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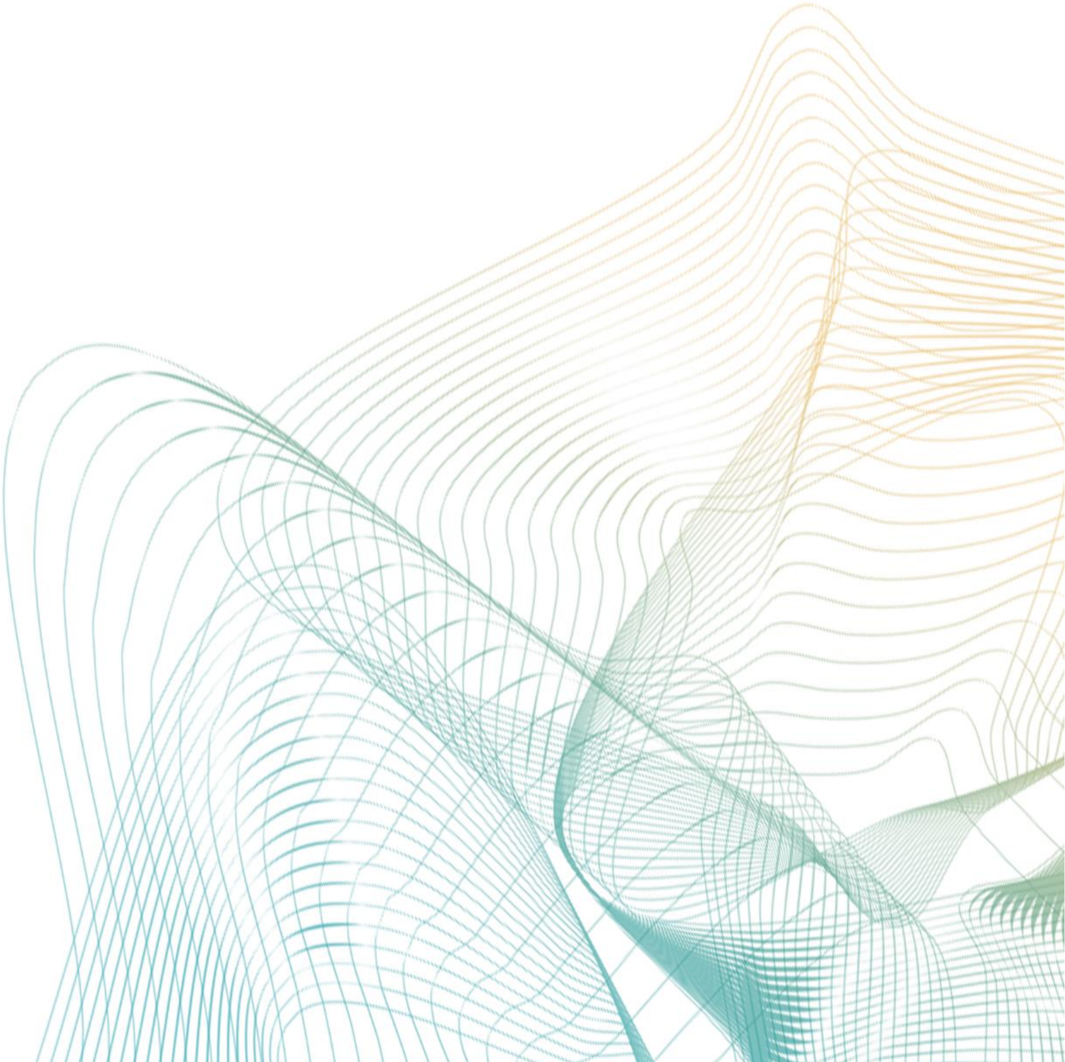
Orhun SEVİNÇ

August 2019

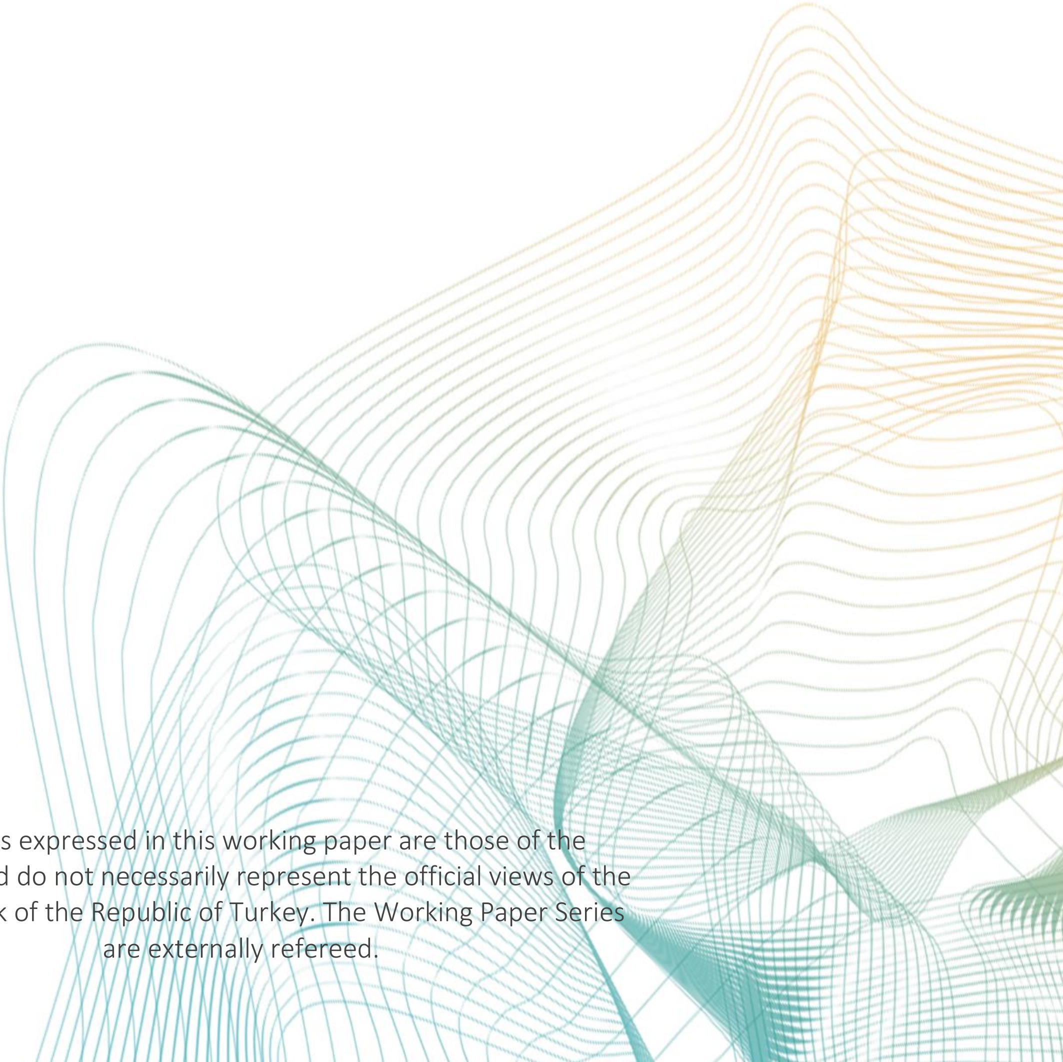
Working Paper No: 19/18



Address:
Central Bank of the Republic of Turkey
Head Office
Structural Economic Research Department
Hacı Bayram Mh. İstiklal Caddesi No: 10
Ulus, 06050 Ankara, Turkey

Phone:
+90 312 507 80 04

Facsimile:
+90 312 507 78 96



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ABSTRACT

This paper, based on a model of trade in the presence of sectoral distortions, develops a one dimensional sectoral misallocation index. It estimates the index using product-level bilateral trade data at the sector-country-year level since 1962. The geographical distribution of the misallocation index suggests substantial within-region differences across countries and across time. Notably, a large and historical allocative efficiency gap exists across the West and the East of Europe, while the latter shows a remarkable progress in catching up. On the other hand, the substantial gap between the North and South America is highly persistent. The paper then investigates the negative association of misallocation to economic performance through multivariate regression analysis. The index of misallocation inversely and robustly predicts cross-country productivity differences, contains valuable information on top of factors of production, and outperforms measures of diversification, product sophistication, and openness when time invariant country characteristics are accounted for.

KEYWORDS: *Trade, Misallocation, Comparative Advantage*

JEL CODES: *F10; F14; O10*

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[*] Central Bank of the Republic of Turkey and Centre for Economic Performance. E-mail: orhun.sevinc@tcmb.gov.tr

NON-TECHNICAL SUMMARY

A growing literature on allocative efficiency suggests that the resource misallocation across firms has substantial aggregate costs. Hsieh and Klenow (2009) estimate that half of the TFP gap between China or India and the US can be accounted for by misallocation. The main data source in these countries are surveys, which suffer from comparability with respect to time, sector composition, and mismeasurement. The measurement of misallocation is severely constrained by the scarcity and quality of the existing data sources. This paper aims to construct a novel misallocation measure that ensures cross-country comparability and historical availability using trade data.

This paper, based on a model of trade in the presence of sectoral distortions, develops a one dimensional sectoral misallocation index. It estimates the index using product-level bilateral trade data at the sector-country-year level since 1962. The geographical distribution of the misallocation index suggests substantial within-region differences across countries and across time. Notably, a large and historical allocative efficiency gap exists across the West and the East of Europe, while the latter shows a remarkable progress in catching up. On the other hand, the substantial gap between the North and South America is highly persistent. The paper then investigates the negative association of misallocation to economic performance through multivariate regression analysis. The index of misallocation inversely and robustly predicts cross-country productivity differences, contains valuable information on top of factors of production, and outperforms measures of diversification, product sophistication, and openness when time invariant country characteristics are accounted for.

1 Introduction

A growing literature on allocative efficiency led by Rogerson and Restuccia (2008), and Hsieh and Klenow (2009) suggests that the resource misallocation across firms has substantial aggregate costs.[1] Hsieh and Klenow (2009) estimate that half of the TFP gap between China or India and the US can be accounted for by misallocation. The main data source in these countries are surveys, which suffer from comparability with respect to time, sector composition, and mismeasurement (Bils, Klenow, and Ruane, 2018). The measurement of misallocation is severely constrained by the scarcity and quality of the existing data sources. This paper aims to construct a novel misallocation measure that ensures cross-country comparability and historical availability using trade data.

Data on trade are often regarded as a useful source of information in unveiling capabilities of economies as a whole as well as the products made by them. In particular, the information contained in the exports of a country compared to others has been considered to reveal comparative advantages since Balassa (1965), and still attracts attention of academic research (e.g., French, 2018). Existing approaches range from building better indexes than Balassa's original contribution (e.g., Yeats, 1986; Vollrath, 1991), to building theoretically consistent ways to estimate comparative advantage to understand their impact on economic performance (Costinot, Donaldson, and Komunjer, 2012; Levchenko and Zhang, 2016). While most papers in this literature are concerned with the level of comparative advantages, the current paper explores the value of information embedded in the cross-country differences in the *variance* of comparative advantages within sectors.

Asymmetric distortions across firms lead to misallocation of resources such that the within-sector distribution of production factors deviates from that implied by firm productivities. The severity of misallocation is proportional to the within-sector variation of distortions (Hsieh and Klenow, 2009). From the viewpoint of a trade model, distortions, by altering relative prices, also affect the export performance of the country. In this paper, I introduce distortions at the product level to a model of trade in the fashion of Eaton and Kortum (2002). This model delivers an estimable log of exports equation at the product level (French, 2018). From this equation one can identify and consistently estimate comparative advantages by means of product-country fixed effects (Costinot, Donaldson, and Komunjer, 2012).

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[1] See Hopenhayn (2014) for a review of misallocation literature.

This paper models the variation of the log of comparative advantages within a group of similar products (sectors) as a function of a globally shared dispersion in technology and country-specific shocks. The underlying assumption here is that the variance of the log of sectoral technology, i.e., within-sector dispersion in the product know-how, is the same across countries in a given year. The remaining dispersion is imposed by the structure of misallocations in a country. Consequently, the measure of misallocation proposed here is the residualized sectoral variances in log comparative advantages. The focus of this paper is the central tendency of sectoral distortions for a country at a particular time.

After constructing the index of misallocation, the paper is devoted to studying its links with economic performances of nations. The geographical distribution of the misallocation index suggests substantial within-region differences across countries and across time since 1962. Notably, a large and historical allocative efficiency gap exists across the West and the East of Europe, while the latter shows a remarkable progress in catching up. A similar temporal pattern is also observed between North and Central America. On the other hand, the substantial gap between the North and South America is highly persistent and slightly increasing over time. There is evidence of divergence in the East of Asia. South-Eastern Asian countries on average exhibit increasing misallocation over time, contrary to those of East Asia, which gradually increase efficiency in resource allocation.

The paper then investigates the negative association of misallocation to economic performance by employing a multivariate regression analysis. The index of misallocation inversely and robustly predicts cross-country productivity differences using the available data from the Penn World Table. Since the theoretical channel that misallocation affect economic performance is through aggregate TFP, I show that misallocation index contains valuable information in cross-country GDP per capita regressions containing human and physical capital.

The literature provides plenty of evidence on the productivity enhancing impact of trade and diversification. Ades and Glaeser (1999), Alesina, Spalaore, and Wacziarg (2000), and Alcala and Ciccone (2004) estimate significant gains from openness to productivity. Others document the association of diversification and concentration on economic development (e.g., Herfindahl, 1950; Hirschman, 1945; Imbs and Wacziarg (2003)). More recently, a growing literature explores the connection between the structure of exports and economic performance (Hausmann, Hwang and Rodrik, 2006; Hidalgo et al., 2007; Rodrik, 2006). These last set of papers emphasize that what a country exports in the realm of economic complexity matters for the growth and development of economies. Therefore, it is particularly important for this paper's misallocation measure to document whether the association of misallocation index to country performance is driven by other trade-based channels. I test against alternative channels in a country fixed effect estimation setting. The results suggest that the misallocation index outperforms measures of diversification, product sophistication, and openness when time invariant country characteristics are accounted for.

The following section develops an analytical framework where sectoral distortions in a trade model and suggests an alternative way to estimate misallocation at sector-country level. Section 3 introduces data sources and the misallocation measure. Section 4 explores the association between the trade-based misallocation index and economic performance of countries. Section 5 concludes.

2 Misallocation in a Trade Model

Conceptual framework

The analytical framework builds on the trade model of Eaton and Kortum (2002). The variety v from the $[0, 1]$ continuum of product k in sector s of country i from is produced by a single factor of production $\mathrm{L_{vksi}}$ combined with efficiency A_{vksi}. More specifically, the output is generated through monopolistically competitive firms through the production function $Y_{vksi} = A_{vksi}\mathrm{L_{vksi}}$. Variety efficiency is drawn from a Frèchet distribution with cumulative distribution function $F(A_{vksi}) = e^{-T_{ksi}A_{vksi}^{-\theta}}$. T_{ksi} is the sector-country-specific technology term that governs the mean level of technology and θ is the dispersion parameter. I assume product-specific distortions $\tau_{ksi} > 1$ and country-specific input cost c_i. Consequently, the firm profit function is $P_{vksi}A_{vksi}\mathrm{L_{vksi}} - \tau_{ksi}c_i\mathrm{L_{vksi}}$, where P_{vksi} is the price of variety. Profit maximization of the monopolistic competitor yields $P_{vksi} = \frac{\eta}{\eta-1}\ \frac{\tau_{ksi}\, c_i}{A_{vksi}}$, where $\eta > 1$ is the elasticity of substitution across varieties of a product.

I define the product-level TFP as the power mean of product level efficiencies, $A_{ksi} = \left(\int {A_{vksi}}^{\eta-1} dF(A_{vksi})\right)^{\frac{1}{\eta-1}}$. It can be shown that $A_{ksi} = T_{ksi}^{\frac{1}{\theta}}\, \Gamma\left(1 - \frac{\eta-1}{\theta}\right)^{\frac{1}{\eta-1}}$, i.e., the product-specific technology distribution parameters govern the sectoral technology.[2] Similarly, the ideal price index for

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[2] The result follows from the power mean formula for Frèchet distribution. Γ is the gamma function.

the product is $P_{ksi} = \left(\int P_{vksi}{}^{1-\eta} dF(A_{vksi})\right)^{\frac{1}{1-\eta}} = \frac{\eta}{1-\eta}\ \tau_{ksi}\, c_i\, T_{ksi}^{\frac{-1}{\theta}}\, \Gamma\left(1-\frac{\eta-1}{\theta}\right)^{\frac{1}{1-\eta}}$. Following Hsieh and Klenow (2009) I define quantity-based sectoral total factor productivity as $TFPQ_{ksi} = A_{ksi}$, and revenue-based total factor productivity as $TFPR_{ksi} = P_{ksi}\, A_{ksi} = \frac{\eta}{1-\eta}\ \tau_{ksi}\, c_i$.

The elasticity of substitution across different products in a sector is $\sigma > 1$. The sectoral TFP is given by $TFP_{si} = \left(\sum_k \left\{TFPQ_{ksi} \frac{\overline{TFPR}_{si}}{TFPR_{ksi}}\right\}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$, where $\overline{TFPR}_{si}$ the average sector revenue total factor productivity.[3] The implication is that within-sector dispersion of distortions worsens allocative efficiency and negatively affect productivity.

I further assume that each country is open and trade of product k from country i to country n is subject to iceberg costs, $d_{ni}^{ks} = d_{ni}\, d_n^{ks}$, where d_{ni} captures bilateral trade costs affecting all products such as geographical distance, and d_n^{ks} is the product's specific cost to be traded in country n such as import tariffs. Consequently, the price faced by a consumer residing at country n of a variety that is made in country i is $c_{ni}^{vks} = \frac{c_i\, d_{ni}^{ks}}{A_{vksi}}$. Consumers in country n observe the menu of all varieties produced in each country and buy the one that is cheapest to them. Following French (2018), and Eaton and Kortum (2002) one can show that the expenditure of country n for the product k of country i, i.e. country i's exports to country n for product k, $\mathrm{X}_{\mathrm{ni}}^{\mathrm{k}}$, can be expressed as

$$\mathrm{X}_{\mathrm{ni}}^{\mathrm{k}} = \frac{T_{ksi}\left(\tau_{ksi}\, c_i\, d_{ni}^{ks}\right)^{-\theta}}{\sum_{\mathrm{i}}\left(T_{ksi}\left(\tau_{ksi}\, c_i\, d_{ni}^{ks}\right)^{-\theta}\right)}\ \mathrm{X}_{\mathrm{n}}^{\mathrm{k}}\,, \tag{1}$$

where $\mathrm{X}_{\mathrm{n}}^{\mathrm{k}}$ is the sum of expenditure made by country n from the rest of the world. It is clear from the expression that comparative advantages at the product-country level, i.e. the elements that are purely driven by county i and product k, reveal themselves by a combination technology and distortions, $T_{ksi}\,(\tau_{ksi})^{-\theta}$.

As proposed by Costinot, Donaldson, and Komunjer (2012), a fixed effects estimation strategy helps identifying the relative revealed comparative advantages:

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[3] See Hsieh and Klenow (2009) equation 15.

$$ln\left(\mathrm{X}_{\mathrm{ni}}^{\mathrm{k}}\right) = \gamma_{ni} + \gamma_{kn} + \gamma_{ki} + \epsilon_{kni} \ , \qquad (2)$$

where the γ terms capture fixed-effects corresponding to subscripts, and ϵ_{kni} is the disturbance term. Comparison of equations (1) and (2) imply that the regression estimate of the product-country fixed term $\hat{\gamma}_{ki}$ captures the comparative advantage term in logs, i.e., $\ln\left(T_{ksi}\ \tau_{ksi}^{-\theta}\right)$.[4]

A measure of misallocation

The preceding discussion suggests that the severity of distortions within a sector is increasing in the variability of τ_{ksi}, which is manifested by the dispersion of $TFPR_{ksi}$.[5] From equation (1), it is also clear that distortions as well as product-specific technology shows up in the revealed comparative advantages. Therefore one can infer the extent of sectoral distortions by examining the variation in within-sector revealed comparative advantages provided that the variance of technology is known. Here I make the identifying assumption that within detailed sectors, the variance of technology at a given time is the same across the world. This assumption implicitly builds on the paradigm that the know-how on similar product groups are distributed similarly throughout the globe. In the extreme case, when the common variance is zero, then the product group shares a uniform technology.

In particular, I impose that the product-level technology parameter T_{ksi} is distributed following a log-normal distribution. The probability density function is

$$f(T_{ksi}) = \frac{1}{\sqrt{2\,\pi}\sigma_s T_{ksi}} \exp\left\{-\frac{(\ln(T_{ksi}) - \mu_{si})^2}{2\sigma_s^2}\right\} \ s.t. T_{ksi} > 0, \mu_{si} \in \ \mathbb{R}, \sigma_s > 0.$$

The sectoral common variance assumption is captured by the term σ_s. Hence, the variance of the log of the technology term is σ_s. This does not impose an extremely strict structure for the technology process. The expected value of technology parameter governed by μ_{si} can take very different values depending on the country and sector. Here it is allowed that the watch making sector is expected to intrinsically possess

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[4] Specifically, it captures $\ln\left(T_{ksi}\ \tau_{ksi}^{-\theta}\right) - \ln\left(T_{k_0 s_0 i_0}\ \tau_{k_0 s_0 i_0}^{-\theta}\right)$, where terms with subscript zero denote a reference product, sector, and country, respectively.

[5] When technology and distortions are jointly log-normally distributed, the sectoral TFP can be expressed as the variance of distortions (see equation 16 in Hsieh and Klenow, 2009).

a superior technology in Switzerland than many other countries. It is only the variance of the logs that are, conditional on the sector, expected to be the same across all countries.

The within-sector variance of the log of technology and independent country distortions within the sector is therefore $\sigma_s + \theta^2 var_s(ln(\tau_{ksi}))$, where var_s indicates that the variance is over the sector.

With this identifying assumption, one can estimate the sectoral technology variances by sector fixed effects, $\hat{\delta}_s$, from the following regression:

$$var_s(\hat{\gamma}_{ki}) = \delta_s + \varepsilon_{si} \;, \qquad (3)$$

where ε_{si} is the standard regression residual. Our interest is on the variance of non-technology shocks on the comparative advantages. I define sectoral misallocation as the residualized variance term, $var_s(\hat{\gamma}_{ki}) - \hat{\delta}_s$ from the estimation of equation (3), which captures the variance of the log distortion term, $\theta^2 var_s(ln(\tau_{ksi}))$.[6]

The aggregate TFP of each economy can be expressed as some average of sectoral TFPs as outlined in the previous section (Hsieh and Klenow, 2009). Hence, the variance of the log of sectoral distortions can be aggregated to country level by a measure of central tendency. Other things equal, the TFP and GDP per capita of a country is expected to be lower in economies with a higher level of misallocation.

In the next section, I introduce the data sources and provide long-run cross-country evidence that our one dimensional index of misallocation has predictive value for cross country differences in economic performance.

3 Data

The main data provide trade volumes at the product-origin-partner-year level and come from Feenstra et al. (2005) for 1962-2000 and from U.N. Comtrade for 2001-2014. The dataset is downloaded from the

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[6] Here the nature of firm is adopted following Hseh and Klenow (2009). However, the comparative advantage term captured by γ_{ki} in equation (2) could potentially reflect country and product-specific markups (De Loecker and Warzynski, 2012) and quality (Khandelwal, Schott, and Wei, 2013). The identification based on the variation of distortions is valid as long as the variance of the logarithm of these additional elements are sector-specific.

MIT’s Observatory of Economic Complexity (Simoes and Hidalgo, 2011). The product categorization follows SITC4 2nd Revision. 4-digit items define products, and the first three digits identify a narrowly defined sector throughout the analysis. The data consist of 117,815,053 bilateral trade observations including 986 products, 260 sectors, and 251 countries.

The measures of economic performance is from the Penn World Table (Feenstra et al., 2015). The main indicator of cross country productivity differences is the natural logarithm of the real GDP per capita at Purchasing Power Parity (PPP). The theory suggests that a measure of misallocation should operate its impact on economic performance particularly through efficiency. Therefore, I use the logs of physical and human capital as controls. In alternative specifications, I also employ the log of TFP calculated as the Solow residual.

Revealed comparative advantages are the estimated product-country fixed effects for each year using equation (2). Their variance within each 3-digit sector is then residualized using sector fixed effects as in equation (3). The country level measure of misallocation is the median of residualized sector variances of the comparative advantages.[7] For robustness checks, I calculate the median comparative advantages and their variance for each country and year. Additionally, as a commonly used measure of diversity, I construct a Herman Herfindahl (HH) index using the dataset as the sum of squared product export shares.

Other variables used are Economic Complexity Index (ECI) from Simao and Hidalgo (2011), and openness to trade data from the World Bank. ECI is a measure of diversity and product sophistication, and shown to be related to economic performance and inequality. Openness to trade is calculated as the share of a country’s total trade to its GDP in a given year.

A visual summary of the regional patterns of misallocation

Figure 1 shows the geographic distribution of the long-run average of the standardized misallocation index across the world. A couple of patterns immediately catch the eye. The wealthiest countries particularly those in North America, Western Europe as well as Australia and Japan rank among the lowest distorted.

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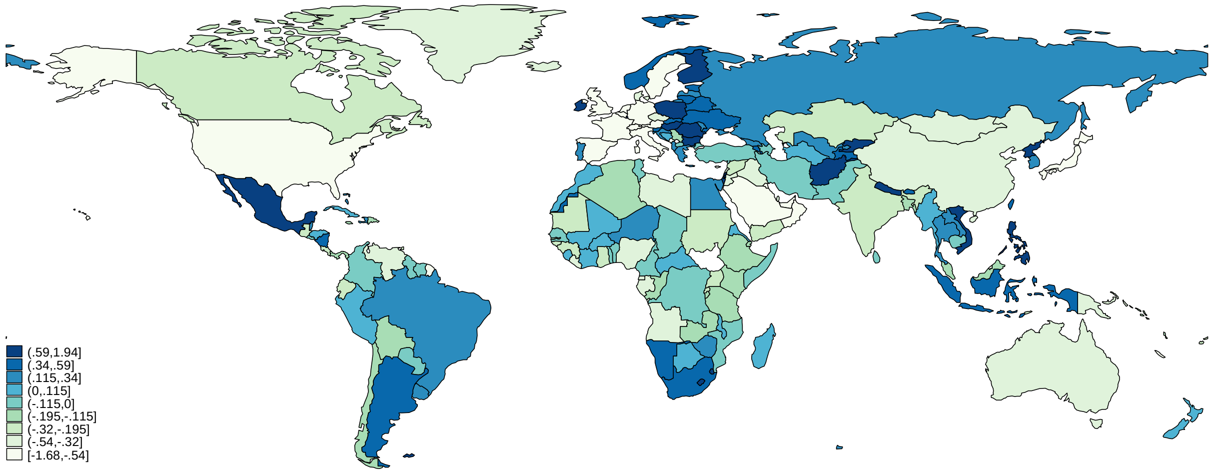
[7] The number of products within each sector-country-year observation is different. Therefore in the calculation of residualized variances I also control for the number of observations in sectors. Ignoring observation number adjustment and using other central tendency measures does not affect the main results .See the section on robustness for discussion.

Figure 1. Geographical Distribution of Misallocation, 1962-2014



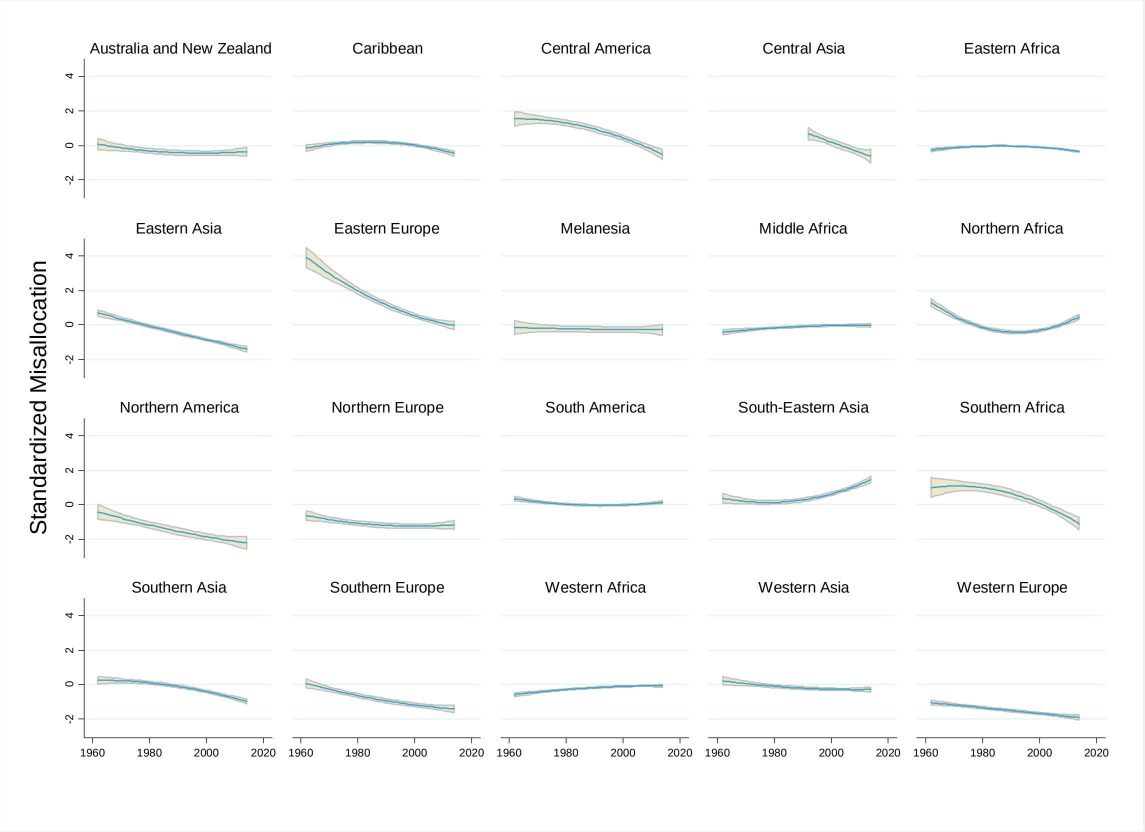
Note: Long-run average misallocation index by country. The misallocation index is standardized to have zero mean and unitary standard deviation in each year. The map visualizes the misallocation index in 9 brackets where dark blue and light green indicate greater and lower misallocation, respectively. The calculation averages over 1962-2014 period however each country score is calculated based on data availability. No data available for South Sudan.

Eastern European and Latin American countries are highly homogeneous in terms of having high degree of misallocation.

The time variation of the standardized misallocation measure by subregions is illustrated in Figure 2. The figure plots population-weighted fractional polynomial fit of pooled country and year observations by subregion. The geographical distribution of the misallocation index suggests substantial within-region differences across countries and across time since 1962. A large allocative efficiency gap exists across the West and the East of Europe, while the latter shows a remarkable progress in catching up. A similar temporal pattern is also observed between North and Central America. On the other hand, the substantial gap between the North and South America is highly persistent and slightly increasing over time.

Historically, the greatest decline in misallocation is observed in Eastern Europe, followed by Southern Africa and Central America. Western and Northern Europe, and Northern America have persistently low levels of misallocation, yet showing trends of decline. A notable exception of an upward misallocation trend is observed in South-Eastern Asian economies, which is largely accounted for by Philippines, Vietnamese and Indonesian economies. This contrasts with the declining misallocation trend of Eastern Asian countries.

Figure 2. Regional Trends of Misallocation



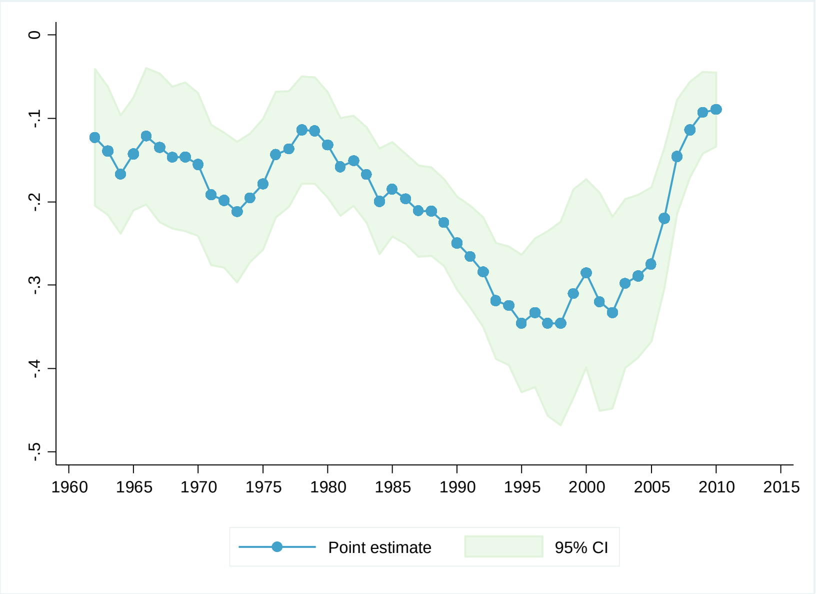
Note: Fractional polynomial fit of the standardized misallocation measure on time with 95 percent confidence interval by region. The fractional polynomial fit uses population weights.

4 Economic Performance and Misallocation

Cross-country income differences

I examine the misallocation measure's association with cross-country differences in economic performance, more particularly with GDP pc at constant PPP. The raw relationship in the pooled data from regressing GDP pc on the misallocation index suggests a slope of -0.32 and F statistic of 308.45. This correlation suggests that one standard deviation higher misallocation is associated with 32 percent higher GDP pc. However, the theoretical framework suggests a particular channel of misallocation on productivity through TFP. Therefore, it is of interest to evaluate the predictive performance of the constructed measure when other factors of production are also taken into account.

Figure 3. Conditional Correlation of GDP pc and Misallocation, 5 Year Rolling Window



Note: The figure plots the coefficient and 95 percent confidence interval of the standardized misallocation measure from the regression of log GDP pc with additional controls of log of physical and human capital, and year dummy variables. Each point shows the estimate for 5-year framed regression starting with the corresponding year. Confidence intervals are computed based on robust standard errors.

I start by providing some visual evidence on both the magnitude and the temporal evolution of the relationship. Figure 3 shows the estimated coefficient of misallocation measure as well as robust 95 percent confidence interval for 5 year moving time frames. The regression also controls for the log of physical and human capital, and assumes a potentially different constant term for each year. The long run average association of log GDP pc to the standardized misallocation index is around the levels of raw correlation. A notable pattern is the significant drop of the coefficient, i.e. increasing impact of misallocation on efficiency, during the 1980s until mid-1990s and its reversal around the Great Recession.

I formally summarize the relationship between misallocation and GDP pc for the pooled long-run sample in Table 1. Our primary interest is the estimate of coefficient α below as well as its standard error:

$$\ln(GDPpc_{it}) = \alpha\ Misallocation_{it} + \gamma_t + X'\beta + v_{it}\ ,$$

where γ_t is the time fixed effect, X' is the vector of physical and human capital, and v_{it} is the error term. The reported standard errors in parentheses are two-way clustered at country and year level, allowing for both correlations of error term across countries in a year and autocorrelation across years for each country.

Table 1. Conditional Correlations of Misallocation and GDP pc, 1962-2014

(Dependent Variable: Log of GDP pc)					
	(1)	(2)	(3)	(4)	(5)
Misallocation Ind.	-0.32***	-0.19***	-0.20***	-0.18***	-0.18***
	(0.10)	(0.05)	(0.05)	(0.04)	(0.04)
Physical capital		0.11***	0.11***	0.08***	0.08*
		(0.03)	(0.03)	(0.03)	(0.03)
Human capital		2.34***	2.54***	2.38***	2.38***
		(0.16)	(0.16)	(0.22)	(0.39)
Year FE	-	-	Yes	-	-
Region × Year FE	-	-	-	Yes	Yes
SE Cluster	Country, Year	Country, Year	Country, Year	Country, Year	Region, Year
Observations	6,631	6,631	6,631	6,631	6,631
Adjusted R^2	0.04	0.64	0.66	0.72	0.72

Note: Dependent variable is log of GDP per capita. Misallocation index is standardized to have zero mean unitary standard deviation each year. Physical and human capital are in logs. Column (3) includes year fixed effects. Columns (4)-(5) include region-year fixed effects. Two way cluster-robust standard errors are shown in parentheses. Columns (1)-(4) cluster by country and year, and column (5) by region and year. *** p<0.01, ** p<0.05, * p<0.1

Column (1) shows the unconditional OLS estimate. Column (2) includes variables for both types of capital. Column (3) adds year fixed effects. Regional shocks could affect all variables and the omission of it might bias the estimates. Columns (4)-(5) further include region-year fixed effects, and allows to observe the relationship within a region at a given time. Column (5) reports the results when standard errors are clustered by region instead of country. In all specifications the association between misallocation index and GDP pc is significant. The most conservative estimate is statistically significant at 1 percent level and suggests 16 percent increase of GDP pc following one standard deviation reduction in misallocation.

Country fixed effect specification

A more cautious examination could display discontent with the results shown above. I start here with the concern that is the result of omission of many potentially relevant variables. GDP pc differences are large and stem from many other variables other than factors of production of the neoclassical growth model. A lot of these alternative factors are persistent and country-specific such as geography and natural resources. The country fixed effect estimation exploits variation in the temporal dimension. Table 2 reports the results of the estimation of the model including country fixed effects, γ_i below:

$$\ln(GDPpc_{it}) = \alpha \, Misallocation_{it} + \gamma_t + \gamma_i + X'\beta + v_{it} \, .$$

Table 2. Conditional Correlations of Misallocation and GDP pc with Country Fixed-Effects, 1962-2014

	Dependent Variable: Log of GDP pc				
	(1)	(2)	(3)	(4)	(5)
Misallocation Ind.	-0.10***	-0.08***	-0.11***	-0.04**	-0.04**
	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)
Physical capital		0.55***	0.57***	0.43***	0.43***
		(0.05)	(0.06)	(0.06)	(0.05)
Human capital		-0.08	0.52	0.38	0.38*
		(0.31)	(0.31)	(0.26)	(0.19)
Period	1962-2014	1962-2014	<1970 & >2000	1962-2014	1962-2014
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	-	-
Region × Year FE	-	-	-	Yes	Yes
SEs clustered by	Country, Year	Country, Year	Country, Year	Country, Year	Region, Year
Observations	6,631	6,631	1,870	6,631	6,631
Adjusted R^2	0.93	0.95	0.96	0.96	0.96

Note: Dependent variable is log of GDP per capita. Misallocation index is standardized to have zero mean unitary standard deviation each year. Physical and human capital are in logs. Column (3) includes observations earlier than 1970 and later than 2000. Others use all available years between 1962 and 2014.Columns (1)-(3) include year and country fixed effects. Columns (4)-(5) include region-year, and country fixed effects. Two way cluster-robust standard errors are shown in parentheses. Columns (1)-(4) cluster by country and year, and column (5) by region and year. *** p<0.01, ** p<0.05, * p<0.1

The inclusion of country fixed effects drastically improves the R^2 of the model, which also reflects that there is too little variation in the data that fixed effects do not capture. Not surprisingly, the estimated coefficient of misallocation drops to -0.10. Yet, estimated coefficient is still significant at 1 percent level. Column (2) includes physical and human capital measures and slightly moves the misallocation coefficient down.[8] Column (3) compares the pre-1970 and post-2000 sample and confirms that the estimate does not change too much if one sharply focuses on the long-run changes. The most cautious estimation could call for regional-shocks affecting GDP per capita each year. The region-year and country fixed effects estimation in columns (4) and (5) indicate that the coefficient shrinks to -0.04 while statistically significant at 5 percent level.

Taking column (2) of Table 2 as the benchmark for the misallocation coefficient one can make a crude comparison to Hsieh and Klenow. (2009). Interpreting the residuals from column (2) as the TFP, the efficiency gap between China and the US would narrow down by 12 percent if China achieves the allocative efficiency of the US in 1997. As for India, the gap declines by about 14 percent. Though sizable,

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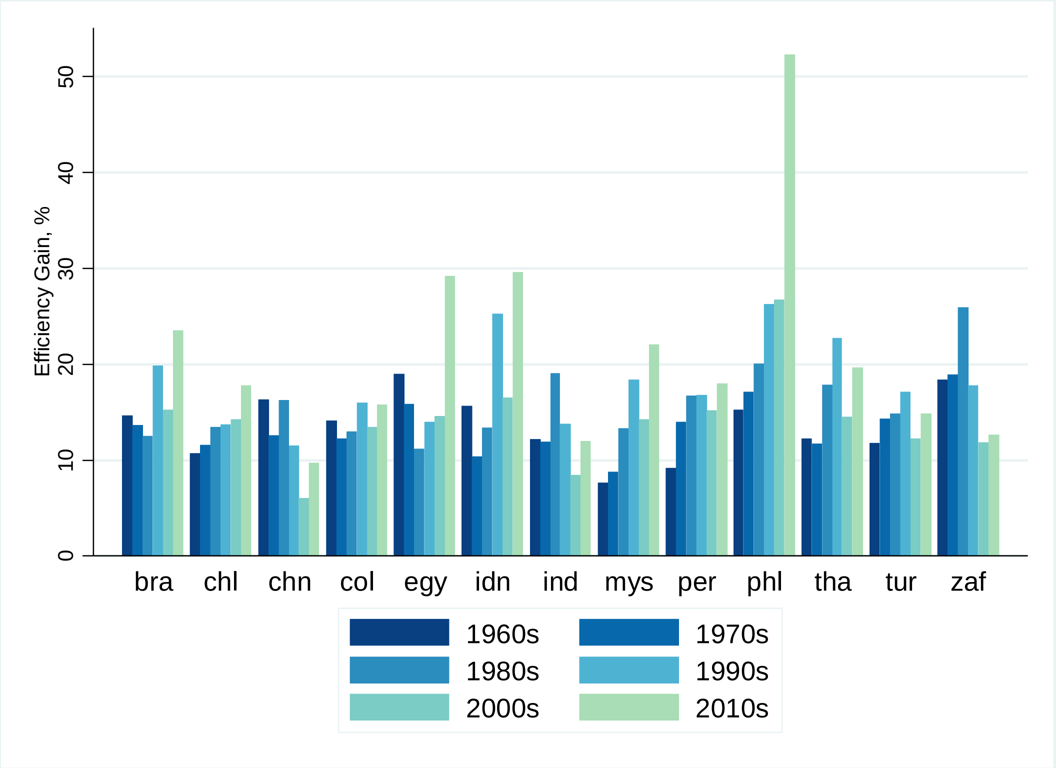
[8] Unlike physical capital, coefficients of the human capital measure in specifications with country fixed effects are insignificant, possibly due to the persistence of human capital differences across countries.

Figure 4. Potential Efficiency Gains from Superior Reallocation



Note: The figure shows the potential TFP gains from achieving a similar level of misallocation to the best performing country with the least misallocation index score. The gains are calculated annually as the distance of the misallocation index from the minimum index score times the coefficient of misallocation index reported in column (2) of Table (2) and then averaged over each decade. 1960s start with 1962 and 2010s end in 2014.

these are significantly smaller than the calculation of Hsieh and Klenow (2009). Similar calculations for 2014 suggest a decline of the gap by 22 and 15 percent in China and India, respectively.

The existence of misallocation estimates for many countries and years enables a wider comparison. Figure 4 illustrates the efficiency gains in a set of emerging economies following a hypothetical equivalence to the least misallocated economy in each decade since the 1960s. The gains from better reallocation is non-negligible and around 16 percent on average. While there are some interesting decade- and country-specific patterns in the figure, the rise in the efficiency gains from reallocation during the 2010s particularly stands out. This move takes place sharpest in Philippines where the potential efficiency gain doubles to 52 percent.

Table 3. Testing Against Alternatives, 1962-2014

	Dependent Variable: Log of GDP pc					
	(1)	(2)	(3)	(4)	(5)	(6)
Misallocation Ind.						-0.06**
						(0.03)
Comp. Adv. (CE)	0.02					-0.01
	(0.02)					(0.03)
Variance of CE		-0.04**				-0.00
		(0.02)				(0.03)
HH Index			0.04			-0.03
			(0.19)			(0.29)
ECI				-0.03		0.01
				(0.05)		(0.06)
Openness					0.07**	0.05
					(0.03)	(0.04)
Physical capital	0.56***	0.56***	0.56***	0.55***	0.52***	0.51***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)
Human capital	-0.08	-0.09	-0.08	-0.39	0.06	-0.20
	(0.32)	(0.32)	(0.30)	(0.37)	(0.32)	(0.33)
Observations	6,631	6,631	6,631	5,044	5,829	4,496
Adjusted R^2	0.95	0.95	0.95	0.95	0.96	0.95

Note: Dependent variable is log of GDP per capita. Misallocation index is standardized to have zero mean unitary standard deviation each year. Physical and human capital are in logs. See the text and data section for variable definitions. All columns include year and country fixed effects. Columns (4)-(5) include region-year, and country fixed effects. Two way cluster-robust standard errors by country and year are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Testing against alternative explanations

A first potential source of concern questions the measure itself. It could be the case that the residualized within-sector variances of comparative advantage seems a good predictor because it captures other forces of trade and measurement rather than misallocation. In such a case the true measure itself should perform better in the model, and possibly remove the estimate from the table when jointly present. Table 3 reports the country fixed effect regressions including alternative variables.

Column (1) shows the median comparative advantage based on the sector fixed effects of equation (2). It is an overall measure of efficiency reflecting the combination of technology and distortions. It is positively associated to GDP pc growth but yields a much lower and an imprecise estimate.

Column (2) uses the within country-year variance of comparative advantages rather than the median for the following reason. It could be the case that variances reflect measurement issues so that less developed countries have less precise measurement of trade, and therefore within-sector variation is also higher for poorly-performing countries. Some of this concern should be eliminated country fixed effects and human capital controls, given the persistent and human-capital-dependent nature of measurement quality. The variance of comparative advantages has a much lower coefficient yet statistically significant at 5 percent level.

Column (3) includes the specification when HH index is used as the measure of diversity. One could suspect that the within-sector variation of residualized comparative advantages reflect the level of diversification. The HH measure is negatively related to diversity, hence a negative coefficient is expected. According to column (3), there is evidence on the contrary.

A related measure is the ECI, which shows the country's sophistication based on diversity and ubiquity. ECI is shown to be closely related to level of development, inequality and future growth of countries. In column (4) it has the unexpected sign and statistically imprecisely estimated. However, this is not very much surprising because economic complexity variable is not intended to explain the variance in economic performance net of factors of production as this specification tries to test.

Column (5) employs a simple measure of the importance of the openness to trade, calculated as the share of total trade in GDP. The concern addressed here is similar to others. A country has potentially poor overall economic performance, jointly with poor trade performance. The latter suggests that such a country perhaps have a quite unorganized trade structure which mechanically drives up the within-sector variance. In fact, a coefficient of 0.07 is estimated with a statistical significance of 5 percent.

In the last column of Table 3, the results from the joint presence of all alternatives are reported. The inclusion of all variables do not help increasing the R^2 of the model. Furthermore, none of the proposed alternatives are significant. On the contrary, column (6) estimates a statistically significant coefficient of -0.06, which is a bit smaller compared to the benchmark estimate of -0.11 from column (2) of Table 2.

Other robustness issues

The theoretical source of the negative link between high misallocation and poor economic performance is through TFP. Adding physical and human capital measures to GDP per capita regressions has been the proposed solution of this paper. Alternatively, one could take the human capital augmented Solow model seriously and examine the association of misallocation index with the Solow residual. However, there is the issue of poor comparability of capital series across countries, which affects also the comparability of

TFP series across countries. Therefore I only report country fixed effect results here. The Solow residual of the PWT data additionally benefits from adjustment for average hours and employment. Appendix Table A1 summarizes the results on TFP for the misallocation measure alone and jointly with other alternative variables in columns (1) and (2), respectively. The results indicate 4 percent higher TFP following a standard deviation reduction of misallocation.

Columns (3)-(4) report the results when baseline specifications without and with country fixed effects are estimated using population shares as weights. Columns (5)-(6) employ the mean within-sector residualized variances instead of the median. Columns (7)-(8) use misallocation variable that is adjusted for sector fixed effects but unadjusted for number of products within sector. The last two columns of Table A1 report the results for GDP per worker as an alternative economic performance measure. The results are robust to weighting, alternative calculations of misallocation, and alternative dependent variables.

The focus of interest of this paper is mainly on the association between the cross sectional association of misallocation index and economic performances. Although, country fixed effects can be interpreted as the measuring temporal relationship within countries, the final analysis here explores the predictive capacity of the misallocation index of future growth in the spirit of Mankiw, Romer, and Weil (1992).

Column (1) of Appendix Table A2 shows the results of the estimation of the following equation:

$$\ln\left(\overline{GDP}pc_{i,d+1}/\overline{GDP}pc_{i,d}\right) = \beta \ln\left(\overline{GDP}pc_{i,d}\right) + \alpha\, Misallocation_{i,d} + \gamma_d + \gamma_i + v_{it},$$

where $\overline{GDP}pc_{i,d}$ denotes average GDP per capita of country i and decade d, γ_d and γ_i are decade- and country fixed effects, and v_{it} is the error term on the decadal growth. The estimated coefficient of -0.09 is statistically significant and remarkably close to the benchmark country fixed effect estimate in column (2) of Table 2.

The specification above is similar to the one employed in Hidalgo and Hausmann (2009). Column (2) brings the equation closer to Mankiw, Romer, and Weil (1992) by using GDP per worker instead of per capita measure, and introducing investment rate, human capital, and population growth. It reports a coefficient of -0.07.

5 Conclusion

A straightforward result of the extension of a widely used family of trade models with distortions in production is that export performances of countries depend on the combination of technology and distortions. Motivated by the key insight of Hsieh and Klenow (2009) that sectoral and country efficiencies depend on the within-sector dispersion of distortions, this paper develops an index of misallocation at the sector level, defined as the residual within-sector variance of log comparative advantages net of sectoral variability of technology at the global level.

The greatest advantage of developing the trade-based misallocation index is that it allows studying the structure of misallocation across the globe for the last fifty years. Aggregated to the country level, the proposed measure of misallocation is a robust predictor of the cross country productivity differences as well as temporal changes in GDP per capita. The misallocation index provides valuable information on top of production factors, and diversity and sophistication measures. Back of the envelope calculations suggest sizable productivity gains to equalizing allocative efficiency of developing countries to the best performers, though these gains are smaller than the calculations of Hsieh and Klenow (2009). While this study focuses on the implications of the developed measure at the country level the framework also enables comparison at the sector level.

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Table A1. Alternative Dependent and Misallocation Variables

Dependent Variable	Log TFP		Log GDP per capita						Log GDP per worker	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Misallocation (Median)	-0.04***	-0.04*	-0.14***	-0.07**					-0.21***	-0.07***
	(0.01)	(0.02)	(0.05)	(0.03)					(0.05)	(0.02)
Misallocation (Mean)					-0.27***	-0.05***				
					(0.05)	(0.02)				
Misallocation (Unadjusted)							-0.19***	-0.07***		
							(0.05)	(0.02)		
Comp. Adv. (CE)		0.00								
		(0.02)								
Variance of CE		0.01								
		(0.02)								
HH Index		0.22								
		(0.22)								
ECI		0.02								
		(0.03)								
Openness		0.07**								
		(0.03)								
Physical capital			-0.01	0.48***	0.09***	0.55***	0.10***	0.55***	0.10***	0.47***
			(0.04)	(0.05)	(0.03)	(0.06)	(0.03)	(0.05)	(0.04)	(0.05)
Human capital			3.13***	0.86*	2.45***	-0.10	2.52***	-0.10	2.24***	-0.44
			(0.18)	(0.44)	(0.16)	(0.32)	(0.16)	(0.32)	(0.19)	(0.35)
Observations	5,039	3,865	6,631	6,631	6,631	6,631	6,631	6,631	6,257	6,257
Adjusted R^2	0.54	0.53	0.80	0.96	0.68	0.95	0.66	0.95	0.58	0.94

Note: Dependent variable in columns (1)-(2) is log TFP calculated as Solow residual, columns (3)-(8) is log GDP pc, columns (9)-(10) is log GDP per worker. Misallocation variable in the first row is the one used in the main results. Second row uses mean sectoral misallocation by country and year, instead of median. Third row uses misallocation variable that is adjusted for sector fixed effects but unadjusted for number of products within sector. Physical and human capital are in logs. See the text and data section for other variable definitions. Columns (1), (2), (4), (6), (8), (10) include year and country fixed effects. Columns (3), (5), (7), (9) include year fixed effects. Columns (3)-(4) use population shares as weights. Two way cluster-robust standard errors by country and year are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2. Predicting Decadal Productivity Growth

Dependent Variable	Δ Log GDP pc	Δ Log GDP pw
	(1)	(2)
Initial Misallocation Index	-0.09***	-0.07**
	(0.03)	(0.03)
Initial GDP per capita in Logs	-0.44***	
	(0.05)	
Initial GDP per worker in Logs		-0.52***
		(0.05)
Initial Investment Rate in Logs		0.10***
		(0.04)
Initial Human Capital in Logs		0.83***
		(0.20)
Population Growth Rate in Logs		0.43
		(0.28)
Observations	622	583
Adjusted R^2	0.41	0.48

Note: Dependent variable is the decadal change in the log of GDP per capita in column (1) and GDP per worker in column (2). Misallocation index is standardized to have zero mean unitary standard deviation each year. All columns include decade and country fixed effects. Robust standard errors by country and year are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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