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Volatility and Development

Miklós Koren and Silvana Tenreyro

Abstract

Why is GDP growth so much more volatile in poor countries than in rich ones? We identify four possible reasons: (i) poor countries specialize in more volatile sectors; (ii) poor countries specialize in fewer sectors; (iii) poor countries experience more frequent and more severe aggregate shocks (e.g. from macroeconomic policy); and (iv) poor countries' macroeconomic fluctuations are more highly correlated with the shocks of the sectors they specialize in. We show how to decompose volatility into these four 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 level of specialization declines with development at early stages, and slowly increases at later stages of development. Third, the volatility of country-specific macroeconomic shocks falls with development. Fourth, the covariance between sector-specific and country-specific shocks does not vary systematically with the level of development. We argue that many theories linking volatility and development are not consistent with these findings and suggest new directions for future theoretical work.

Keywords: volatility, specialization, diversification, development, economic fluctuations.

JEL Classifications: O11, O14, E32

Data: World Bank Development Indicators, UNIDO CDRM

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Miklós Koren can be contacted at the Federal Reserve Bank of New York. E-mail: miklos.koren@ny.frb.org. Silvana Tenreyro is an Associate of the Macro programme at the Centre for Economic Performance, London School of Economics and Political Science. Contact email: s.tenreyro@lse.ac.uk.

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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 1, 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 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 four 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 the degree of specialization: an economy whose productive structure is highly concentrated in few sectors will tend to be more risk prone. The third component relates to aggregate country-specific shocks: some countries are subject to greater policy and political instability. The fourth 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 as the sum of these four components.

The breakdown of volatility into these four components 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., excessive 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 Second, sectoral concentration sharply 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 60 percent of the differences in volatility between poor and rich countries can be accounted for by differences in country-specific volatility, whereas the remaining 40 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 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 a 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) and Saint-Paul (1992)) or implicitly (e.g., Acemoglu and Zilibotti (1997) and Greenwood and Jovanovic (1990)) take a “portfolio choice” view: high sectoral productivity comes at the cost of higher risk. This view is inconsistent with the empirical lack of trade-off between volatility and productivity levels in sectoral data.³

¹In the analysis we distinguish between global sectoral shocks, which are common to all countries, and idiosyncratic sectoral shocks, which differ across countries. Both dimensions of sectoral risk decrease monotonically with the level of development.

²Acemoglu 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.

³A different view is taken by Kraay and Ventura (2001). Their model of comparative advantage is consistent with the lack of tradeoff between risk and productivity; the model only features macroeconomic

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 we look 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

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.

The remainder of the paper is organized as follows. In Section 1, we introduce the methodology to study the different components of volatility. 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

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: excessive 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 us to first break down 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 , ($j = 1, \dots, J$) denoted by q_j , can then be expressed, as a first-order approximation,

shocks (and differential sectoral responses to these shocks), but could potentially be extended to feature sector-specific shocks.

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

⁵Studies on aggregate volatility, most notably Ramey and Ramey (1995), Kose, Otrok and Whiteman (2003) 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) study 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.

⁶See, 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).

⁷See, for example, Hopenhayn and Muniagurria (1996), and Gavin and Hausmann (1998).

as the weighted sum of the innovations in the growth rates of value-added per worker in every sector, y_{js} , with $s = 1, \dots, S$:

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

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 , $\text{Var}(q_j)$, and its components.

To separate the role of domestic aggregate risk from that of the sectoral composition of the economy, we can further breakdown 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. Similarly, 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

⁸In 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 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. Recall that in specification (1), the differential impact of these shocks is captured by the residual

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

1.1 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, $\text{Var}(q_j)$, can be written as:

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

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

Given (1), simple matrix algebra shows that the variance-covariance matrix of country j 's sectoral shocks can be written as:⁹

$$\text{E}(\mathbf{y}_j \mathbf{y}'_j) = \Omega_{\boldsymbol{\lambda}} + \Omega_{\varepsilon_j} + \omega_{\mu_j}^2 \mathbf{1} \mathbf{1}' + (\Omega_{\boldsymbol{\lambda} \mu_j} \mathbf{1}' + \mathbf{1} \Omega'_{\boldsymbol{\lambda} \mu_j}) + \Gamma_j \quad (3)$$

where:

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

$\mathbf{1}$ denotes the $S \times 1$ vector of ones, and $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ denote the vectors of sectoral shocks (λ_s) and country shocks (μ_j), respectively. The matrix $\Omega_{\boldsymbol{\lambda}}$ is the variance-covariance of sector-specific global shocks; Ω_{ε_j} is the matrix collecting the variances of the sector- and country-specific residuals ε_{js} , $\sigma_{js}^2 = \text{E}(\varepsilon_{js}^2)$; $\omega_{\mu_j}^2$ is the variance of country-specific shocks; $\Omega_{\boldsymbol{\lambda} \mu_j}$ is the covariance between country-specific and global sectoral shocks; and finally, as shown in Appendix A, the matrix Γ_j collects the remaining components of $\text{E}(\mathbf{y}_j \mathbf{y}'_j)$, that is, the covariances between the residuals and the sectoral and country-specific shocks, $\text{E}(\varepsilon_{js} \boldsymbol{\lambda})$ and $\text{E}(\varepsilon_{js} \mu_j)$, respectively, and the covariance among residuals, $\text{E}(\varepsilon_{js}, \varepsilon_{js'})$, for $s \neq s'$.¹⁰

As we later show, 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

term ε_{js} . When we later estimate this alternative model, we find that B_j and b_s are fairly close to 1, and hence the quantitative measures of risk we derive are not sensitive to this alternative decomposition. This implies that, empirically, the term ε_{js} in (1) reflects mostly country- and sector-specific shocks (rather than differential exposure by sector or by country).

⁹Appendix A presents the matrix algebra.

¹⁰The 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.

in Section 4.3.¹¹ 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:

$$\mathbf{E}(\mathbf{y}_j \mathbf{y}_j') = \Omega_\lambda + \Omega_{\varepsilon_j} + \omega_{\mu_j}^2 \mathbf{1}\mathbf{1}' + (\Omega_{\lambda\mu_j} \mathbf{1}' + \mathbf{1}\Omega'_{\lambda\mu_j}). \quad (4)$$

Plugging (4) into (2), we get:

$$\text{Var}(q_j) = \mathbf{a}'_j \mathbf{E}(\mathbf{y}_j \mathbf{y}_j') \mathbf{a}_j = \mathbf{a}'_j \Omega_\lambda \mathbf{a}_j + \mathbf{a}'_j \Omega_{\varepsilon_j} \mathbf{a}_j + \omega_{\mu_j}^2 + 2(\mathbf{a}'_j \Omega_{\lambda\mu_j}). \quad (5)$$

It is convenient to further decompose the term $\mathbf{a}'_j \Omega_{\varepsilon_j} \mathbf{a}_j$ into the sum of a pure Herfindahl concentration index $c \mathbf{a}'_j \mathbf{a}_j = c \sum_{s=1}^S a_{js}^2$, and the purely idiosyncratic-risk component, $\mathbf{a}'_j (\Omega_{\varepsilon_j} - c\mathbf{I}) \mathbf{a}_j = \sum_{s=1}^S (\sigma_{js}^2 - c) a_{js}^2$, where c is a (constant) scalar, obtained as the average of σ_{js}^2 .¹² Aggregate volatility can hence be written as:

$$\text{Var}(q_j) = \mathbf{a}'_j \mathbf{E}(\mathbf{y}_j \mathbf{y}_j') \mathbf{a}_j = \mathbf{a}'_j \Omega_\lambda \mathbf{a}_j + \mathbf{a}'_j (\Omega_{\varepsilon_j} - c\mathbf{I}) \mathbf{a}_j + c \mathbf{a}'_j \mathbf{a}_j + \omega_{\mu_j}^2 + 2(\mathbf{a}'_j \Omega_{\lambda\mu_j}). \quad (6)$$

This formulation clearly shows that production 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, $\mathbf{a}'_j (\Omega_{\varepsilon_j} - c\mathbf{I}) \mathbf{a}_j = \sum_{s=1}^S (\sigma_{js}^2 - c) a_{js}^2$, relates to idiosyncratic sectoral shocks. This term is large when sectors with high idiosyncratic volatility, σ_{js}^2 , account for a large share of employment. For example, suppose textiles is particularly volatile in country j (and also more volatile than other sectors in j); then, if the share a_{js} of textiles in country j is large, the country will exhibit a large value for $\sum_{s=1}^S (\sigma_{js}^2 - c) a_{js}^2$.

¹¹Note 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 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. 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.

¹²A constant σ_{js}^2 would result if we imposed the restriction that sectoral shocks are uncorrelated and homoscedastic.

2. if the country specializes in *few* sectors. This is reflected in a large value for the Herfindahl concentration index $c \mathbf{a}'_j \mathbf{a}_j = c \sum_{s=1}^S a_{js}^2$. This component reaches its maximum when the country is totally concentrated in one sector ($a_{j\bar{s}} = 1$ and $a_{js} = 0$ for $s \neq \bar{s}$).
3. if country risk ($\omega_{\mu_j}^2$) is big, that is, the country is more volatile if aggregate domestic shocks are larger and more frequent.
4. 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.

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 indices) as a measure of diversification. This is an ideal measure to capture the riskiness of the sectoral structure (and the lack of diversification) under the assumption that sectors are homoscedastic and uncorrelated. In this case, efficient diversification clearly dictates an even distribution of sectors, and any deviation from this can be coined a “lack of diversification.” The decomposition we perform indicates that to measure diversification it is important to take into account the riskiness embedded in a particular sectoral structure.

1.2 Estimating the Model

In order to quantify the various components of volatility in equation (6), we need to estimate the variance-covariance matrices Ω_{λ} , Ω_{ε_j} , $\omega_{\mu_j}^2$, 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,

$$\begin{aligned}\hat{\lambda}_{st} &\equiv \frac{1}{J} \sum_{j=1}^J y_{jst}, \\ \hat{\mu}_{jt} &\equiv \frac{1}{S} \sum_{s=1}^S (y_{jst} - \hat{\lambda}_{st}) \\ \hat{\varepsilon}_{jst} &\equiv y_{jst} - \hat{\lambda}_{st} - \hat{\mu}_{jt}\end{aligned}\tag{7}$$

Note that we normalize shocks so that $\sum_{j=1}^J \mu_{jt} = 0$, 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 (B).) The econometric specification is:¹³

$$y_{jst} = \lambda_{1t}d_1 + \dots + \lambda_{St}d_S + \mu_{1t}h_1 + \dots + \mu_{Jt}h_J + \varepsilon_{jst}\tag{8}$$

where d_s , $s = 1, \dots, S$, are dummy variables that take the value 1 for sector s , and 0 otherwise, and h_j , $j = 1, \dots, J$, 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 Ω_{λ} , $\Omega_{\lambda\mu_j}$, $\omega_{\mu_j}^2$, and Ω_{ε_j} are then computed using the estimated shocks. In particular, $\hat{\Omega}_{\lambda} = \frac{1}{T} \sum_{t=1}^T \hat{\lambda}_t \hat{\lambda}_t'$ is the estimated variance-covariance of global-sectoral shocks;¹⁴ $\hat{\omega}_{\mu_j}^2 = \frac{1}{T} \sum_{t=1}^T \hat{\mu}_{jt}^2$ is the estimated variance of country- j -specific shocks; $\hat{\Omega}_{\lambda\mu_j} = \frac{1}{T} \sum_{t=1}^T \hat{\lambda}_t \hat{\mu}_{jt}$ is the estimate of the covariance between sectoral shocks and country- j shocks; and $\hat{\sigma}_{j_s}^2 = \frac{1}{T} \sum_{t=1}^T \hat{\varepsilon}_{jst}^2$, with $s = 1, \dots, S$ are the estimated variances of the sectoral idiosyncratic shocks.¹⁵

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

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

¹⁵A 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 (8) 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 non-zero, though they are quantitatively small and this is why we opt to ignore them. This is a result, not an assumption.

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

$$\text{GSECT}_{jt} = \mathbf{a}'_{jt} \hat{\Omega}_{\lambda} \mathbf{a}_{jt} \quad (9)$$

$$\text{ISECT}_{jt} = \mathbf{a}'_{jt} (\hat{\Omega}_{\varepsilon_j} - c\mathbf{I}) \mathbf{a}_{jt} \quad (10)$$

$$\text{HERF}_{jt} = c \mathbf{a}'_{jt} \mathbf{a}_{jt} \quad (11)$$

$$\text{CNT}_j = \hat{\omega}_{\mu_j}^2 \quad (12)$$

$$\text{COV}_{jt} = 2\mathbf{a}'_{jt} \hat{\Omega}_{\lambda} \mathbf{a}_{\mu_j} \quad (13)$$

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 country j ; HERF_{jt} measures the level of sectoral concentration of country j at time t ; CNT_j is the part of volatility due to country shocks (which, by construction, does not depend on time); and COV_{jt} is the covariance of global sectoral shocks with the j th country shock at time t .

1.3 Related Empirical Applications

The econometric model specified in (8), 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.

The factor model could also be estimated by maximum likelihood, treating only the covariance matrix of fluctuations as observed but not the realizations of shocks themselves. (See finance applications in Connor and Korajczyk, (1986) and (1988); Lehmann and Modest, (1985a) and (1985b); and Brooks and Del Negro (2002).) Del Negro (2002) uses this methodology to analyze aggregate 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. In this approach, the estimation assumes a particular joint distribution of shocks (typically orthogonal standard normals) in order to estimate the factor loadings. They focus on identifying the world business cycle, captured by a common world factor. Our model is more general in the sense that we allow for as many global factors as the number of sectors. We discuss differences with our approach in the robustness section.

Our use of “cross-sectional regression” methodology is convenient 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 C, 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 .

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 sectoral employment and value added. 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 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.

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 worker) in U.S. dollars.¹⁶ 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.

Our benchmark analysis focuses on a broad set of countries with 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 these data is likely higher, and it covers all sectors in the economy. As we comment later in the Robustness Section, applying the factor model to this subsample confirms the empirical regularities found in the UNIDO manufacturing data.

We focus on the variance of the growth rate of value added per worker. In the benchmark exercise, we take five-year moving averages of growth rates on the grounds that the relevant fluctuations that influence the choice of sectoral structure of a country may occur over the medium to long horizon. In this way we can also reduce high frequency noise due to measurement error. It turns out that, in practice, similar patterns emerge when using one-year growth rates of value-added per worker. (These results are not reported in the paper, but are available at request from the authors).

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

¹⁶We use the CPI to convert figures into constant dollars.

3 Results

This section is split into three subsections. The first (3.1) briefly introduces the reader to the estimates of the five components of volatility. The second (3.2) investigates more systematically the relationship between the various measures of risk and economic development. The third (3.3) presents the results of a volatility accounting exercise. The results reported in this section are based on the benchmark UNIDO data set.

3.1 Decomposition of Risk

We begin in Table 3 by illustrating the decomposition of risk, by country in 1990. (The Figures in the next Section display the corresponding numbers for all years.) The numbers are expressed as variance components (not standard deviations).¹⁷

The first column shows our measure of global sectoral risk, as gauged by expression (9): $\text{GSECT}_{jt} = \mathbf{a}'_{jt} \Omega_{\lambda} \mathbf{a}_{jt}$. 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 1990 the top three countries according to this dimension of risk are Pakistan, Iran, and India, whereas Singapore, Israel and Ireland exhibit the lowest levels of global sectoral risk.

The second column shows the idiosyncratic sectoral risk, as expressed in (10): $\text{ISECT}_{jt} = \mathbf{a}'_{jt} (\Sigma_j - c\mathbf{I}) \mathbf{a}_{jt} = \sum_s (\sigma_{js}^2 - c) a_{js}^2$. This term captures the role played by the idiosyncratic variances of sectoral shocks, σ_{js}^2 . A positive (negative) number implies that the sectoral structure of the country exhibits higher (lower) idiosyncratic risk than the benchmark of constant variance ($\sigma_{js}^2 = c$). The countries with highest idiosyncratic sectoral risk in 1990 are Ecuador, Philippines, and Iran. In contrast, Denmark, Sweden, and Japan display the lowest level of idiosyncratic sectoral risk.

The third column shows the concentration index resulting from expression (11): $\text{HERF}_{jt} = c \mathbf{a}'_j \mathbf{a}_j = c \sum_s a_{js}^2$. The countries with highest Herfindahl indices are Bolivia, Uruguay, Kenya, Ecuador, and Philippines. Canada, South Africa, and Korea are the countries with lowest concentration levels.

The fourth column displays the country-specific risk, $\omega_{\mu_j}^2$. Peru, Philippines, Iran, Bolivia, and Israel are the riskiest countries, whereas Ireland, the United States, Finland, Austria, and Canada qualify as the the safest.

The fifth column indicates the sector-country covariance, that is, the covariance between sector and country specific shocks: $\text{COV}_{jt} = \mathbf{a}'_{jt} \Omega_{\lambda \mu_j}$. Peru, Chile, Greece, and Japan show the highest covariance, whereas India, Pakistan, South Africa exhibit the lowest covariances.

The sixth and final column presents the sum of the five components.

¹⁷We express them in terms of variance components so as to emphasize the additive contribution to total variance. Since growth of labor productivity is computed over a five-year interval (moving averages), the reader interested in *annualized* standard deviations should compute the squared root after dividing by 5.

Note that not only are there important differences in the quantitative measures of risk across countries, but also there is enormous variance across countries regarding the shares of the different dimensions of risk. For example, in Iran, the 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 (33 percent) is explained by the high covariance between country- and sector-specific risk. The United Kingdom, in contrast, has a relatively large negative sector-country covariance, which contributes to lower overall risk.

Even though Kose et al. (2003) do not address sectoral 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, 16.8 percent of overall risk is attributable to global sectoral shocks. Our median share of country shocks (including here the covariance with sectors) is 69.9 percent, compared to their 65.0 (Kose et al. (2003)). 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 in the next Section.

In Table 4 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 innovations in the growth rate of value-added per worker, and the second displays the average correlations of each sector with the rest. The range of standard deviations goes from 4 percent to 14 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 $i = 1, \dots, N - 1$. 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.¹⁸ 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 country fixed effects.

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 subsections.

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 method described before.

We first turn to the relationship between global sectoral risk (GSECT) and real GDP per capita. Figure 2 exhibits the estimated cross-country relationship, and Figure 3 exhibits the corresponding within-country relationship. Both plots uncover a negative correlation between global sectoral risk and the level of development, 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 global sectoral risk 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 a given component of risk by shifting the curve.)

Figure 4 shows the cross-country estimated relationship between idiosyncratic sectoral risk (ISECT) and (the log of) real GDP per capita, and Figure 5 shows the corresponding within-country estimated relationship. Both Figures show a mostly negative association between this component of risk and development. In particular, as shown in Figure 4, rich countries feature the lowest levels of idiosyncratic sectoral risk in absolute terms.

Figures 6 and 7 display the cross-country and within-country relationship between the Herfindahl index and development. The graphs exhibit a declining curve 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 Figures.

¹⁸The 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 $j = i - k, \dots, i + k$ are: $w_j = \left[1 - \left(\frac{|x_j - x_i|}{D}\right)^3\right]^3$, and $D = 1.0001 \max(x_{i+k} - x_i, x_i - x_{i-k})$

Putting all pieces together, the Figures show 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 both global and idiosyncratic sectoral risks together with a decrease in concentration. Later in the development process, while global and idiosyncratic sectoral risks continue to decline, concentration tends to flatten out and even reverses to higher levels at sufficiently large values of per capita GDP. However, this higher levels of concentration at later stages of development tends to fall into sectors with lower levels of global and idiosyncratic risk.

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 through 11 plot the employment shares in the textile industry (a highly risky sector with a standard deviation of shocks of 8 percent) and the electric machinery industry (the safest sector, with a standard deviation of 4 percent) against the log-level of GDP per capita. The plots present both the cross country and the within-country relations. As anticipated, the electric machinery sector expands with development while textile monotonically 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 1990 for each country. 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.

Finally, the evolution of the covariance between sector and country specific shocks along the development process is shown in Figures 13 and 14, both in the cross-country and the within-country versions. While there is considerable variability in the covariances, the cross-sectional evidence indicates no systematic relationship with the level of development.

Parametric results This section briefly summarizes 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 higher-order polynomials, but the additional functional freedom turns out to be insignificant.) The results are summarized in Table 5.

As already suggested by the graphs, global sectoral risk decreases during the development process, both in the cross-sectional and in the within-country evidence. The coefficient on the squared GDP term in the regression without fixed effects is positive, suggesting that the curve eventually flattens out; the estimated critical point at which the curve is perfectly flat occurs at very high values of income (out of sample).

The within-country evidence provides perhaps cleaner measures for the assessment of theoretical models, as it characterizes the evolution of each component of risk in the development path for the typical country.

Turning to the idiosyncratic sectoral risk component, the regressions show a generally decreasing pattern (there appears to be a slightly increasing phase at early stages of development, but it turns out not to be statistically significant).

Regarding the Herfindahl index, the within variation confirms that it first decreases with (the log of per capita) GDP, until GDP reaches the critical point of US \$6,433 (with US \$292 standard error). From this point on, the index starts increasing with 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.¹⁹

Country risk is negatively correlated with the level of development. (The coefficient on the (log) GDP in this last case is -0.031 , with a 0.02 robust standard error). Finally, the sector-country covariance does not show any systematic pattern in the data.

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 \$16,520 (with US \$1,822 standard error) in the cross section and US \$10,156 (with US \$1,099 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 global and idiosyncratic sectoral risk as well as country risk continue to decline at higher stages of development (counteracting the flattening out of the weighted Herfindahl index).

3.3 Volatility Accounting

As documented in the previous Figures and Tables, poor countries are more volatile because they exhibit higher levels of *i*) global sectoral risk (GSECT), *ii*) idiosyncratic sectoral risk (ISECT), *iii*) concentration (HERF), and *iv*) country-specific risk. The covariance term, while showing non-negligible dispersion, is not systematically related to the level of development. In the volatility accounting exercise that follows, we hence focus on the first four components.²⁰

The question we ask in this section 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 vis-à-vis aggregate domestic risk. To do this, we take the averages of the various measures of risk for the countries in the bottom and top income decile and compute the differences between the two groups in each of the components. We then express them as a proportion of the total

¹⁹Population weights were used to compute the percentiles. The unweighted percentile is 50.

²⁰One 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.

difference in volatility between the two groups. Hence, the contribution of country-specific risk (CTY) to the difference in volatility ($\text{Var}(q)$) between poor and rich countries is:

$$\text{CTY}^{\text{share}} = \frac{\text{CTY}^{\text{poor}} - \text{CTY}^{\text{rich}}}{\text{Var}(q^{\text{poor}}) - \text{Var}(q^{\text{rich}})} = 57\%,$$

where “poor” denotes the average of the bottom income decile and “rich” the corresponding average for the top decile. The remaining 43 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 12 percent of the total difference, and sectoral risk, which makes up the remaining 31 percent (7 percent due to Global Sectoral Risk and 25 percent due to Idiosyncratic Sectoral Risk).

All components of volatility account for a non-negligible share of the differences in total volatility. In particular, the sectoral composition of a country, which jointly determines the level of sectoral risk and the concentration level, accounts for 43 percent of the difference; this underscores the usefulness of looking at the sectoral composition of the economy. However, the volatility-accounting exercise also highlights the huge role of aggregate domestic risk in explaining the differences in volatility between poor and rich countries. The volatility breakdown suggests that policy efforts should probably focus on reducing macroeconomic-policy volatility rather than following the more intricate and delicate path of directed diversification (a path popular in Latin American countries), which, though potentially successful in terms of reducing volatility, might entail high costs in terms of economic distortions.

4 Robustness and Extensions

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

4.1 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 long series on value added and employment in agriculture, manufacturing, and services for a only a small sample of OECD countries. Table 6 displays the decomposition of risk for 1990.

Interestingly, the empirical regularities we document, in particular the sharp decline in the two measures of sectoral risk with the level of development, are exacerbated when one takes into account agriculture and services in the analysis. This is illustrated in Figures 15 and 16, which display global sectoral risk against development, and Figures 17 and 18, which display the corresponding graphs for the idiosyncratic sectoral component. The reason for this result is that agriculture, a relatively important sector at lower-income levels, behaves like the high-volatility industries, whereas Services, an important sector in developed countries, mimics

the behavior of less volatile industries. More specifically, as shown in Table 7, 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.²¹ The Herfindahl index increases at high levels of development (given that the sample only shows high-income countries, Figures 19 – 20 show mainly the increasing part); country risk tends to decline with development (Figure 21), though the relationship here is visually less striking than before, since there is much less variation in income levels; finally, there is no strong relationship between the covariances and the level of development (Figures 22 and 23).

4.2 An Alternative Way of Partitioning the Data

In section 1, we have proposed the partition (1) as our benchmark breakdown of the data. Shocks to the value-added growth 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 the following:

$$y_{js} = B_j \lambda_s + b_s \mu_j + \varepsilon_{js}, \quad (14)$$

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 cyclicity of the sector). Writing this factor model in vector notation:

$$\mathbf{y}_j = B_j \boldsymbol{\lambda} + \mu_j \mathbf{b} + \boldsymbol{\varepsilon}_j, \quad (15)$$

which implies the following variance decomposition,²²

$$\tilde{\mathbf{E}}(\mathbf{y}_j \mathbf{y}_j') = B_j^2 \Omega_{\boldsymbol{\lambda}} + \omega_{\mu_j}^2 \mathbf{b} \mathbf{b}' + (B_j \Omega_{\boldsymbol{\lambda} \mu_j} \mathbf{b}' + B_j \mathbf{b} \Omega'_{\boldsymbol{\lambda} \mu_j}) + \Omega_{\boldsymbol{\varepsilon}_j}. \quad (16)$$

²¹Previous 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).

²²Ignoring, as we did before, the term Γ_j , which we discuss next.

Our modified risk measures are defined as follows.

$$\widetilde{\text{GSECT}}_{jt} = B_j^2 \mathbf{a}'_{jt} \Omega_\lambda \mathbf{a}_{jt} \quad (17)$$

$$\widetilde{\text{ISECT}}_{jt} = \mathbf{a}'_{jt} (\Omega_{\varepsilon_j} - c\mathbf{I}) \mathbf{a}_{jt} \quad (18)$$

$$\widetilde{\text{HERF}}_{jt} = c \mathbf{a}'_{jt} \mathbf{a}_{jt} \quad (19)$$

$$\widetilde{\text{CNT}}_j = \omega_{\mu_j}^2 (\mathbf{a}'_{jt} \mathbf{b})^2 \quad (20)$$

$$\widetilde{\text{COV}}_{jt} = 2 \mathbf{a}'_{jt} B_j \mathbf{b} \Omega'_{\lambda \mu_j} \quad (21)$$

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. 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 similar patterns to those generated by the benchmark model, 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. The similarity of the results from the two different factor models should perhaps not be surprising. The differential exposures were previously captured in the residual term ε_{js} . As mentioned before, the term Γ_j which previously captured the correlations between ε_{js} and μ_j and between ε_{js} and λ_s , played a small quantitative role, which suggests that B_j and b_s would not be too different from 1.

As mentioned before, one implication of this result is that the term ε_{js} in (1) empirically reflects mostly shocks that are specific to a sector and country, rather than differential exposures to global sectoral or country-specific shocks.

Specification (15) 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 earlier, 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 effect of specialization.

4.3 Are Residual Shocks Idiosyncratic?

Throughout the paper, we have maintained the working hypothesis that the residual (ε_{js}) is idiosyncratic, that is, it is uncorrelated with each other and with country and sector 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 $\text{Var}(q_j)$ 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 0.99 (0.90 if looking at log-variances). Furthermore, not only is $\mathbf{a}'_j\Gamma_j\mathbf{a}_j$ zero on average, but the range of values (from -0.04 to 0.05) is considerably smaller than that of $\text{Var}(q_j)$ (from $0.004 - 0.19$).

Finally, and perhaps more importantly for the assessment of theories, the term $\mathbf{a}'_j\Gamma_j\mathbf{a}_j$,

$$\mathbf{a}'_j\Gamma_j\mathbf{a}_j = \text{Var}(q_j) - \left[\mathbf{a}'_j\Omega_\lambda\mathbf{a}_j + \mathbf{a}'_j\Omega_{\varepsilon_j}\mathbf{a}_j + \omega_{\mu_j}^2 + 2(\mathbf{a}'_j\Omega_{\lambda\mu_j}) \right], \quad (22)$$

is uncorrelated with the level of development.

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. The data shows that on average sectoral volatility is lower in the post-1980 period and, as before, countries tend to move to less risky sectors (that is, sectors with lower global and idiosyncratic risk) with development. Pooling together the results obtained from the two subsamples, we find that the sectoral risk decreases even more 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 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. In other words, our benchmark results, which should be viewed as summaries for the whole period, do not mask different trends in the two subperiods.

4.5 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 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 global sector-specific factors in each of the two subsamples. 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. 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 indicates that our initial estimates capture the global shocks to the sector fairly well.

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. Hence, in this case, the resulting impact in labor productivity is different for developed economies.

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. In other words, the benchmark model captures global sectoral shocks almost as well as this more permissive extension.

4.6 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 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 addressing the more specific question of whether more open countries have different exposure to sectoral shocks than relatively closed countries. We test this hypothesis by following a procedure similar to the one described before. That is, we split the sample into two groups, according to a given 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.²³ 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.

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. We conclude from this exercise that the split between small and large countries does not point to a significant departure from the benchmark specification.

4.7 Alternative Measures of Labor Productivity

We checked the robustness of our results by 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. Since value-added is more meaningful as an indicator of well-being, we prefer to focus on this measure.

Second, we checked whether the UNIDO data in US dollars led to different findings than the data in domestic currency. We redid our exercise both for value added and output per capita in both US dollars and domestic currency. As before, the patterns we document

²³The data come from Kaminsky and Schmukler (1999).

remain unaltered. The only difference lies on a smaller average correlation of shocks among sectors when using domestic currencies.

5 Concluding Remarks

Why is GDP growth so much more volatile in poor countries than in rich ones? The volatility-accounting analysis points to three sources: *(i)* poor countries specialize in more volatile sectors (explaining 31 percent of the differences in volatility); *(ii)* poor countries specialize in fewer sectors (explaining 12 percent of the difference); *(iii)* poor countries experience more frequent and more severe aggregate shocks (explaining 57 percent of the difference).

The dynamic evolution of volatility along the development path displays robust 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 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.

These results suggests that a possible next step will be to explore the hypothesis that low-risk sectors are high-skill intensive, or more generally, they are more intensive in the use of sophisticated skills and technology. In Koren and Tenreyro (2005) we argue that 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 individual inputs. This causes the productivity of sectors employing sophisticated technology to become less volatile.²⁴ Ultimately, we need a theory of what prevents countries from adopting more complex technologies.

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²⁴For 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.

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Appendix

A Derivation of the Variance-Covariance Decomposition

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

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

Multiplying this vector by its traspose, we get:

$$\begin{aligned} \mathbf{y}_j \mathbf{y}'_j &= (\boldsymbol{\lambda} + \mu_j \mathbf{1} + \boldsymbol{\varepsilon}_j)(\boldsymbol{\lambda}' + \mu_j \mathbf{1}' + \boldsymbol{\varepsilon}'_j) \\ &= \boldsymbol{\lambda} \boldsymbol{\lambda}' + \mu_j^2 \mathbf{1} \mathbf{1}' + \mu_j \boldsymbol{\lambda} \mathbf{1}' + \mu_j \mathbf{1} \boldsymbol{\lambda}' + \boldsymbol{\varepsilon}_j \boldsymbol{\varepsilon}'_j + \boldsymbol{\lambda} \boldsymbol{\varepsilon}'_j + \boldsymbol{\varepsilon}_j \boldsymbol{\lambda}' + \mu_j (\mathbf{1} \boldsymbol{\varepsilon}'_j + \boldsymbol{\varepsilon}_j \mathbf{1}') \end{aligned} \quad (23)$$

The term $\boldsymbol{\varepsilon}_j \boldsymbol{\varepsilon}'_j$ 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

$$\boldsymbol{\varepsilon}_j \boldsymbol{\varepsilon}'_j = \text{diag}(\varepsilon_{j1}^2 \dots \varepsilon_{jS}^2) + \text{crossprod}(\varepsilon_{js}), \text{ where}$$

$$\begin{aligned} \text{diag}(\varepsilon_{j1}^2, \dots, \varepsilon_{jS}^2) &= \begin{bmatrix} \varepsilon_{j1}^2 & 0 & \dots & 0 \\ 0 & \varepsilon_{j2}^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \varepsilon_{jS}^2 \end{bmatrix} \text{ and} \\ \text{crossprod}(\varepsilon_{js}) &= \begin{bmatrix} 0 & \varepsilon_{j1} \varepsilon_{j2} & \dots & \varepsilon_{j1} \varepsilon_{jS} \\ \varepsilon_{j2} \varepsilon_{j1} & 0 & \dots & \varepsilon_{jS} \varepsilon_{j1} \\ \dots & \dots & \dots & \dots \\ \varepsilon_{jS} \varepsilon_{j1} & \varepsilon_{jS} \varepsilon_{j2} & \dots & 0 \end{bmatrix} \end{aligned}$$

Taking expectations in (23) and introducing some notation,

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

we obtain:

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

B Cross-Sectional Dummy Regression and Sample Means

This appendix proves the equivalence between the cross-sectional mean estimator (7) discussed in Section 1.2 and the cross-sectional dummy regression estimator (8).

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

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

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} ,

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

The full set of dummies is perfectly collinear (the sum of the last J columns is zero), 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:

$$\mathbf{D}'\mathbf{D} \begin{pmatrix} \lambda \\ \mu \end{pmatrix} = \mathbf{D}'\mathbf{Y}, \text{ and} \tag{24}$$

$$\mathbf{1}'_J \mu = 0. \tag{25}$$

In what follows, we verify that ((24)) and (25) hold for $\hat{\lambda}$ and $\hat{\mu}$ defined in (7).

Let $l = \sum_j \mathbf{y}_j$ 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 $\sum_s y_{js}$, and $g = \mathbf{1}'l$ denote the overall sum of shocks, across countries and sectors. It is easy to see from (7) that $\hat{\lambda} = l/J$ and $\hat{\mu} = m/S - \mathbf{1}g/(JS)$.

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

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, 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.

C 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.

$$\hat{\lambda} = \lambda + \frac{1}{J} \sum_{i=1}^J \varepsilon_i, \tag{26}$$

$$\hat{\mu}_j = \mu_j + \frac{1}{S} \left[\frac{J-1}{J} \sum_{s=1}^S \varepsilon_{js} - \frac{1}{J} \sum_{s=1}^S \sum_{i \neq j} \varepsilon_{is} \right] \tag{27}$$

Then the second moments of these estimated factors are

$$\begin{aligned} \mathbb{E}(\hat{\lambda}\hat{\lambda}') &= \Omega_\lambda + \frac{\sigma^2}{J}\mathbf{I}, \\ \mathbb{E}(\hat{\lambda}\hat{\mu}_j) &= \Omega_{\lambda\mu_j} \\ \mathbb{E}(\hat{\mu}_j^2) &= \omega_{\mu_j}^2 + \frac{J-1}{SJ}\sigma^2. \end{aligned} \tag{28}$$

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 and 19 sectors in the data, the estimated factors are close to 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 ($\hat{\Omega}_\lambda$) is of the order 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 negligible fraction of the average sectoral risk. For country risk, the bias would be of order 0.0026. This is about 5 percent of the average country risk. Note that there is no bias in the covariance term.

Table 1. List of Countries

Australia	Indonesia	Philippines
Austria	Iran, Islamic Rep.	Poland
Bolivia	Ireland	Portugal
Canada	Israel	Singapore
Chile	Italy	South Africa
Colombia	Japan	Spain
Denmark	Kenya	Sweden
Ecuador	Korea, Rep.	Turkey
Finland	Malaysia	United Kingdom
France	New Zealand	United States
Greece	Norway	Uruguay
Hungary	Pakistan	Venezuela, RB
India	Peru	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, 1990.

Country	Global Sectoral Risk (1)	Idiosyncratic Sectoral Risk (2)	Concentration (3)	Country Risk (4)	Sector-Country Covariance (5)	Overall Risk (6)= $\Sigma(j)$
Australia	0.327	-0.488	0.547	0.678	-0.632	0.432
Austria	0.325	-0.471	0.555	0.550	-0.131	0.828
Bolivia	0.317	1.491	0.884	6.579	-0.659	8.612
Canada	0.339	-0.400	0.470	0.581	-0.324	0.666
Chile	0.342	-0.448	0.741	3.304	0.865	4.804
Colombia	0.297	-0.391	0.572	1.525	-0.128	1.875
Denmark	0.266	-0.638	0.731	0.595	-0.254	0.700
Ecuador	0.310	0.352	0.825	1.058	0.309	2.854
Finland	0.340	-0.430	0.553	0.432	-0.140	0.755
France	0.323	-0.492	0.541	0.585	0.492	1.449
Greece	0.320	-0.475	0.595	1.923	0.963	3.326
Hungary	0.300	0.496	0.558	2.558	0.289	4.201
India	0.402	-0.275	0.725	2.416	-1.115	2.154
Indonesia	0.340	0.155	0.668	0.616	-0.160	1.619
Iran, Islamic Rep.	0.412	0.303	0.683	6.825	-1.063	7.160
Ireland	0.258	-0.442	0.623	0.317	-0.215	0.541
Israel	0.256	-0.485	0.623	4.192	0.579	5.165
Italy	0.345	-0.446	0.533	1.765	0.360	2.557
Japan	0.299	-0.552	0.603	1.108	0.729	2.187
Kenya	0.338	-0.384	0.835	0.852	0.092	1.733
Korea, Rep.	0.321	-0.290	0.492	1.706	-0.646	1.584
Malaysia	0.282	-0.220	0.656	1.249	-0.666	1.301
New Zealand	0.299	-0.494	0.687	0.873	-0.355	1.010
Norway	0.332	-0.489	0.655	0.649	-0.392	0.756
Pakistan	0.476	0.169	1.120	2.223	-1.065	2.922
Peru	0.345	0.081	0.567	16.746	1.289	19.028
Philippines	0.262	0.316	0.769	7.506	-1.225	7.628
Portugal	0.319	-0.310	0.538	2.989	-0.221	3.315
Singapore	0.237	-0.422	1.044	1.591	-0.568	1.882
South Africa	0.333	-0.320	0.487	1.007	-0.735	0.772
Spain	0.325	-0.354	0.514	0.796	0.440	1.722
Sweden	0.367	-0.580	0.672	1.039	0.350	1.847
Turkey	0.393	-0.303	0.657	2.045	-0.456	2.336
United Kingdom	0.307	-0.473	0.540	0.654	0.364	1.393
United States	0.311	-0.483	0.514	0.320	-0.291	0.370
Uruguay	0.287	0.216	0.838	3.821	-0.012	5.151
Venezuela, RB	0.339	-0.141	0.568	3.571	-0.062	4.274
Zimbabwe	0.361	-0.118	0.585	2.556	0.375	3.760

Notes: The calculation of the risk measures is described in the text. All measures are additive components of the variance (and not standard deviations). All measures have been multiplied by 100 to ensure readability. The figures in the five columns (1) through (5) add up to the total in (6).

Table 4. Variance and Correlations, by Sector

Sector	Standard Deviation	Average Correlation
1 Food products; Beverages; Tobacco	0.057	0.50
2 Textiles	0.089	0.72
3 Wearing apparel, except footwear	0.050	0.58
4 Leather products	0.087	0.65
5 Footwear, except rubber or plastic	0.072	0.60
6 Wood products, except furniture	0.090	0.71
7 Furniture, except metal	0.065	0.46
8 Paper and products	0.108	0.56
9 Printing and publishing	0.046	0.71
10 Industrial chemicals; Petroleum refineries; Petroleum and coal products	0.070	0.59
11 Rubber products	0.080	0.52
12 Plastic products	0.075	0.69
13 Pottery, china, earthenware; Glass; Other non-metallic mineral prod.	0.051	0.69
14 Iron and steel; Non-ferrous metals	0.141	0.65
15 Fabricated metal products; Machinery, except electrical	0.061	0.66
16 Machinery, electric	0.050	0.52
17 Transport equipment	0.085	0.57
18 Professional & scientific equipment	0.066	0.52
19 Other manufactured products	0.070	0.56

Notes: The first column displays the standard deviation of global sectoral shocks in the sector. The second column is the average pairwise correlation of global shocks with the rest of the sectors.

Table 5. Different Dimensions of Risk and Economic Development, 1963-1998

Linear Relation		Dependent Variable:										
		Global sectoral risk		Idiosyncratic sectoral risk		Concentration		Country risk	Sector-country covariance		Overall risk	
		Overall	Within	Overall	Within	Overall	Within	Overall	Overall	Within	Overall	Within
Log GDP per capita (constant PPP \$)		-0.028** (0.009)	-0.059** (0.002)	-0.316** (0.079)	-0.046** (0.012)	-0.134** (0.034)	0.043** (0.012)	-3.174 (2.054)	-0.008 (0.261)	0.017** (0.004)	-3.659* (2.000)	-0.045** (0.017)
R-squared		0.23	0.50	0.32	0.01	0.34	0.01	0.13	0.00	0.01	0.13	0.01

Quadratic Relation		Dependent Variable:										
		Global sectoral risk		Idiosyncratic sectoral risk		Concentration		Country risk	Sector-country covariance		Overall risk	
		Overall	Within	Overall	Within	Overall	Within	Overall	Overall	Within	Overall	Within
Log GDP per capita (constant PPP \$)		-0.345* (0.129)	-0.063** (0.021)	1.324 (1.259)	0.542** (0.142)	-1.236 (0.701)	-2.084** (0.128)	-31.553 (46.293)	-2.245 (5.873)	0.105* (0.050)	-3.406 (52.496)	-1.501** (0.198)
Log GDP per capita squared		0.018* (0.007)	0.000 (0.001)	-0.095 (0.071)	-0.033** (0.008)	0.064 (0.039)	0.119** (0.007)	1.637 (2.556)	0.129 (0.326)	-0.005 (0.003)	1.753 (2.899)	0.081** (0.011)
R-squared		0.31	0.50	0.34	0.03	0.40	0.21	0.15	0.01	0.02	0.15	0.05
Critical Point		12,344	3.20e+55	1,093	3,817	16,719	6,433	15,339	5,990	43,897	16,520	10,157
S.E. of Critical Point		(3,785)	(1.79e+58)	(15,559)	(947)	(8665)	(299)	(14,217)	(5,675)	(4.72e+6)	(1,823)	(1,100)

Notes: 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=1,175. All coefficients have been multiplied by 100 to ensure readability.

Table 6. Different Dimensions of Risk, by Country, 1990. OECD Subsample

Country	Global Sectoral Risk (1)	Idiosyncratic Sectoral Risk (2)	Concentration (3)	Country Risk (4)	Sector-Country Covariance (5)	Overall Risk (6)
Australia	0.224	-0.036	0.263	0.407	-0.219	0.640
Austria	0.259	-0.121	0.180	0.149	-0.090	0.377
Belgium	0.216	-0.077	0.258	0.186	-0.030	0.553
Canada	0.221	-0.045	0.268	0.390	0.000	0.833
Denmark	0.223	-0.091	0.246	0.129	-0.147	0.359
Finland	0.232	-0.152	0.216	0.109	-0.053	0.352
France	0.224	-0.140	0.240	0.152	-0.185	0.292
Italy	0.228	-0.140	0.210	0.115	-0.190	0.223
Japan	0.232	-0.160	0.204	0.191	0.061	0.530
Korea, Rep.	0.259	0.152	0.160	0.496	0.353	1.421
Netherlands	0.220	-0.034	0.262	0.214	0.056	0.719
Norway	0.225	-0.193	0.264	0.091	-0.015	0.372
Portugal	0.253	-0.114	0.174	0.378	-0.348	0.344
Spain	0.239	-0.099	0.209	0.107	0.086	0.542
Sweden	0.218	0.043	0.257	0.470	0.299	1.286
United Kingdom	0.215	-0.166	0.269	0.194	0.128	0.640
United States	0.217	-0.139	0.284	0.150	0.076	0.588

Notes: The calculation of the risk measures is described in the text. All measures are additive components of the variance (and not standard deviations). All measures have been multiplied by 100 to ensure readability. The figures in the five columns (1) through (5) add up to the total in (6).

Table 7. Variance and Correlations, by Sector. OECD Subsample

Sector	Standard Deviation	Average Correlation
Agriculture	0.081	0.28
Manufacturing	0.054	0.28
Services	0.047	0.30

Notes: The first column displays the standard deviation of global sectoral shocks in the sector. The second column is the average pairwise correlation of global shocks with the rest of the sectors.

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

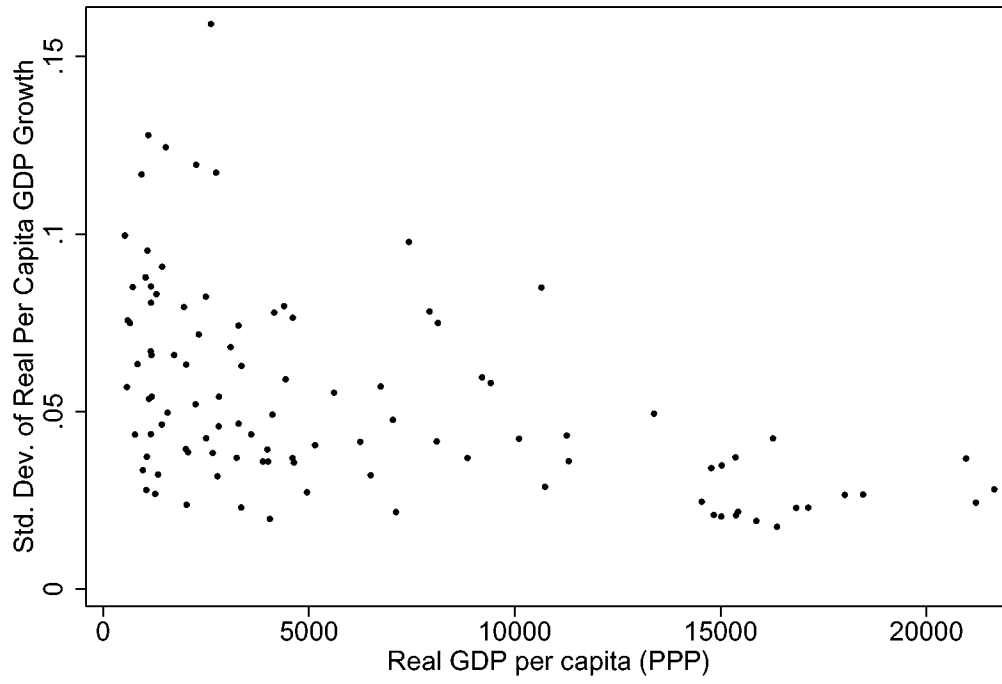


Figure 2: Global Sectoral Risk
Mean adjusted smooth

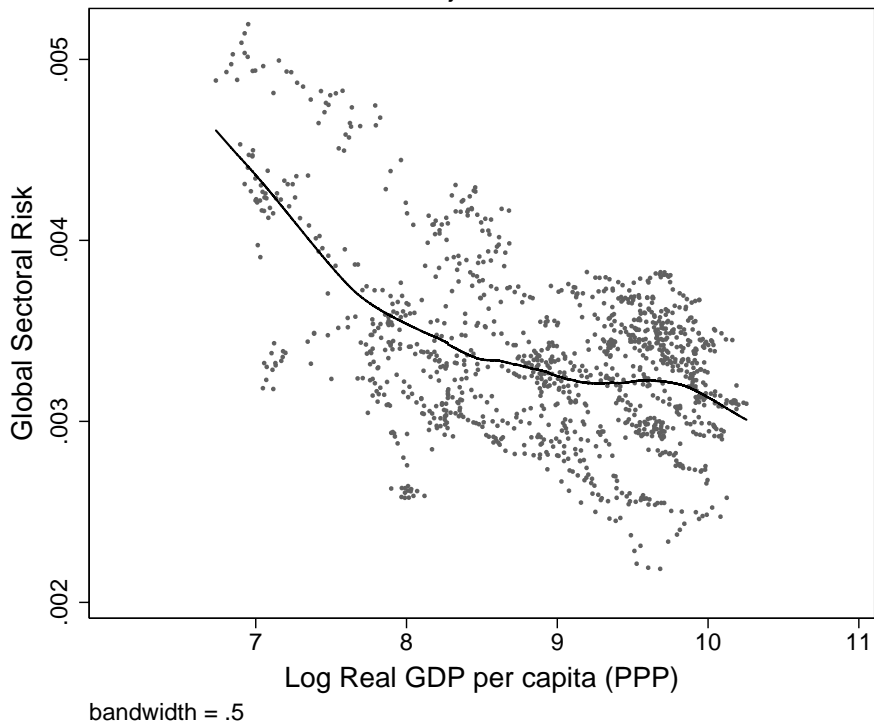


Figure 3: Global Sectoral Risk (within)
Mean adjusted smooth

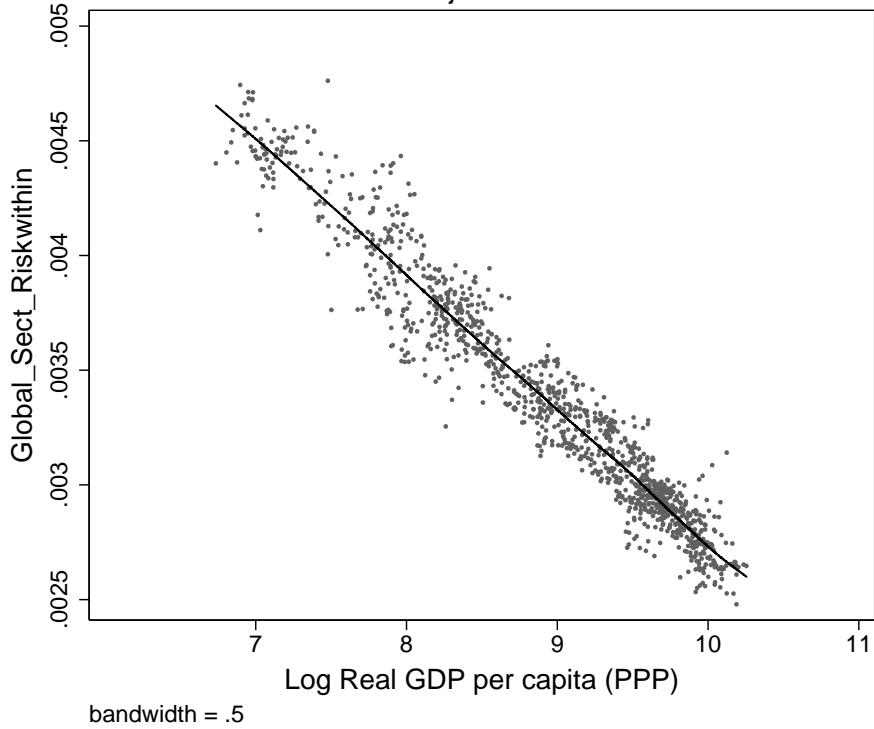


Figure 4: Idiosyncratic Sectoral Risk
Mean adjusted smooth

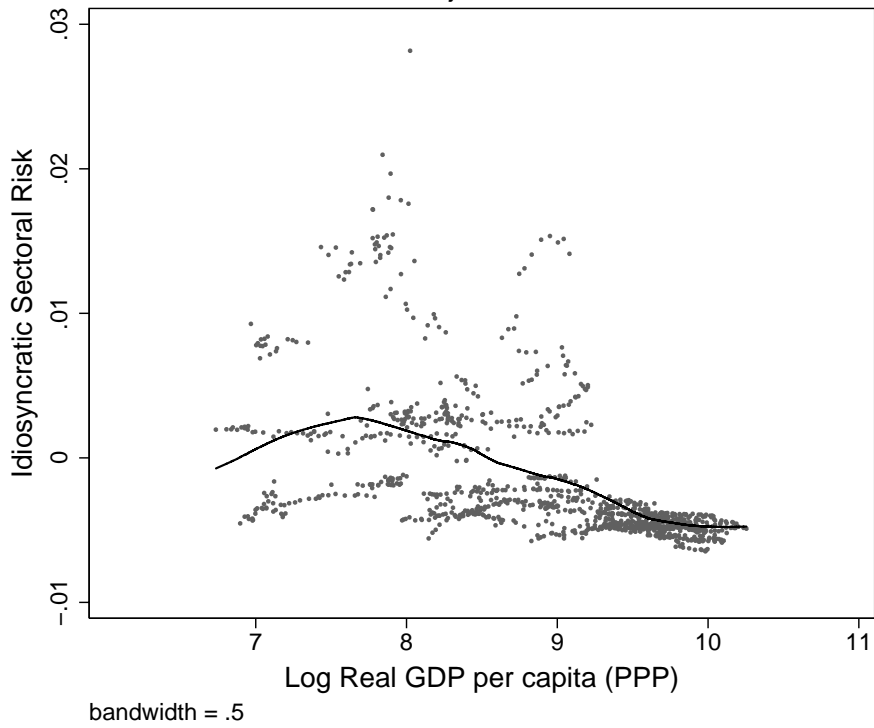


Figure 5: Idiosyncratic Sectoral Risk (within)
Mean adjusted smooth

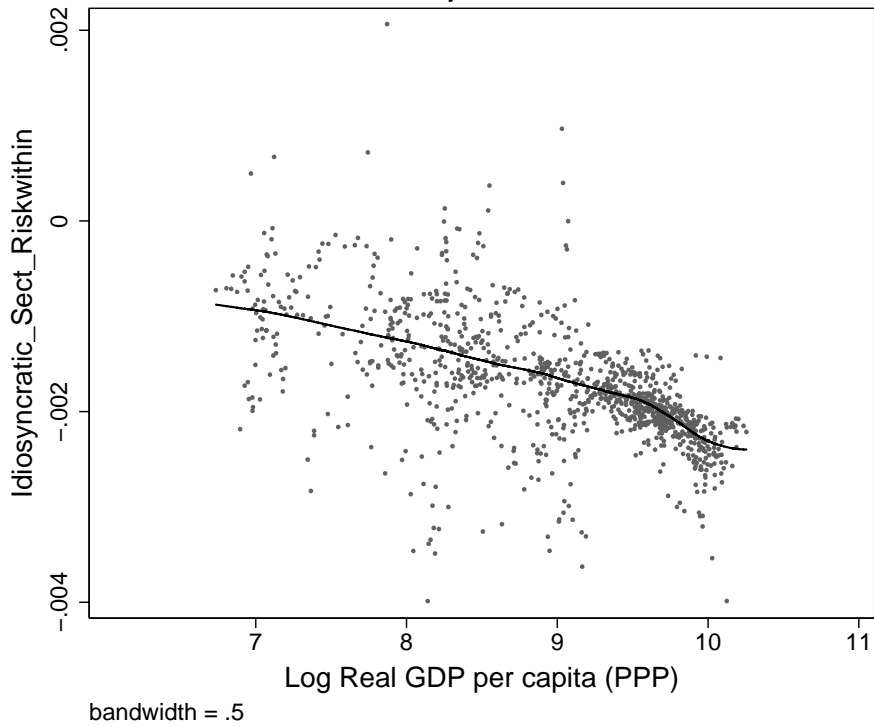


Figure 6: Herfindahl Index
Mean adjusted smooth

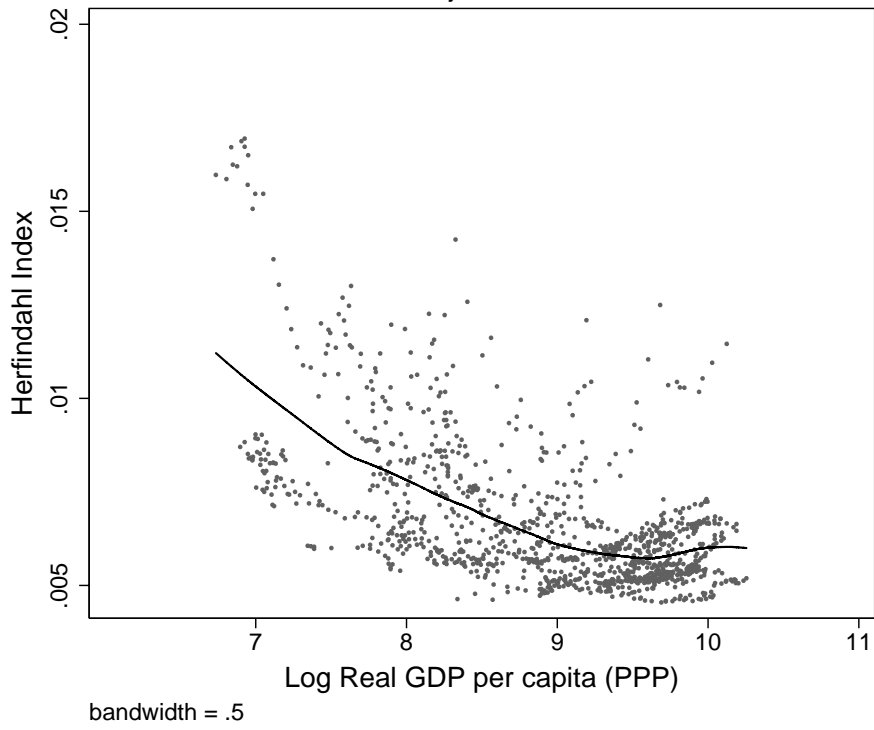


Figure 7: Herfindahl Index(within)
Mean adjusted smooth

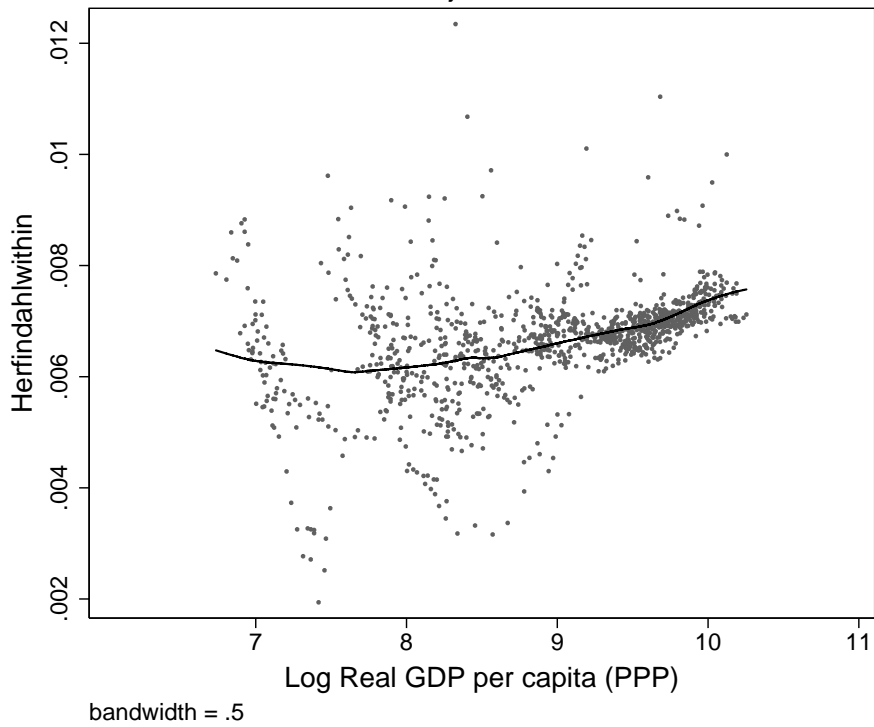


Figure 8: Textiles Share
Mean adjusted smooth

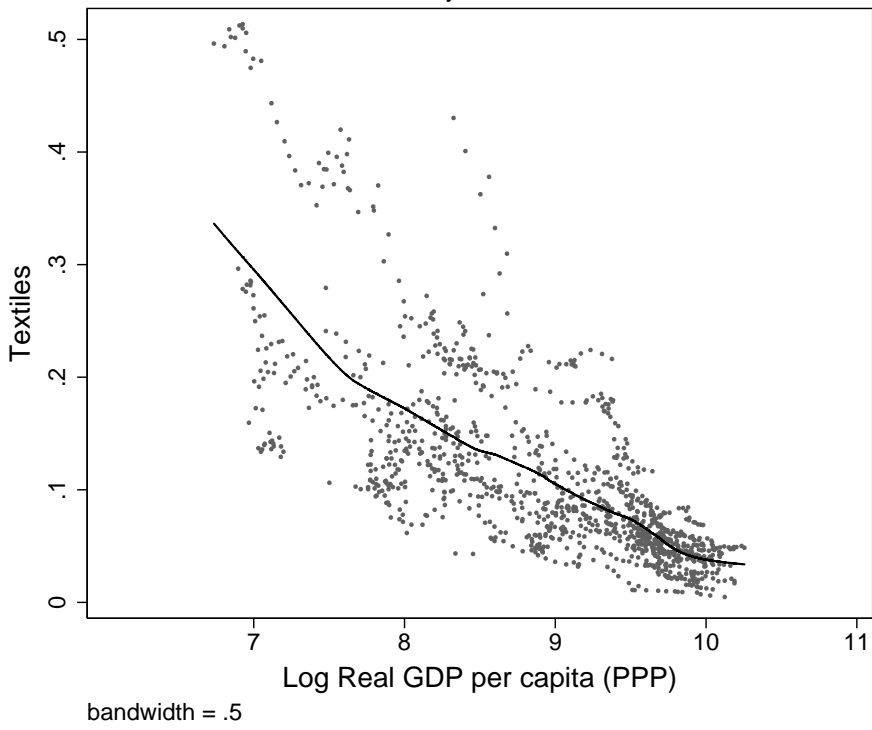


Figure 9: Textiles Share (within)
Mean adjusted smooth

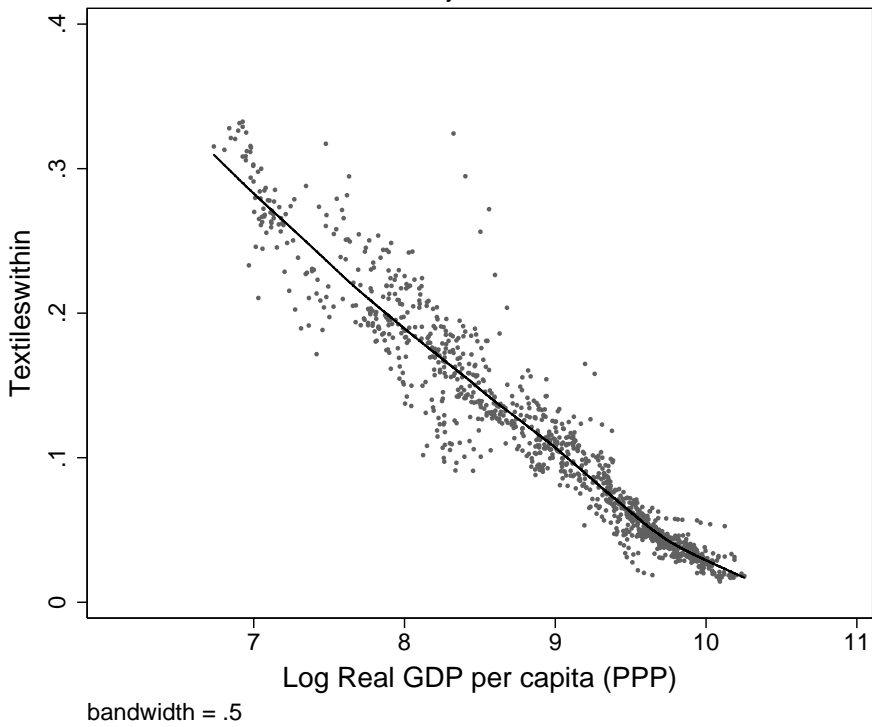


Figure 10: Electric Machinery Share
Mean adjusted smooth

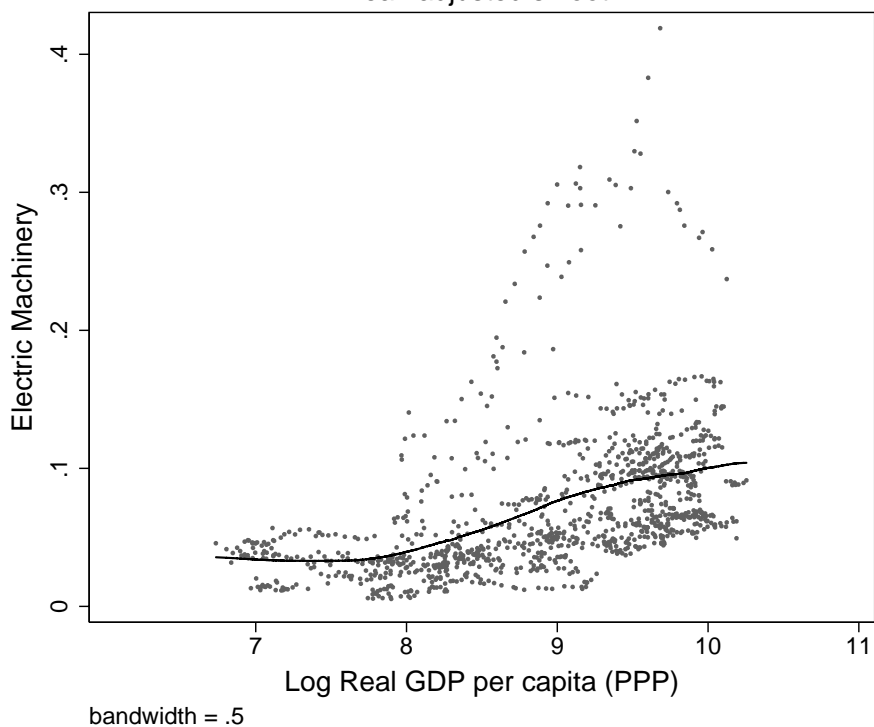


Figure 11: Electric Machinery Share(within)
Mean adjusted smooth

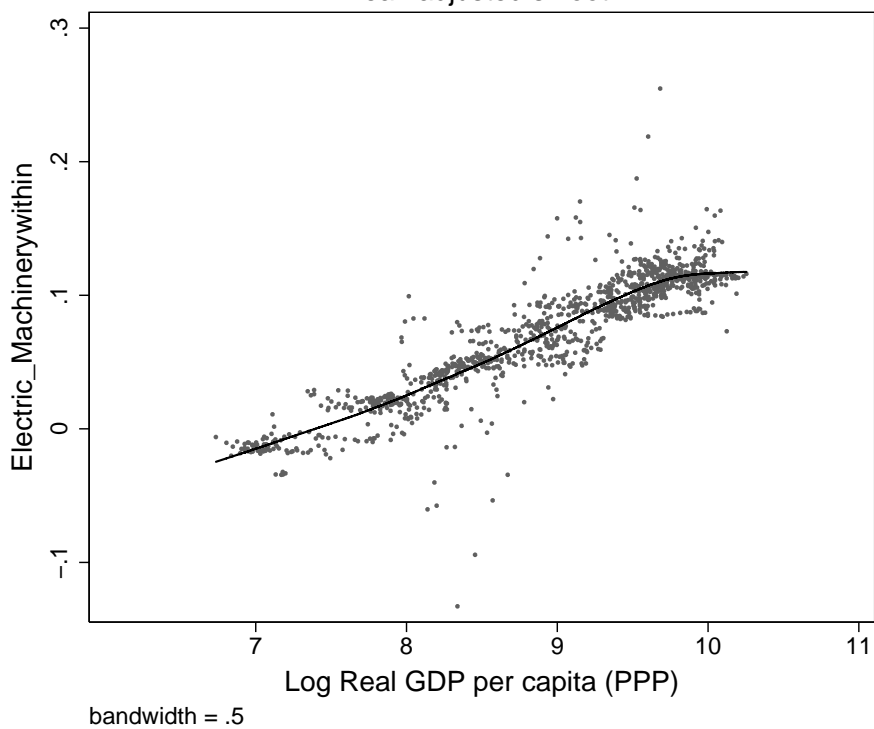


Figure 13: Sector–Country Covariance
Mean adjusted smooth

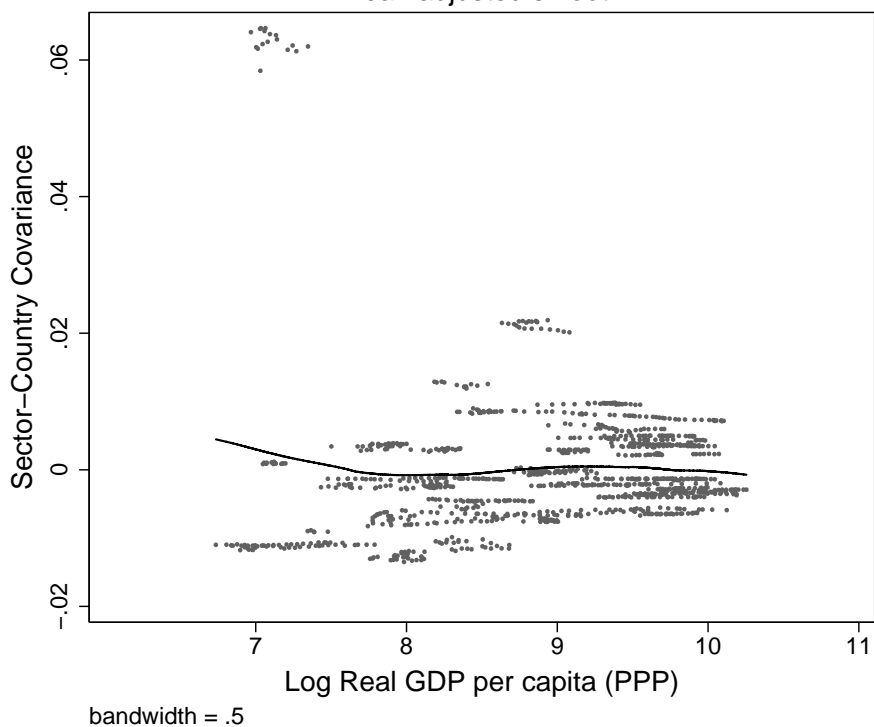


Figure 14: Sector–Country Covariance(within)
Mean adjusted smooth

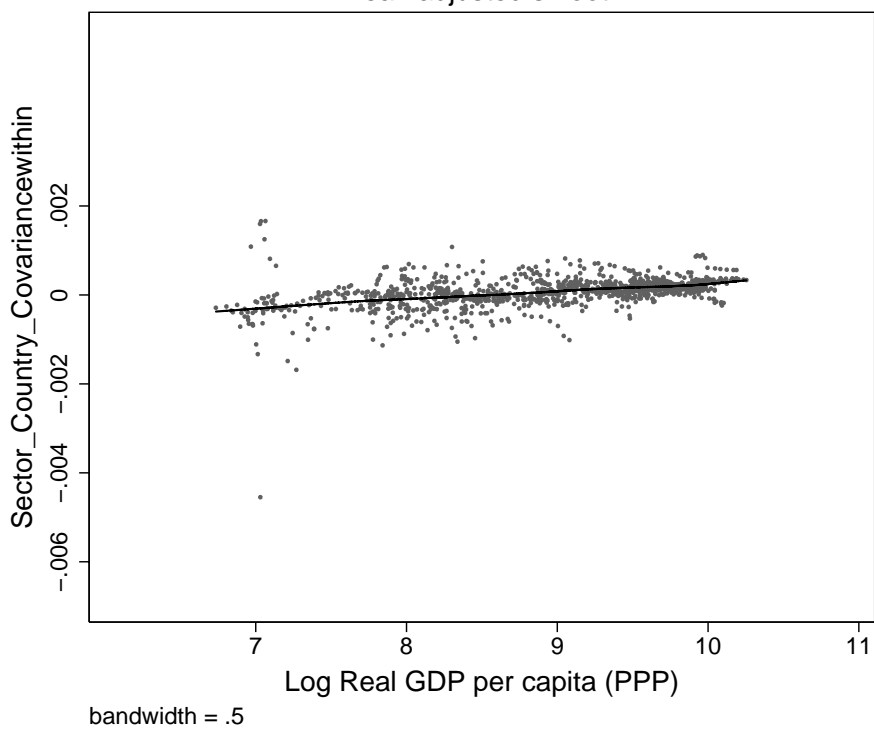


Figure 15: Sectoral Risk OECD Sample
Mean adjusted smooth

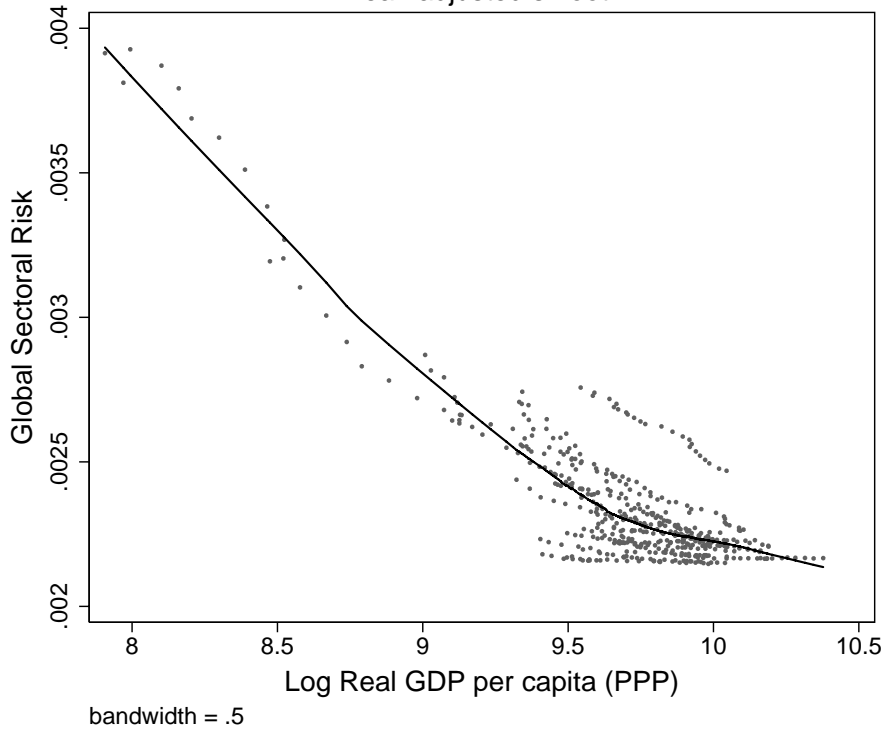


Figure 16: Sectoral Risk (within) OECD Sample
Mean adjusted smooth

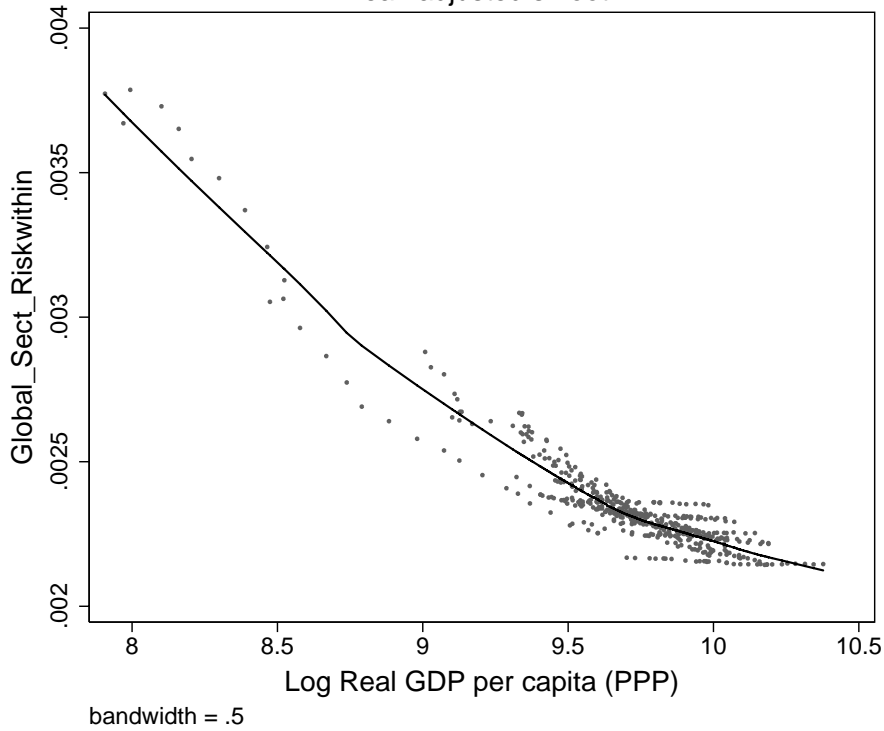


Figure 17: Idiosyncratic Risk OECD Sample
Mean adjusted smooth

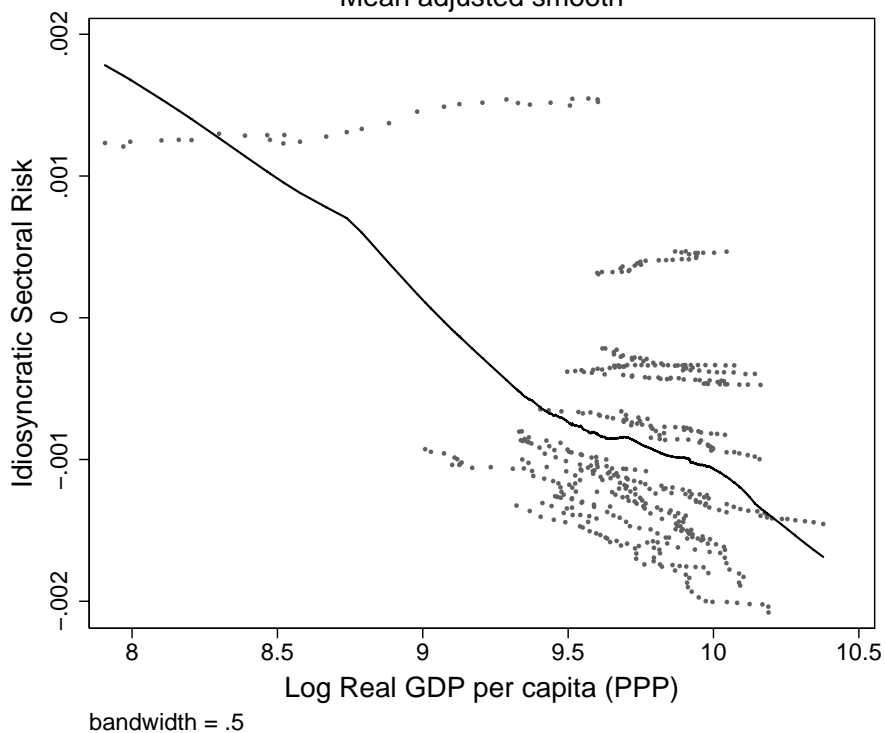


Figure 18: Idiosyncratic Risk (within) OECD Sample
Mean adjusted smooth

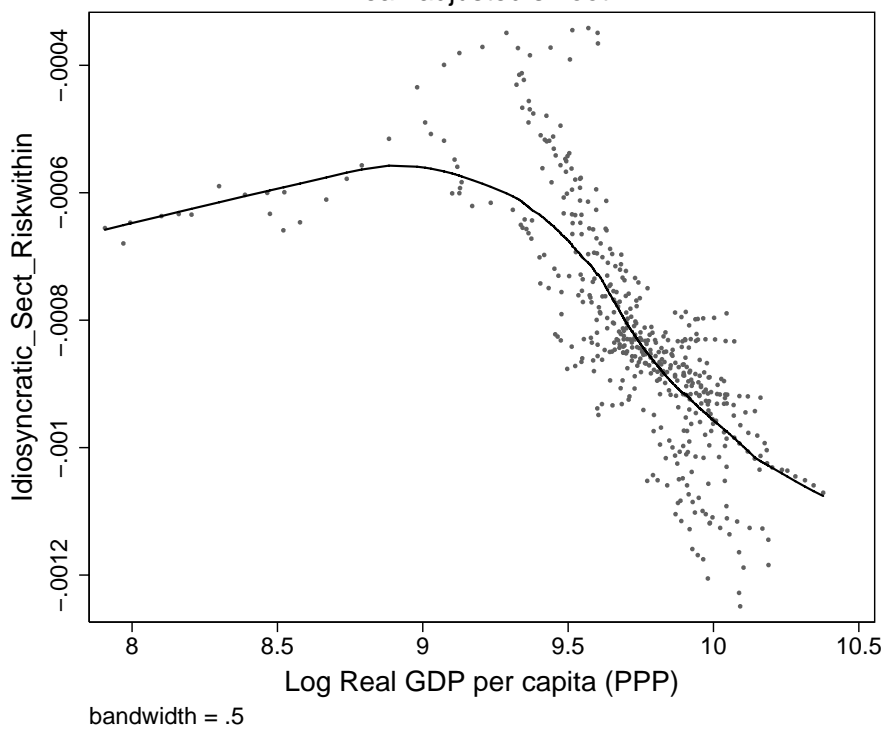


Figure 19: Herfindahl Index OECD Sample
Mean adjusted smooth

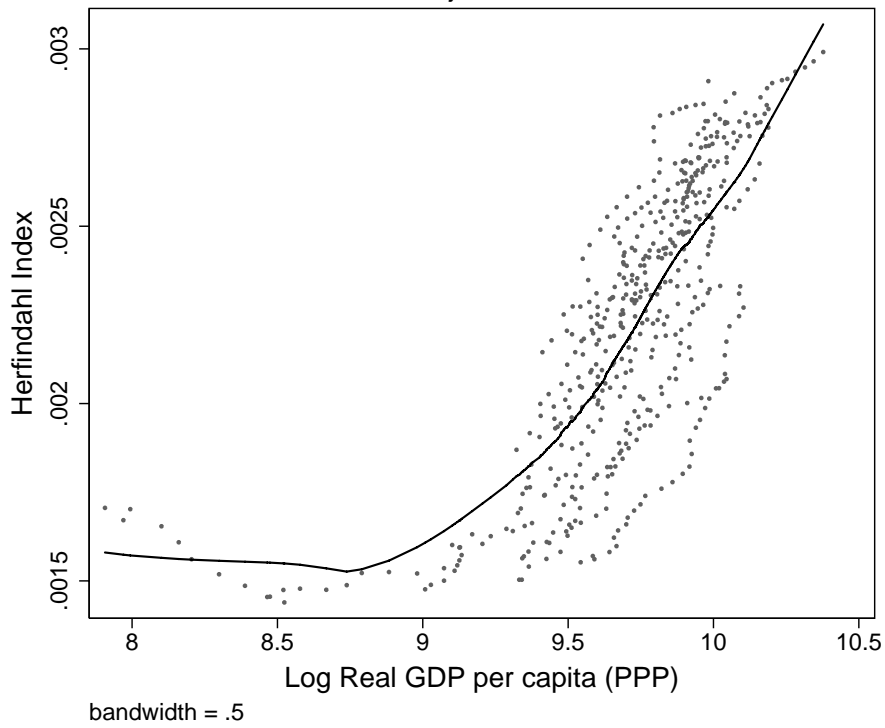


Figure 20: Herfindahl Index (within) OECD Sample
Mean adjusted smooth

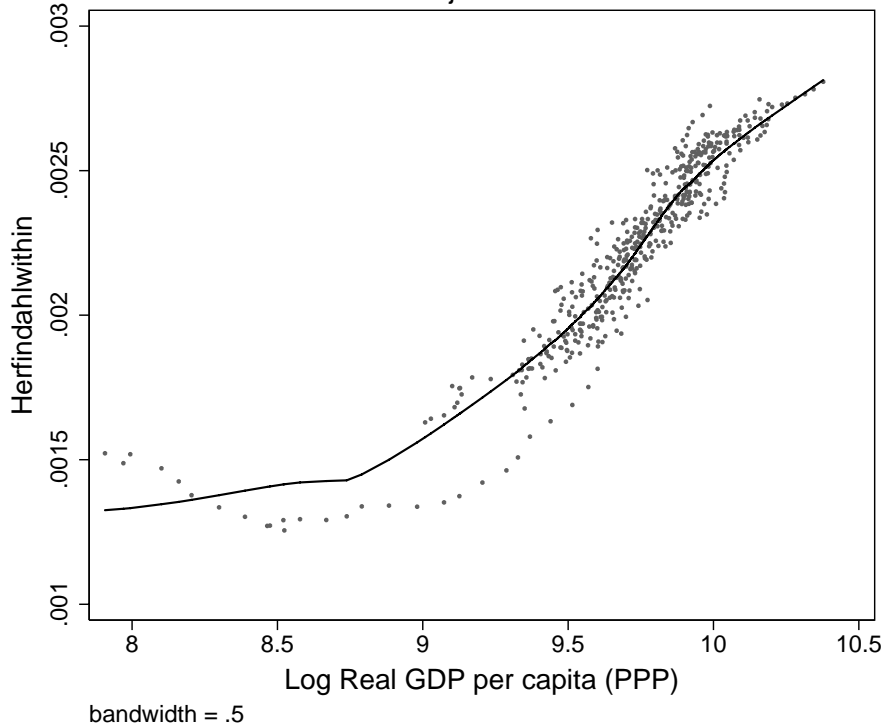


Figure 21: Country Risk OECD Sample

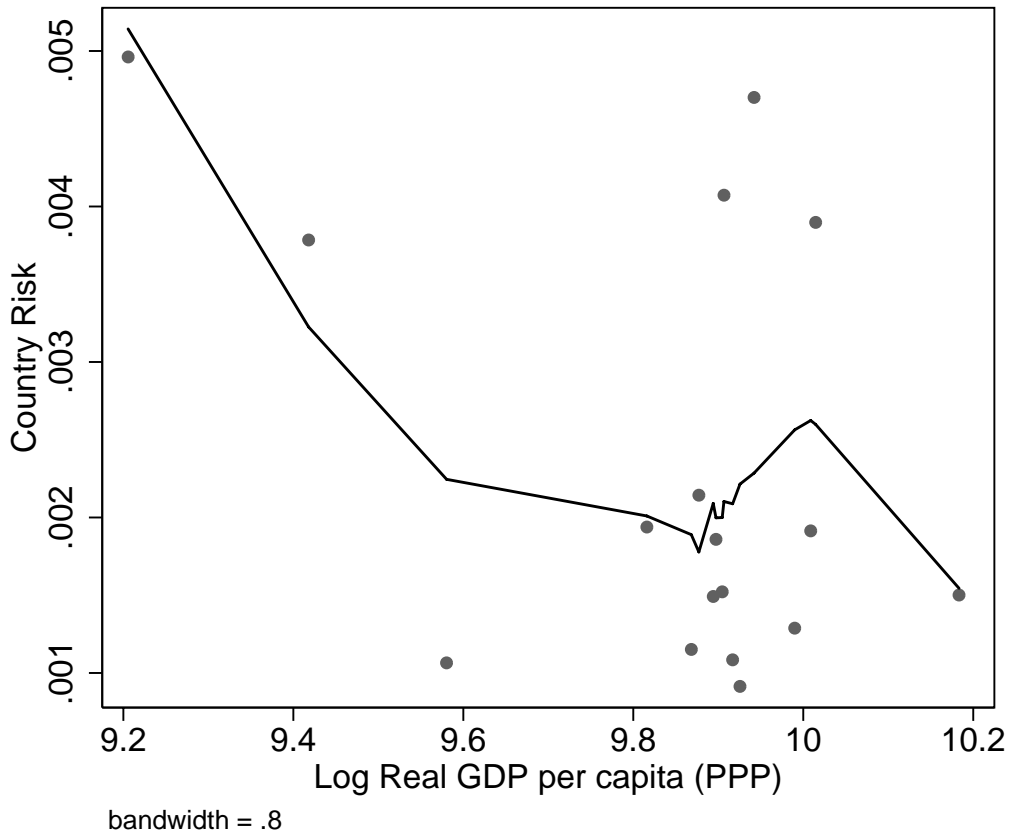


Figure 22: Sector–Country Covariance OECD Sample
Mean adjusted smooth

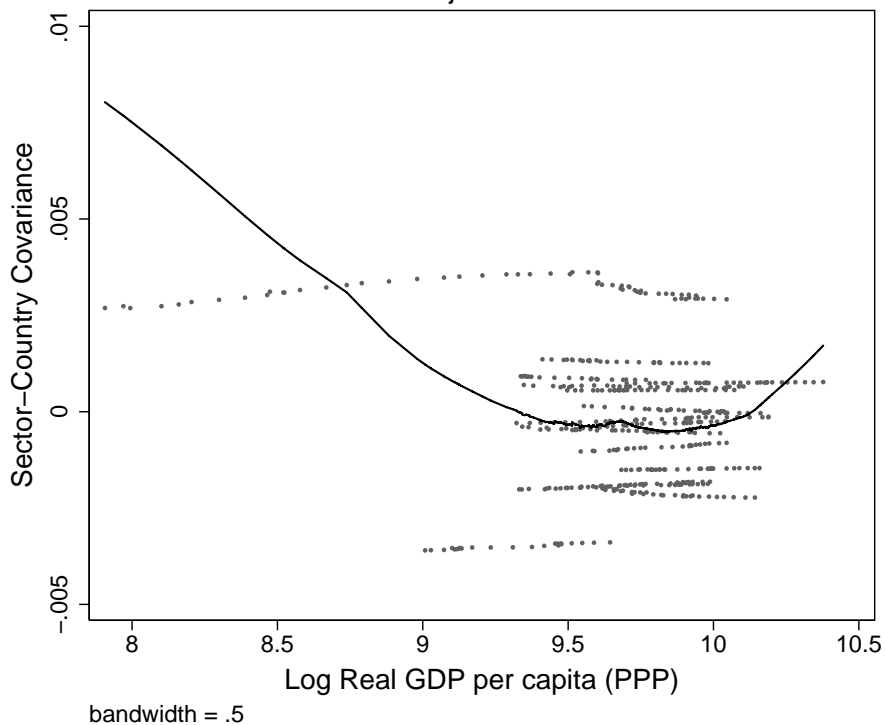
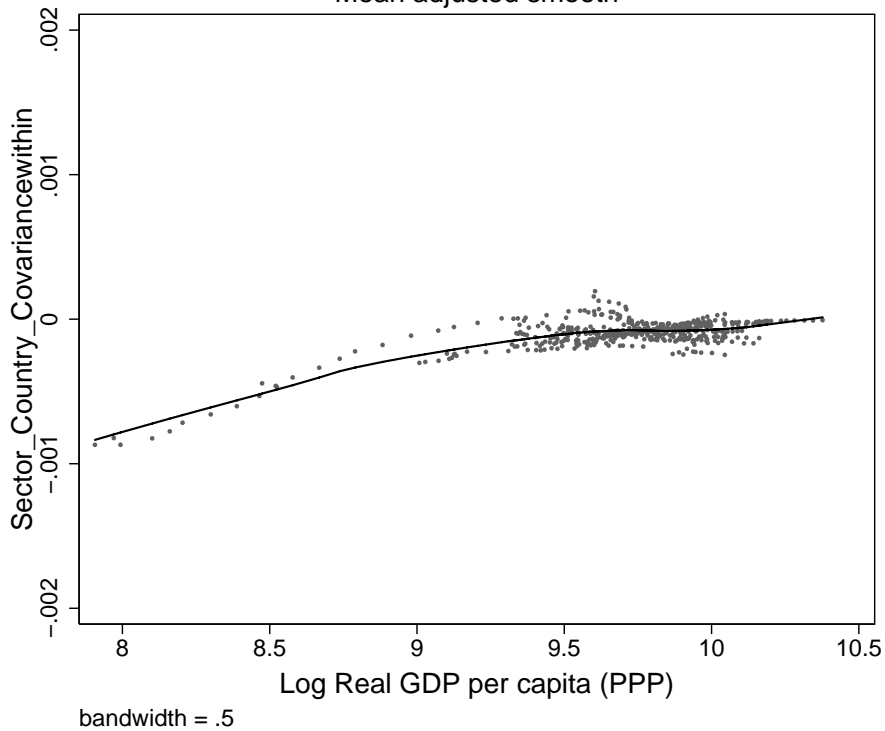


Figure 23: Sector–Country Covariance (within) –OECD Sample
Mean adjusted smooth



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