.395	−0.122	0.417
Nicaragua	0.070	0.546	0.282	1.933	3.881	0.938	5.437
Norway	0.072	0.071	0.097	0.733	0.124	−0.059	0.209
Pakistan	0.086	0.308	0.268	1.150	0.712	0.032	1.140
Philippines	0.072	0.299	0.112	2.655	2.839	0.228	3.439
Poland	0.065	0.154	0.101	1.522	1.654	0.078	1.953
Portugal	0.072	0.092	0.099	0.926	0.408	−0.073	0.500
Singapore	0.061	0.176	0.142	1.233	0.296	−0.120	0.413
South Africa	0.071	0.057	0.089	0.650	0.263	−0.217	0.175
Spain	0.067	0.035	0.085	0.417	0.360	−0.135	0.328
Sri Lanka	0.073	0.311	0.123	2.516	0.731	−0.042	1.073
Sweden	0.075	0.032	0.109	0.295	0.350	0.085	0.543
Turkey	0.076	0.177	0.136	1.303	0.618	−0.083	0.789
United Kingdom	0.067	0.026	0.097	0.272	0.271	−0.052	0.312
United States	0.065	0.011	0.093	0.120	0.063	−0.066	0.073
Uruguay	0.066	0.334	0.119	2.795	1.700	−0.179	1.921
Venezuela	0.068	0.193	0.092	2.077	0.975	−0.178	1.058
Zimbabwe	0.072	0.231	0.107	2.149	0.552	−0.241	0.614

Note: The table reports the different components of volatility of Manufacturing growth for the UNIDO sample. The formulas for the different components are derived in the text. The four measures of risk (1), (2), (3), and (4) are additive components of the variance (not standard deviations); they have been multiplied by 100 to ensure readability.

TABLE V
STANDARD DEVIATIONS AND CORRELATIONS, BY SECTOR (UNIDO sample)

Sector	Standard deviation	Average correlation
1 Food products; Beverages; Tobacco	0.032	0.419
2 Textiles	0.037	0.463
3 Wearing apparel, except footwear	0.036	0.479
4 Leather products	0.049	0.245
5 Footwear, except rubber or plastic	0.032	0.324
6 Wood products, except furniture	0.043	0.526
7 Furniture, except metal	0.033	0.347
8 Paper and products	0.062	0.381
9 Printing and publishing	0.025	0.427
10 Industrial chemicals; Petroleum refineries; Petroleum and coal products	0.039	0.355
11 Rubber products	0.040	0.474
12 Plastic products	0.042	0.498
13 Pottery, china, earthenware; Glass; Other non-metallic mineral prod.	0.033	0.370
14 Iron and steel; Non-ferrous metals	0.072	0.332
15 Fabricated metal products; Machinery, except electrical	0.026	0.501
16 Machinery, electric	0.026	0.473
17 Transport equipment	0.043	0.413
18 Professional & scientific equipment	0.029	0.144
19 Other manufactured products	0.038	0.352

Note: The table reports the standard deviations of global sectoral shocks and the average correlation between a global sector-specific shock and the global sector-specific shocks to the remaining 18 sectors, for the UNIDO sample.

the increased concentration at higher levels of development tends to occur in relatively low-risk sectors).

Table VII presents the volatility and average correlations of the 18 sectors. Agriculture and mining and quarrying tend to be more volatile than all the manufacturing sectors, and the services sectors tend to be less volatile than manufacturing. Although the periods covered by the two samples (UNIDO and STAN-OECD) and the aggregation of manufacturing sectors are different, the volatility ranking of comparable sectors in manufacturing is roughly the same across the two samples.

IV.B. Diversification Along the Development Process

A Note on the Method. To characterize the relationship between each dimension of risk and the level of development, we use

TABLE VI
DIFFERENT DIMENSIONS OF RISK, BY COUNTRY, 1980 (STAN-OECD sample)

Country	Global sectoral risk $a'\Omega_\lambda a$ (1)	Idiosyncratic sectoral risk $\Sigma\sigma_{ij}^2 a_{ij}^2$: Total $\Sigma\sigma_{ij}^2 a_{ij}^2$ (2)	Herfindahl index of concentration Σa_{ij}^2 (2a)	Average idiosyncratic variance $(\Sigma\sigma_{ij}^2 a_{ij})/\Sigma a_{ij}^2$ (2b)	Country-specific risk ω_μ (3)	Sector–Country covariance $2a'\Omega_{\lambda\mu}$ (4)	Overall risk (5) = (1) + (2) + (3) + (4)
Australia	0.019	0.029	0.137	0.214	0.081	−0.032	0.097
Austria	0.031	0.013	0.125	0.107	0.030	−0.045	0.030
Belgium	0.017	0.015	0.142	0.105	0.079	0.042	0.153
Canada	0.017	0.015	0.151	0.100	0.061	0.027	0.122
Denmark	0.018	0.020	0.154	0.133	0.075	−0.041	0.072
Finland	0.023	0.031	0.121	0.257	0.045	0.047	0.147
France	0.019	0.010	0.130	0.083	0.037	−0.024	0.043
Italy	0.025	0.014	0.114	0.123	0.031	0.016	0.087
Japan	0.023	0.012	0.118	0.108	0.056	−0.010	0.081
Korea	0.046	0.125	0.179	0.699	0.131	0.101	0.404
Norway	0.018	0.019	0.149	0.127	0.050	−0.023	0.064
Portugal	0.030	0.034	0.130	0.264	0.087	−0.019	0.132
Spain	0.026	0.014	0.123	0.113	0.016	0.018	0.075
Sweden	0.017	0.025	0.177	0.146	0.106	0.002	0.151
United Kingdom	0.016	0.013	0.134	0.097	0.062	0.022	0.115
United States	0.016	0.007	0.173	0.041	0.053	−0.013	0.064

Note: The table reports the different components of volatility of GDP growth for the STAN-OECD sample. The formulas for the different components are derived in the text. The four measures of risk (1), (2), (3), and (4) are additive components of the variance (not standard deviations); they have been multiplied by 100 to ensure readability.

TABLE VII
STANDARD DEVIATIONS AND CORRELATIONS OF GLOBAL SHOCKS, BY SECTOR
(STAN-OECD sample)

Sector	Standard deviation	Average correlation
1 Agriculture, hunting, forestry, and fishing	0.049	0.365
2 Mining and quarrying	0.074	0.008
3 Food products, beverages, and tobacco	0.020	0.012
4 Textiles, textile products, leather, and footwear	0.021	0.282
5 Wood and cork	0.045	0.345
6 Pulp, paper, paper products	0.038	0.222
7 Chemical, rubber, plastics, and fuel products	0.034	0.247
8 Other nonmetallic mineral products	0.029	0.349
9 Basic metals and fabricated metal products	0.048	0.283
10 Machinery and equipment	0.018	0.338
11 Transport equipment	0.031	0.201
12 Other manufacturing products	0.019	0.238
13 Electricity, gas and water supply	0.030	0.007
14 Construction	0.019	0.269
15 Wholesale and retail trade; restaurants and hotels	0.018	0.431
16 Transport and storage and communication	0.015	0.319
17 Finance, insurance, real estate, and business services	0.017	0.287
18 Community social and personal services	0.011	0.271

Note: The table reports the standard deviations of global sectoral shocks and the average correlation between a global sector-specific shock and the global sector-specific shocks to the remaining 17 sectors, for the STAN-OECD sample.

a nonparametric method known as LOWESS (locally weighted scatter smooth). LOWESS elicits the shape of the relationship between two variables imposing practically no structure on the functional form. More specifically, it 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 $i = 1, \ldots, N - 1$. For each value z_i, the method calculates a smoothed value, z_i^s, obtained by running a regression of z_i on x_i using a small number of data points near this point; the regression is weighted so that the central point (x_i, z_i) receives the highest weight and points farther away get less weight.[20] The

20. 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 within the interval, x_j, with $j = i - k, \ldots, i + k$ are *tricubic:* $w_j = [1 - (|x_j - x_i|/D)^3]^3$, and $D = \max\,(x_{i+k} - x_i,\ x_i - x_{i-k})$.

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. We measure this by repeating the above LOWESS procedure, controlling for country fixed effects in each local regression.[21]

Different Dimensions of Risk in the Development Process. This section presents the relationship between the various dimensions of risk and (the log of) real GDP per capita. For each component of risk, we display the cross-country (pooled) and within-country relationship with development. The solid line shows the point estimates from LOWESS and the two dashed lines display one-standard-error bands around the LOWESS line, obtained from the bootstrap.[22] Each graph is presented on a log scale (except for COV, which may be negative) and demeaned to make the scales comparable. A reading of 0.04, for example, means that the risk measure is 4 percent higher than that of the *average* country.

UNIDO sample. The top panel in Figure IIa shows the cross-country (top left) and within-country (top right) relationships between the global sectoral risk component (GSECT) and development. Both plots uncover a negative correlation: Poorer countries specialize in sectors with higher exposure to global shocks, and, as the typical country develops, it moves towards sectors with lower exposure to global shocks. The second panel shows the corresponding relationship for the idiosyncratic sectoral risk component (ISECT). The cross-sectional evidence shows a negative

21 Note that since we restrict the variance–covariance of shocks to be constant throughout the time period, the time-series variation of our risk measures comes solely from the changing sectoral composition of the countries. In Section V we discuss an alternative specification, in which the variance of shocks is allowed to change over time, with very similar results.

22. The bootstrap procedure consists of sampling years with replacement, pooling all countries and sectors within a year. This amounts to allowing standard errors to be clustered within years. This is important because we have made no restrictions on how country and sector-specific shocks may correlate. In each iteration, we estimate the covariance matrix and calculate the risk measures. We then estimate the nonparametric relationship of the volatility components and the level of development. In iteration n, a risk measure x in country i, year t, will be $x_{it}(n)$ and the non-parametric estimate will be $f(n;\text{GDP})$. The estimated standard error is $\frac{1}{100}\sqrt{\sum_{n=1}^{100}[f(n{:}\text{GDP}) - f(\text{GDP})]^2}$.

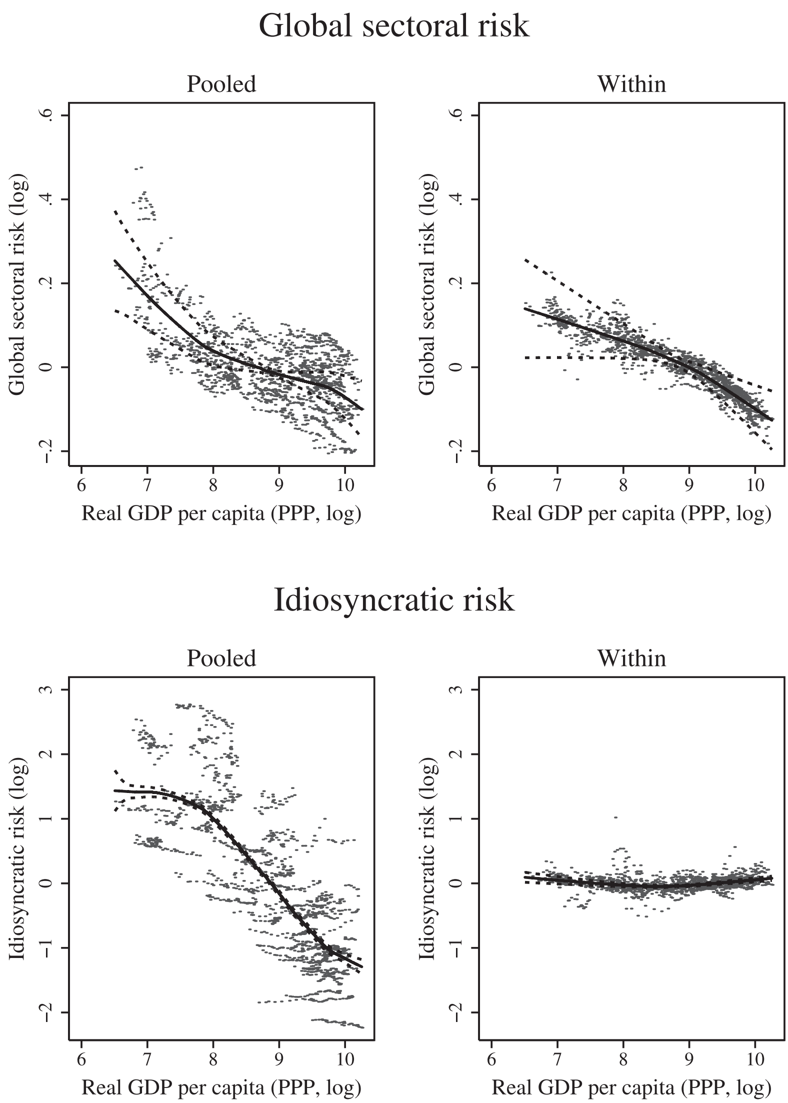
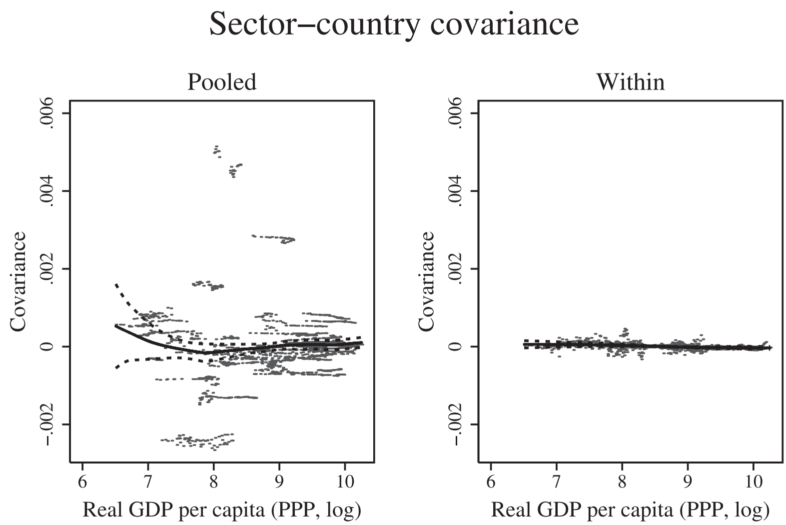


FIGURE IIa

Components of Volatility and Development (UNIDO Sample)

The global sectoral risk and idiosyncratic risk graphs show the log of the various components of volatility against the log-level of development; all components are demeaned. The sample corresponds to manufacturing sectors from UNIDO. The left and right panels show, respectively, the pooled cross-sectional and the within-country variation. Solid lines show the LOWESS estimates; dashed lines display 1-standard-error bands obtained from the bootstrap.



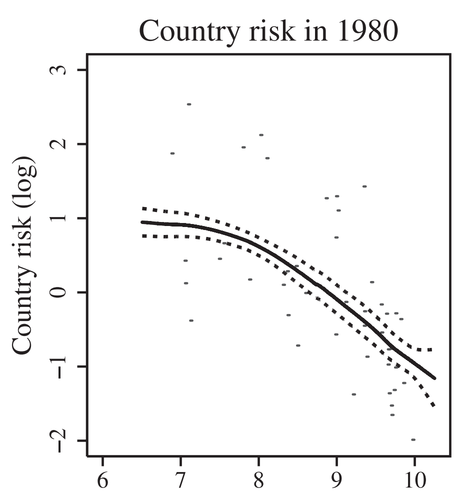


FIGURE IIb

The sector-country covariance and country risk graphs show the various components of volatility against the log-level of development. The sector-country covariance component is expressed in levels, country risk is in logs, all components are demeaned. The sample corresponds to manufacturing sectors from UNIDO. The left and right panels show, respectively, the pooled cross-sectional and the within-country variation. For the country-risk component, only the cross-sectional estimates are displayed and the level of development corresponds to 1980. Solid lines show the LOWESS estimates: dashed lines display 1-standard-error bands obtained from the bootstrap.

association between this component of risk and development. In particular, rich countries feature the lowest levels of idiosyncratic sectoral risk in absolute terms. The within-country relationship is flat, suggesting that, for a given country, development does not alter the idiosyncratic component of volatility. The top panel of Figure IIb displays the plots for the covariance between sector- and country-specific shocks (COV) along the development process. While there is considerable variability in the covariances, the cross-sectional and the within country evidence indicates no systematic relationship with the level of development. Finally, the relationship between country-specific risk and the level of development is displayed in the bottom panel. Recall that, by construction, there is no within-country variation over time for this dimension of risk, hence we only plot the data corresponding to a single cross-section. The evidence points to a negative relationship, indicating that countries at higher levels of development enjoy higher macroeconomic stability, which could be the result of lower political risk and better conduct of fiscal and monetary policies, among other factors.

Figure III further decomposes ISECT into the Herfindahl index of concentration (top panel) and the average idiosyncratic variance (bottom panel). The plots show a decline in concentration at low levels of income, which flattens out at medium levels of income and starts increasing again at higher levels. The relationship between the extent of concentration and development has been recently studied by Imbs and Wacziarg [2003], who reported a U-shape relationship as the one displayed in these plots. The average variance declines with development in the cross-section and is flat in the within-country plot, suggesting that the pattern of relationship between ISECT and development is overwhelmingly driven by the behavior of the idiosyncratic variance, rather than by the level of concentration.

Putting all pieces together, Figures II and III show that countries at early stages of development tend to concentrate heavily on relatively high-risk sectors. With development, production shifts towards lower-risk sectors, causing a decrease in both global and idiosyncratic sectoral risks together with a decrease in concentration. At later stages, while global and idiosyncratic sectoral risks continue to decline with development, concentration flattens out and even reverses to higher levels at sufficiently large values of per capita GDP. The higher levels of

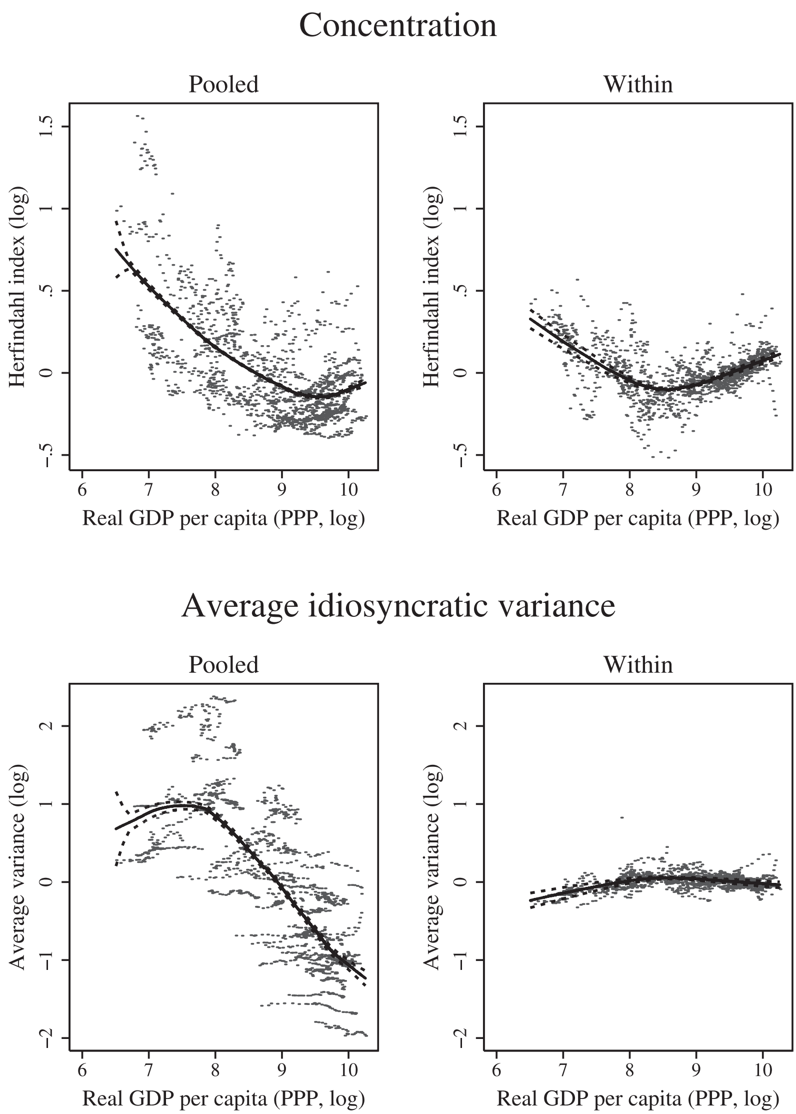


FIGURE III

Idiosyncratic Risk: Concentration and Volatility (UNIDO Sample)

The graphs plot, correspondingly, the log of the Herfindahl index of concentration and the log of the average idiosyncratic variance against the log-level of development (both components are demeaned). The estimates are based on manufacturing sectoral data from UNIDO. The left and right panels show, respectively, the pooled cross-sectional and the within-country variation. Solid lines show the LOWESS estimates: dashed lines display 1-standard-error bands obtained from the bootstrap.

concentration at later stages of development tend to fall into sectors with lower levels of intrinsic volatility.

STAN-OECD sample. The empirical regularities documented for the UNIDO sample, in particular the decline in the two measures of sectoral risk (GSECT and ISECT) with the level of development, are exacerbated when one takes into account agriculture, mining, and services in the analysis. This is illustrated in Figure IVa. The top panel displays the global sectoral risk component against development (both the cross-sectional and within-country relationships), and the second panel displays the corresponding graphs for the idiosyncratic sectoral risk component.

The reason for the strong decline in the sectoral risk components is that the employment shares of agriculture and mining, which exhibit relatively higher intrinsic volatility, sharply decline with the level of development (standard deviations of shocks are 5 and 7 percent in agriculture and mining, respectively). The share of services, which are relatively low-risk (with standard deviations below 2 percent), tends to increase with development. In terms of volatility, manufacturing is in between these two groups, with standard deviations within the range of 2–4 percent. This leads to a marked decline in sectoral risk as countries shift the composition of the economy from agriculture to manufacturing to services.[23] The covariance and country risk components, shown in the top and bottom panels of Figure IVb, also display declining patterns with respect to development, although standard error bands are large for these components.

Finally, Figure V shows the decomposition of the idiosyncratic risk (ISECT) into the Herfindahl index and the average idiosyncratic variance. The Herfindahl index shows the U-shaped pattern commented before; since the sample mainly shows high-income countries, the plots have a larger mass of countries in the increasing part; finally, the average variance declines with the level of development and indeed this is the driving element in the overall decline of ISECT.

23. Previous studies of structural transformation in the development process have emphasized the shift from low to high productivity sectors. (See for example Caselli and Coleman [2001] and the references therein.) Our results indicate that the structural transformation process is also characterized by a shift from high to low volatility sectors.

IV.C. Volatility Accounting

Poor countries are more volatile because they exhibit higher levels of (i) global sectoral risk (GSECT), (ii) idiosyncratic sectoral risk (ISECT) (both because of higher concentration and higher idiosyncratic variance), and (iii) country-specific risk. The covariance term, while showing nonnegligible dispersion, is not systematically related to the level of development. In the volatility accounting exercise that follows, we hence focus on the first three components.[24]

The question we ask is, What fraction of the difference in volatility between poor and rich countries can be quantitatively accounted for by differences in each of the sources of volatility? Or, perhaps more relevant from a policy point of view: What fraction of the difference in volatility is due to the sectoral composition of the economy as opposed to aggregate domestic risk?

To do this, we compute the differences between the various components of risk for the countries in the top five percentile of income (rich) and bottom five percentile (poor) in the UNIDO sample. We then express them as a proportion of the corresponding difference in total volatility.[25] Hence, the contribution of country-specific risk (CTY) to the difference in volatility between poor and rich countries is

$$\mathrm{CTY}^{\mathrm{share}} = \frac{\mathrm{CTY}^{\mathrm{poor}} - \mathrm{CTY}^{\mathrm{rich}}}{\mathrm{Var}\,(q^{\mathrm{poor}}) - \mathrm{Var}\,(q^{\mathrm{rich}})} = 46\%.$$

The remaining 54 percent of the difference in volatility is due to the sectoral composition of the economy. This in turn is decomposed in the part due to pure concentration, which accounts for 6 percent of the total difference, and the part due to sectoral risk, which makes up the remaining 48 percent (7 percent due to global sectoral risk and 41 percent due to idiosyncratic sectoral risk).

For the STAN-OECD sample, the breakdown yields a contribution of 40 percent for country risk; the remaining 60 percent is

24. One possibility for the accounting exercise is to add the covariance term to the country-specific component, since the first does not follow any systematic pattern with respect to development. In particular, if one interprets the covariance term as the domestic-policy response to sectoral shocks, the covariance would be inextricably linked to the measure of country-risk. We follow this path here, but invite interested readers to try other alternatives.

25. For the OECD-STAN data base, rather than the 95–5 percentiles, we take an average of the risk measures for the two highest-income and the two lowest-income countries and compute the contribution of the various components to the difference in volatility in similar fashion.

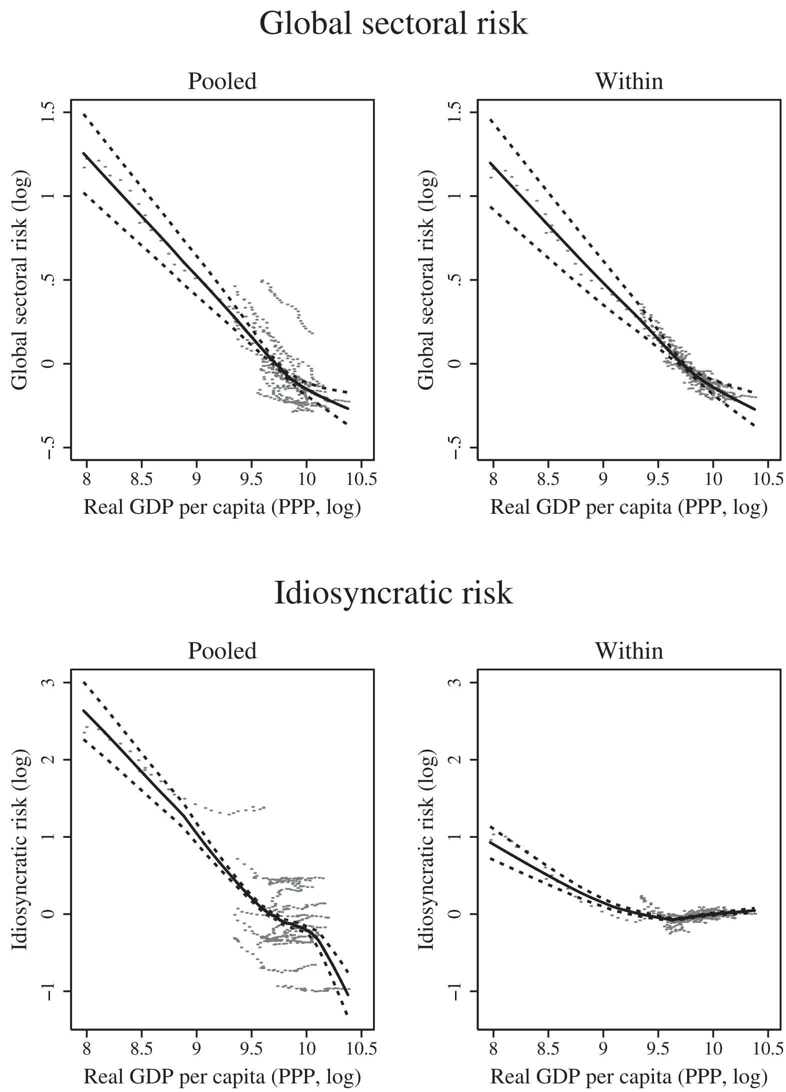
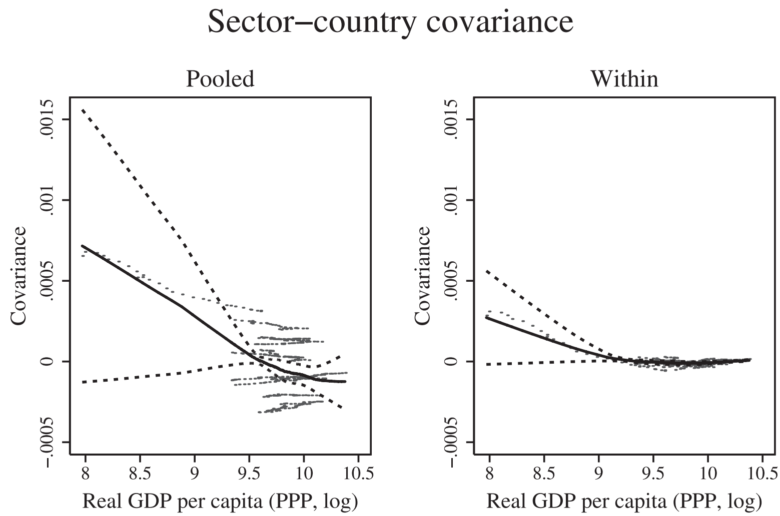


FIGURE IVa

Components of Volatility and Development (OECD Sample)

The global sectoral risk and idiosyncratic risk graphs show the log of the various components of volatility against the log-level of development; all components are demeaned. The estimates are based on sectoral data from STAN-OECD. The left and right panels show, respectively, the pooled cross-sectional and the within-country variation. Solid lines show the LOWESS estimates; dashed lines display 1-standard-error bands obtained from the bootstrap.



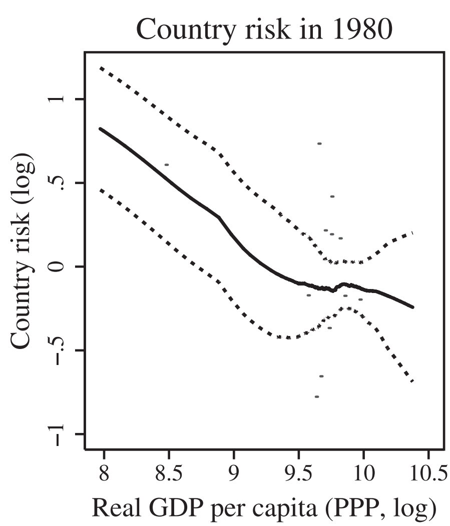


FIGURE IVb

The graphs show the log of the various components of volatility against the log-level of development. The sector-country covariance component is expressed in levels, country risk is in logs, all components are demeaned. The estimates are based on sectoral data from STAN-OECD. The left and right panels show, respectively, the pooled cross-sectional and the within-country variation. For the country-risk component, only the cross-sectional estimates are displayed and the level of development corresponds to 1980. Solid lines show the LOWESS estimates; dashed lines display 1-standard-error bands obtained from the bootstrap.

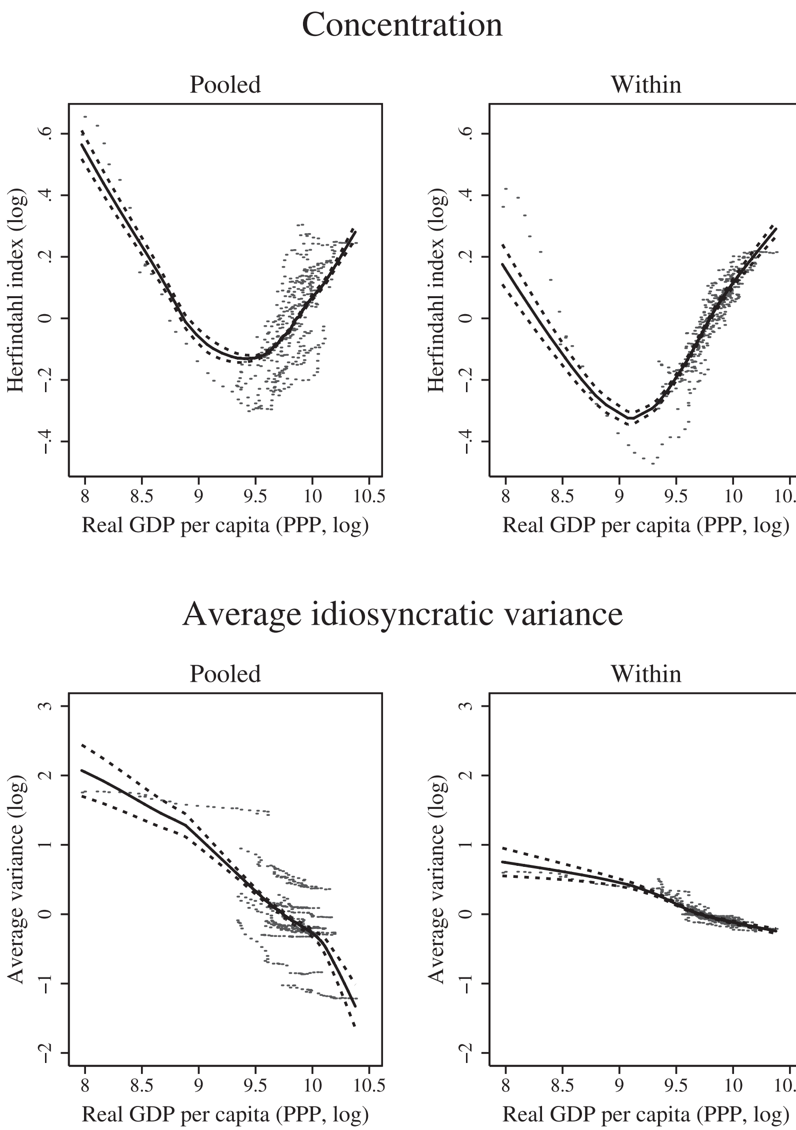


FIGURE V

Idiosyncratic Risk: Concentration and Volatility (UNIDO Sample)

The graphs plot, correspondingly, the log of the Herfindahl index of concentration and the log of the average idiosyncratic variance against the log-level of development (both components are demeaned). The estimates are based on sectoral data from STAN-OECD. The left and right panels show, respectively, the pooled cross-sectional and the within-country variation. Solid lines show the LOWESS estimates; dashed lines display 1-standard-error bands obtained from the bootstrap.

due to differences in sectoral composition: the global sectoral component accounts for 20 percent of the difference and the idiosyncratic sectoral risk component accounts for 40 percent (all of which is due to differences in the idiosyncratic variance).[26]

All components of volatility account for a nonnegligible share of the differences in total volatility. In particular, the sectoral composition of a country, accounts for roughly 54 percent of the difference (somewhat more in the STAN-OECD sample), underscoring the usefulness of studying the sectoral composition of the economy. Moreover, the volatility-accounting exercise also highlights the huge role of aggregate domestic risk in explaining the differences in volatility between poor and rich countries.

V. Robustness and Extensions

In the interest of space, we do not report the results referred to in this section; they are available at request from the authors.

Sensitivity of sectoral risk measures to sectoral classifications. As mentioned before, although the Herfindahl index of sectoral risk is sensitive to the aggregation and definition of sectors, the theoretical sectoral risk components (global and idiosyncratic) are invariant to changes in classification. To see this, suppose there are 3 sectors, with labor shares $\{a_1,a_2,a_3\}$, and idiosyncratic variances $\{\sigma_1^2,\sigma_2^2,\sigma_3^2\}$. (It is straightforward to extend the proof for $S > 3$ sectors.) The Herfindahl index of concentration is $\Sigma_{s=1}^3\ a_s^2$. The idiosyncratic sectoral risk component is $\Sigma_{s=1}^3\ \sigma_s^2 a_s^2$. The thought experiment we carry out consists of aggregating the first two sectors into one. The concentration index becomes

$$\mathrm{HERF} = (a_1 + a_2)^2 + a_3^2 = 2a_1a_2 + \sum_{s=1}^{3} a_s^2,$$

which is different from the previous expression.

The new sector's idiosyncratic productivity shock is given by $\varepsilon_{1+2} = [a_1/(a_1 + a_2)]\varepsilon_1 + [a_2/(a_1 + a_2)]\varepsilon_2$. Under the null hypothesis that ε_1 and ε_2 are uncorrelated, the idiosyncratic

26. Of the 40 percent corresponding to the idiosyncratic sectoral risk, 44 percent is due to difference in idiosyncratic variances. The Herfindahl index of concentration contributes (slightly) negatively to the difference in volatility between rich and poor countries. This reflects the fact that at higher levels of development, concentration increases with development. The contribution is a negative 4 percent.

variance of the new sector is $\sigma^2_{1+2} = [a_1/(a_1 + a_2)]^2\sigma^2_1 + [a_2/(a_1 + a_2)]^2\sigma^2_2$. The labor share in the new sector is $(a_1 + a_2)$, and so the idiosyncratic sectoral risk component is

$$\text{ISECT} = (a_1 + a_2)^2\sigma^2_{1+2} + \sigma^2_3 a^2_3$$
$$= (a_1+a_2)^2\left[\left(\frac{a_1}{a_1+a_2}\right)^2\sigma^2_1 + \left(\frac{a_2}{a_1+a_2}\right)^2\sigma^2_2\right] + \sigma^2_3 a^2_3 = \sum_{s=1}^{3} \sigma^2_s a^2_s,$$

identical to the initial expression; that is, this component is robust to reclassifications.

To show the invariance to classification of the *global sectoral risk* component, we denote the global sectoral variances by s_{11}, s_{22}, and s_{33}; and covariances $s_{ij} = s_{ji}$, for $j \neq i$. The global sectoral risk component is then:

$$\text{GSECT} = a^2_1 s_{11} + a^2_2 s_{22} + a^2_3 s^2_3 + 2a_1a_2s_{1,2} + 2a_1a_3s_{13} + 2a_2a_3s_{23}$$

Suppose we aggregate sectors 1 and 2 as before. The new sector-specific global productivity shock is $\lambda_{1+2} = \frac{a_1}{a_1 + a_2}\lambda_1 + \frac{a_2}{a_1 + a_2}\lambda_2$. The variance of the new sector is $s_{1+2,1+2} = \left(\frac{a_1}{a_1 + a_2}\right)^2 s_{11} + \left(\frac{a_2}{a_1 + a_2}\right)^2 s_{22} + 2\frac{a_1a_2}{(a_1 + a_2)^2} s_{12}$. The covariance between the productivity shock of the new sector λ_{1+2} and the productivity shock of the third sector λ_3 is $s_{1+2,3} = \frac{a_1}{a_1 + a_2} s_{13} + \frac{a_2}{a_1 + a_2} s_{23}$. The labor share in the new sector is $(a_1 + a_2)$, so the global sectoral risk component is:

$$(a_1 + a_2)^2 s_{1+2,1+2} + a^2_3 s_{33} + 2(a_1 + a_2)a_3 s_{1+2,3}$$
$$= a^2_1 s_{11} + a^2_2 s_{22} + 2a_1a_2s_{2,1} + a^2_3 s_{33} + 2a_1a_3s_{1,3} + 2a_2a_3s_{2,3},$$

exactly identical to the measure of Global Sectoral Risk under the previous sectoral classification.

We also note that, while the theoretical measures of sectoral risk are insensitive to reclassification, in finite samples, because the elements of the variance–covariance matrices are estimated (the empirical counterparts of σ^2_i, s^2_{ii}, and s_{ij}), the estimated measures of risk, may be affected by classification. As an attempt to assess the importance of finite sample differences, we have repeated our analysis on new data sets obtained by aggregating sectors in our original data. In particular, for the UNIDO and STAN-OECD data sets, we looked at the following alternative groupings: (1) all sectors aggregated into 3 broad sectors, and (2) 10 sectors, grouped into what we thought reasonably comparable categories in terms of the similarity of output (e.g., textiles is grouped with apparel, etc.).

Overall, our findings are very robust to these experiments. The relationship between the various components of risk and income per capita are very close to our baseline results. We observe, as expected, some differences in the Herfindahl index of concentration. In the UNIDO sample, when we aggregate the data into 3 broad sectors, the concentration index appears to decline with development, without displaying an increase at later stages of development (although the relationship becomes flatter at later stages). Similarly, when we aggregate sectors in the STAN-OECD sample, the Herfindahl-development relationship becomes less clearly U-shaped: the relationship is considerably flatter at early stages.

These results led us to emphasize the decomposition into the four components (8), (9), (10), and (11), and to put less emphasis on the specific patterns of sectoral concentration.

Are residual shocks idiosyncratic? Throughout the paper, we have maintained the working hypothesis that the residuals (ε_{js}) are idiosyncratic, that is, they are uncorrelated with each other and with country- and sector-specific shocks, and hence we have ignored Γ_j in (3). The question is how much is missed by ignoring this term. Not much. The correlation between the actual variance Var (q_j) and the sum of the four components we account for, $[\mathbf{a}_j'\Omega_\lambda\mathbf{a}_j + \mathbf{a}_j'\Omega_{\varepsilon_j}\mathbf{a}_j + \omega_{\mu_j}^2 + 2(\mathbf{a}_j'\Omega_{\lambda\mu_j})]$ is 0.92 (0.95 if looking at log-variances) in the UNIDO sample and 0.83 (0.84 for log-variances) in the STAN-OECD sample. Finally, and perhaps more importantly for the assessment of theories, the term $\mathbf{a}_j'\Gamma_j\mathbf{a}_j$,

$$\mathbf{a}_j'\Gamma_j\mathbf{a}_j = \mathrm{Var}\ (q_j) - [\mathbf{a}_j'\Omega_\lambda\mathbf{a}_j + \mathbf{a}_j'\Omega_{\varepsilon_j}\mathbf{a}_j + \omega_{\mu_j}^2 + 2(\mathbf{a}_j'\Omega_{\lambda\mu_j})], \tag{12}$$

is uncorrelated with the level of development.

An alternative factor model. We have proposed partition (1) as our baseline break-down of the data. Shocks to the growth of value-added in a sector are due to a sector-specific innovation, a country-specific innovation, and a country-sector-specific innovation. In this specification, if a country-specific shock, μ_j, has a different impact depending on the sector, the differential impact is reflected in the country-sector specific disturbance, ε_{js}. Similarly, if a global-sectoral shock has a different impact depending on the country, that is reflected in ε_{js}. We could, however, have adopted a different way of capturing the differential effects (by sector) of country shocks and (by country) of global sectoral shocks. In particular, an alternative way of breaking-down the data would be

$$y_{js} = B_j\lambda_s + b_s\mu_j + \varepsilon_{js}, \tag{13}$$

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). Writing this factor model in vector notation,

$$\mathbf{y}_j = B_j\lambda + \mu_j\mathbf{b} + \varepsilon_j, \tag{14}$$

implies the following variance decomposition,[27]

$$\tilde{\mathrm{E}}(\mathbf{y}_j\mathbf{y}_j') = B_j^2\Omega_\lambda + \omega_{\mu_j}^2\mathbf{bb'} + (B_j\Omega_{\lambda\mu_j}\mathbf{b'} + B_j\mathbf{b}\Omega_{\lambda\mu_j}') + \Omega_{\varepsilon_j}. \tag{15}$$

Our modified risk measures are thus

$$\widetilde{\mathrm{GSECT}}_{jt} = B_j^2\mathbf{a}_{jt}'\Omega_\lambda\mathbf{a}_{jt} \tag{16}$$

$$\widetilde{\mathrm{ISECT}}_{jt} = \mathbf{a}_{jt}'\Omega_{\varepsilon_j}\mathbf{a}_{jt} \tag{17}$$

$$\widetilde{\mathrm{CNT}}_j = \omega_{\mu j}^2(\mathbf{a}_{jt}'\mathbf{b})^2 \tag{18}$$

$$\widetilde{\mathrm{COV}}_{jt} = 2\mathbf{a}_{jt}'B_j\mathbf{b}\Omega_{\lambda\mu_j}' \tag{19}$$

We estimated the exposures to shocks by running time-series OLS regressions of innovations in the growth rate of value-added per worker on the predicted shocks realizations estimated in Section II.B. 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 the new risk measures exhibit fairly similar patterns to those generated by the baseline model, both across countries and within countries. The main reason for this is that

27. Ignoring, as we did before, the term Γ_j.

the estimated exposures are close to one for most sectors and countries. This suggests that the sectoral structure already captures the bulk of exposure to global shocks. The similarity of the results in the two different factor models should perhaps not be surprising. The differential exposures were previously captured in the residual term ε_{js}. As mentioned, the term Γ_j, capturing the correlations between ε_{js} and μ_j and between ε_{js} and λ_s, played a small quantitative role. Note that since our benchmark factor model lets global shocks vary sector by sector, it already incorporates some heterogeneity in the global exposure of countries, the sensitivity to global shocks being determined by the sectoral structure of the economy.[28]

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). To check whether our risk measures mask different patterns over time, we split the UNIDO sample into two subperiods, before and after 1980, and apply the factor-model procedure to these two subsamples (we cannot do this for the STAN-OECD sample given the shorter time span for these data). We find that there has been, on average, a decline in both sectoral and country volatility in the post 1980 period. Surprisingly, the qualitative patterns do not change. The decline in volatility occurred broadly across all sectors, and the volatility ranking of sectors in the two subperiods shows only minor differences. The data show that on average sectoral volatility is lower in the post-1980 period and, as before, countries tend to move to less risky sectors with development.

We plotted the different measures of risk against development, as we did before, by allowing the variance–covariance matrices to be different in the two subperiods, and using the actual employment shares. This exercise shows an even steeper decline in the global sectoral risk component with respect to the level of development. Country-specific risk has also changed over time, and the declining relationship with respect to development is preserved in the two subsamples. Finally, the Herfindahl index does not show significant changes across the two subsamples.

We conclude from this exercise that while there have been

28. Factor models working with aggregates can only capture this variation if they *assume* differential global exposure of countries.

changes in the underlying measures of risk, they lead to a consistent decline in both sectoral and country risk.

Allowing for differences between developing and developed countries. In our analysis, the underlying global shocks to a given sector are assumed to be identical across countries. One concern, however, is that shocks to sectors in developing countries might be different from the corresponding ones in developed countries. To address this point, we relax the restriction in the baseline model, by allowing sectoral shocks to be different between developing and developed countries. To do so, we split the UNIDO 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.[29]

After controlling for country-effects, we estimate the global sector-specific factors in each of the two subsamples.[30] We then compute the standard deviations of each sector in the two subsamples. 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 standard deviations is above 0.80 (similarly, the ranking of cross-sectoral correlations is unchanged). This indicates that our initial estimates capture the global shocks to the sector fairly well. Moreover, the estimated global sectoral risk (GSECT) measure does not appear to be sensitive to whether we extract global shocks from the poorer or richer half of the sample. In other words, using developed countries' variance–covariance of sectoral shocks together with developing countries' employment shares leads to similar results. The correlation between GSECT based on developed countries' variance–covariance and GSECT based on developing countries' variance–covariance matrix of sectoral shocks (together with the actual employment shares) is 0.84.

This exercise suggests that our benchmark model captures global sectoral shocks considerably well, and little is gained by allowing for differences between developing and developed countries.

29. We cannot do this for the STAN-OECD dataset, given the size of the sample.

30. As before, they are estimated as the cross-country average of innovations in the growth rate of value-added per worker in each of the sectors.

Allowing for differences between low-trade and high-trade, financially open and closed countries, small and large. One natural question is whether global sectoral shocks have the same impact regardless of the level of openness and the size of the country. This was addressed in a general way before, by allowing countries to have different exposure to global sectoral shocks. However, we can double check our previous conclusions by following a procedure similar to the one described before. We hence split the UNIDO sample into two groups, according to a given measure of openness or size, and compute the sector-specific factors for each of the two subsamples, after controlling for country effects. We use the following two measures of openness. The first, trade openness, measured as exports plus imports divided by GDP in 1980 from the Penn World Tables (`openc`). The cross-sectoral correlation of the sectoral standard deviations between low-trade and high-trade countries was remarkably high (0.86) and the ranking of sectors according to standard deviations is very similar for the two subsamples. The corresponding cross-country correlation of the GSECT measures using the two variance–covariance matrices (with actual employment shares) is 0.84. 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. The second measure we use is financial openness, measured as a dummy with value 1 if the country was financially open in 1980.[31] The ranking of sectors by standard deviation, is, again, remarkably similar; the correlation of standard deviations of sectoral shocks between the two subsamples is 0.90. The corresponding cross-country correlation of the two GSECT measures is 0.73.[32]

As for size, we 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 0.77; the split between small and large countries hence does not point to a significant depar-

31. The data on financial liberalization dates comes from Kaminsky and Schmukler [1999].

32. We note that this result is somewhat sensitive to the date at which we measure financial openness. If we split the sample according to their financial openness in 1990, the corresponding correlations are 0.59 and 0.64. This might be in part due to sample size: very few countries in our sample classify as financially closed in 1990.

ture from the benchmark specification. The corresponding cross-country correlation of the two GSECT measures is 0.88.

VI. Concluding Remarks

Why is GDP growth so much more volatile in poor countries than in rich ones? The volatility-accounting analysis indicates that poor countries specialize in more volatile sectors (explaining roughly 50 percent of the differences in volatility) and they experience more frequent and more severe aggregate shocks (explaining the other 50 percent).

The various components of risk display the following regularities. First, global and idiosyncratic sectoral risk decrease with the level of development, that is, production tends to shift towards less risky sectors. Second, sectoral concentration first decreases with respect to development until it reaches a critical point at which it starts increasing with development. Thus, the high concentration at early stages of development typically falls in high-risk sectors, which compounds the exposure to risk at early stages. 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.

We argue that many theories linking volatility, diversification, and development are at odds with some of these findings. In particular, an important body of the theoretical literature predicts a move from sectors with low intrinsic volatility towards sectors with high intrinsic volatility as countries develop, a prediction contradicted by the evidence. This theoretical prediction results from the focus on *financial* diversification as the mechanism through which volatility declines with development. In Koren and Tenreyro [2006] we present an alternative theory linking volatility and development that emphasizes the role of *technological* diversification. The key idea is that sectors (or firms) using a larger variety of inputs can mitigate the impact of shocks affecting the productivity of individual inputs. This takes place through two channels. First, with a larger variety of inputs, each individual input matters less in production, and productivity becomes less volatile by the law of large numbers. Second, whenever a shock hits a particular input, firms can adjust the use of the other inputs to partially offset the shock. The model hence predicts that sectors that use a larger variety of inputs (or are more intensive in the use of sophisticated skills and technologies) also exhibit lower volatility. This setup ultimately calls for a theory of what prevents countries from adopting more complex technologies.

Appendix I: Derivation of the Variance–Covariance Decomposition

We are interested in the expected value of $\mathbf{y}_j\mathbf{y}_j'$, where

$$\mathbf{y}_j = \lambda + \mu_j\mathbf{1} + \varepsilon_j$$

Multiplying this vector by its transpose, we get

$$\begin{aligned}(20)\quad \mathbf{y}_j\mathbf{y}_j' &= (\lambda + \mu_j\mathbf{1} + \varepsilon_j)\lambda' + \mu_j\mathbf{1}' + \varepsilon_j') \\ &= \lambda\lambda' + \mu_j^2\mathbf{1}\mathbf{1}' + \mu_j\lambda\mathbf{1}' + \mu_j\mathbf{1}\lambda' + \varepsilon_j\varepsilon_j' + \lambda\varepsilon_j' + \varepsilon_j\lambda' + \mu_j(\mathbf{1}\varepsilon_j' + \varepsilon_j\mathbf{1}')\end{aligned}$$

The term $\varepsilon_j\varepsilon_j'$ can in turn be decomposed as the sum of a diagonal matrix with elements ε_{js}^2 and a matrix containing the cross-products, $\varepsilon_{js}\varepsilon_{js'}$ for $s \neq s'$ that is

$$\varepsilon_j\varepsilon_j' = \text{diag}\,(\varepsilon_{j1}^2 \ . \ . \ . \ \varepsilon_{jS}^2) + \text{crossprod}\,(\varepsilon_{js}), \text{ where}$$

$$\text{diag}\,(\varepsilon_{j1}^2, \ . \ . \ . \ , \ \varepsilon_{jS}^2) = \begin{bmatrix} \varepsilon_{j1}^2 & 0 & \cdots & 0 \\ 0 & \varepsilon_{j2}^2 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \varepsilon_{jS}^2 \end{bmatrix} \text{ and}$$

$$\text{crossprod}\,(\varepsilon_{js}) = \begin{bmatrix} 0 & \varepsilon_{j1}\varepsilon_{j2} & \cdots & \varepsilon_{j1}\varepsilon_{jS} \\ \varepsilon_{j2}\varepsilon_{j1} & 0 & \cdots & \varepsilon_{jS}\varepsilon_{j1} \\ \cdots & \cdots & \cdots & \cdots \\ \varepsilon_{jS}\varepsilon_{j1} & \varepsilon_{jS}\varepsilon_{j2} & \cdots & 0 \end{bmatrix}$$

Taking expectations in (20) and introducing some notation,

$$\begin{aligned}\Omega_\lambda &= \mathrm{E}[(\lambda\lambda'), \\ \Omega_{\varepsilon_j} &= \text{diag}\,(\sigma_{j1}^2 \ . \ . \ . \ \sigma_{jS}^2), \\ \omega_{\mu_j}^2 &= \mathrm{E}(\mu_j^2), \\ \Omega_{\lambda\mu_j} &= \mathrm{E}(\lambda\mu_j), \\ \Gamma_j &= \mathrm{E}[\lambda\varepsilon_j' + \varepsilon_j\lambda' + \mu_j(\mathbf{1}\varepsilon_j' + \varepsilon_j\mathbf{1}') + cp(\varepsilon_{js})]\end{aligned}$$

we obtain

$$\mathbf{y}_j\mathbf{y}_j' = \Omega_\lambda + \Omega_{\varepsilon_j} + \omega_{\mu_j}^2\mathbf{1}\mathbf{1}' + (\Omega_{\lambda\mu_j}\mathbf{1}' + \mathbf{1}\Omega_{\lambda\mu_j}') + \Gamma_j.$$

Appendix II: Cross-Sectional Dummy Regression and Sample Means

This appendix proves the equivalence between the cross-sectional mean estimator (6) discussed in Section II.B. and the cross-sectional dummy regression estimator (7).

The coefficients obtained from the regression of labor productivity on sector and country dummies solve the following least-square-error problem:

$$\min_{\lambda,\mu}\left[\mathbf{Y}-\mathbf{D}\begin{pmatrix}\lambda\\ \mu\end{pmatrix}\right]^2$$
$$\text{s.t. } \mathbf{1}'_J\mu = 0,$$

where $\mathbf{Y}$ is the $JS \times 1$ vector of shocks to labor productivity (containing the S sectors of country 1 above the S sectors of country 2 etc.) and $\mathbf{D}$ is the $JS \times (S + J)$ matrix of S sector and J country dummies.

Note that we want to express country shocks relative to the world average; hence, we subtract $1/J$ from all of the country dummies. Writing out $\mathbf{D}$,

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & \cdots & 1-1/J & -1/J & \cdots \\ 0 & 1 & \cdots & 1-1/J & -1/J & \cdots \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 1 & 0 & \cdots & -1/J & 1-1/J & \cdots \\ 0 & 1 & \cdots & -1/J & 1-1/J & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$
$$= \left[\mathbf{1}_J \otimes \mathbf{I}_S \;\; \left(\mathbf{I}_J - \frac{1}{J}\mathbf{1}_J\mathbf{1}'_J\right) \otimes \mathbf{1}_S\right].$$

The full set of dummies is perfectly collinear (the sum of the last J columns is zero), and so it is not possible to identify all the coefficients independently. This is why we introduce the additional constraint that country coefficients sum to zero, $\mathbf{1}'_J\mu = 0$. The first-order conditions hence require

$$\mathbf{D}'\mathbf{D}\begin{pmatrix}\lambda\\ \mu\end{pmatrix} = \mathbf{D}'\mathbf{Y}, \text{ and} \tag{21}$$

$$\mathbf{1}'_J\mu = 0. \tag{22}$$

In what follows, we verify that (21) and (22) hold for $\hat{\lambda}$ and $\hat{\mu}$ defined in (6).

Let $l = \Sigma_j \, \mathbf{y}_j$ denote the $S \times 1$ vector of the sum of shocks across countries, m denote the $J \times 1$ vector of the sum of shocks across sectors within a country, with elements $\Sigma_s \, y_{js}$, and $g = \mathbf{1}'l$ denote the overall sum of shocks, across countries, and sectors. It is easy to see from (6) that $\hat{\lambda} = l/J$ and $\hat{\mu} = m/S - \mathbf{1}g/(JS)$.

$$\mathbf{D}'\mathbf{Y} = \begin{pmatrix} l \\ m - \frac{1}{J}\mathbf{1}g \end{pmatrix}$$

$$\mathbf{D}'\mathbf{D} = \begin{bmatrix} J\mathbf{I}_s & 0 \\ 0 & S\left(\mathbf{I}_J - \frac{1}{J}\mathbf{1}_J\mathbf{1}_J'\right) \end{bmatrix}$$

Hence,

$$\mathbf{D}'\mathbf{D}\begin{pmatrix} \hat{\lambda} \\ \hat{\mu} \end{pmatrix} = \begin{pmatrix} l \\ m - \frac{1}{J}\mathbf{1}_g \end{pmatrix}$$

as required. It is easy to verify that $\hat{\mu}$ sums to zero, and so it also satisfies the other identification assumption.

This means that $\hat{\lambda}$ and $\hat{\mu}$ will be equal to the coefficients on the sectoral and country dummies (relative to the cross-country average), respectively.

Appendix III: 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:

$$\hat{\lambda} = \lambda + \frac{1}{J}\sum_{i=1}^{J} \varepsilon_i, \tag{23}$$

$$\hat{\mu}_j = \mu_j + \frac{1}{S}\left[\frac{J-1}{J}\sum_{s=1}^{S} \varepsilon_{js} - \frac{1}{J}\sum_{s=1}^{S}\sum_{i \neq j} \varepsilon_{is}\right] \tag{24}$$

Then the second moments of these estimated factors are

$$\text{(25)} \qquad \begin{aligned} E(\hat{\lambda}\hat{\lambda}') &= \Omega_{\lambda} + \frac{\sigma^2}{J}\mathbf{I}, \\ E(\hat{\lambda}\hat{\mu}_j) &= \Omega_{\lambda\mu_j} \\ E(\hat{\mu}_j^2) &= \omega_{\mu_j}^2 + \frac{J-1}{SJ}\sigma^2. \end{aligned}$$

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). In the benchmark analysis, there are 45 countries and 19 sectors in the data, and the estimated factors are close the true factors.

To assess the bias more precisely, take the median idiosyncratic variance, $\sigma^2 = 0.008$. The bias in the sectoral covariance matrix ($\hat{\Omega}_{\lambda}$) is $\sigma^2/J \approx 0.00016$. Our measure of global sectoral risk would then increase by $a_j'(\sigma^2 I/J)a_j$, approximately 0.000017. This is a negligible fraction of even the lowest level of sectoral risk. For country risk, the bias would be of order 0.00041. This is about 5 percent of the average country risk, and so our measure of country risk is somewhat biased upwards. Note that there is no bias in the covariance term.

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