IS SKILL DIVERSITY A SOURCE OF PRODUCTIVITY AND EXPORTS IN DEVELOPING COUNTRIES?

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Abstract. This paper empirically establishes facts about the structure of production which several lines of theoretical literature have taken as a starting point, but for which there is little evidence. I empirically characterize developing country manufacturing sectors by whether skill mix (diversity or similarity) helps explain productivity, and how such productivity differences explain exporting. I find that greater than two thirds of firms in a large cross country sample belong to sectors where skill mix is an important determinant of productivity. Interquartile productivity differences explained by skill mix are comparable to the magnitude of training and imported inputs combined. Furthermore, the majority of sectors best utilize diverse skills which theory suggests are associated with higher wage inequality through "superstar" wage effects. Evaluating the effects of productivity differences on exports, I find skill mix explains intersector variation better than physical or human capital. Put together, the results show that a more detailed view of human capital, beyond that of a simple average, yields insights into productivity and export patterns.

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1. Introduction

A growing theoretical literature which spans a variety of economic contexts has investigated the implications of skill complementarity and substitutability in production. By skill complementarity I refer to production processes which are "similarity loving" or rather, supermodular in skill inputs as typified by the O-Ring production process of Kremer (1993). Skill substitutability in production is the opposite of complementary processes in that they are "diversity loving" or rather, submodular in skill inputs. Skill substitutability is typified by superstar production processes which depend primarily on the most skilled member of a team, an idea which goes back to Rosen (1981). Such a fundamental distinction between methods of production, if they exist, have important implications for growth[1], labor markets in the presence of imperfect information[2], microeconomic theories of the firm[3], wage inequality and trade. Within this paper I focus on two main implications. In light of theory suggesting that "diversity loving" sectors give rise to "superstar" wages that generate inequality, I provide an empirical characterization of which manufacturing sectors these are from the production side. I then turn to the implications for trade, in particular the link from skill mix to productivity and exporting.

Despite the wealth of theoretical implications and their usefulness in providing novel explanations for observed patterns, there is a paucity of evidence for skill complementary and substitutability at the firm level. The focus of this paper is empirically establishing such evidence and providing a characterization of manufacturing sectors as either "similar skill loving", "diverse skill loving" or neutral. My approach is first to motivate an estimable structural form which characterizes the role of skill in production. Second, I estimate the characterization by sector using cross country firm level data, finding evidence of skill similarity and diversity as an explanatory component of firm level productivity. Third, I use the productivity variation explained by skill mix within each sector to account for export patterns. With respect to the trade implications, this approach joins two strains of the trade literature. The first literature, as embodied by Melitz (2003), emphasizes the role of heterogeneous firm level productivity (generated by an exogenous process) as a selection mechanism

[1]Das (2005) considers research and development as a submodular process while consumption goods are produced using a supermodular process. Jones (2008) builds on the idea of complementary production processes and intermediate goods linking sectors in order to explain the 50 fold per capita income differences between developing and developed countries, returning to "several old ideas in the development economics literature."

[2]Delacroix (2003) links unemployment and wage dispersion through a search model involving heterogeneous agents with joint production. See also Acemoglu (1999), Grossman (2004) and Moro and Norman (2005).

[3]For example Hong and Page (2001) who theoretically explore role of diversity in production in a novel way, suggest a search for additional empirical evidence of richer organizational theories.

for exports in the presence of trade frictions. I theoretically and empirically connect productivity differences in such selection frameworks to those that would be generated by a heterogeneous labor force employed in patterns reflecting sector level O-ring or superstar technologies. Such patterns are the implications of a second trade literature which explains heterogeneous productivity differences in a Neo-Ricardian fashion as outcomes of heterogeneous worker matching.

Explaining endogenous firm productivity through input heterogeneity has been approached theoretically by Manasse and Turrini (2001) and Yeaple (2005). Both papers utilize a monopolistically competitive framework where firms are heterogeneous due to single entrepreneurs who can increase the quality of goods or single workers whose skill have different levels of complementarity with a discrete technology. In contrast, I investigate a different channel based on the relationship between sector-specific technology and *skill mix* rather than the level of individual skill as advanced by Grossman and Maggi (2000). I establish that if skills enter into production in a CES form, the elasticity of substitution parameter determines each sector to be relatively complementary or substitutable thereby providing a lever to estimate a ranking of sectors. From a theoretical perspective, the models of Manasse and Turrini (2001) and Yeaple (2005) result in the selection of high skill inputs into export activities and are competing explanations for the stylized facts of a growing skill premium and productivity differences between exporters and non-exporters. In full, my model as developed in Morrow (2008) also relaxes the assumptions of Grossman and Maggi and forms a complementary explanation of these same stylized facts. However, the focus here is to empirically operationalize and estimate the production primitives of Grossman and Maggi and search for direct evidence of the linkage between skill mix and exports.

From an empirical standpoint, I first estimate cross country firm production using observed skill mix variation to identify the *degree* of complementarity or substitutability for each sector.[4] Estimation is conducted for a cross section of firms in developing countries where productivity differences in skill as proxied by education should be most pronounced and important economically, due to both higher heterogeneity in educational attainment and labor abundance. Furthermore, as there are theoretical linkages between the degree of complementarity or substitutability and inequality, the magnitudes of the estimates are particularly relevant in a developing country context.[5]

[4]The closest work I am aware of is Iranzo, Schivardi, and Tosetti (2006) who examine skill dispersion and firm productivity using Italian employer-employee panel match data. They find that productivity is associated with a higher overall dispersion of skills and evidence of complementarity between production and non-production workers.

[5]The relationship between trade and inequality has generated a vast literature. For surveys, see Kremer and Maskin (2003), Winters, Mcculloch, and Mckay (2004) and Goldberg and Pavcnik (2007).

I find that over two thirds of developing country firms (in my sample of 32 countries) belong to sectors which can be significantly characterized as either "similar skill loving" (supermodular) or "diverse skill loving" (submodular). Accounting for the magnitude of productivity differences explained by skill mix in such sectors, I find that interquartile differences are roughly comparable to the effects of training and imported inputs combined and larger for some sectors.

Second, I use the firm level productivity differences explained by skill mix to estimate firms' propensity to export, completing the connection from skill complementarity and substitutability to trade. This echoes, from a micro perspective, the approach of Trefler (1995) who tests the endowment based predictions of Heckscher-Ohlin-Vanek theory against observed patterns and volume of trade; see also Conway (2002). If comparative advantage arises from a relatively high endowment of diverse labor as theory suggests, the predicted pattern and volume of trade for any sector will depend on skill complementarity and substitutability within the sector. Therefore, the results of this paper shed light on the pattern of trade by providing micro level evidence of the magnitude of supermodularity and submodularity across sectors and the extent such differences, once combined with worker skill endowments, translate into exports. Here I find that interquartile productivity differences accounted for by skill mix predict within sector export variation about as well as physical and human capital intensity combined.

The rest of this paper is organized in five sections. Section 2 connects implications of skill complementarity and substitutability and the approach of this paper to the literature. Section 3 puts forth the production estimation methodology and establishes the structural relationship which determines the degree of skill complementarity or substitutability within a sector, which is shown to correspond to the elasticity of substitution in a standard CES form. Section 4 describes the data and discusses the production estimation results. Section 5 discusses the relationship between productivity explained by skill mix and propensity to export. Section 6 concludes.

2. Related Literature

In this Section I briefly highlight the importance of skill complementarity and substitutability in the empirical literature on wage inequality. I then discuss approaches of the trade literature beyond those of Manasse and Turrini (2001) and Yeaple (2005) which explain comparative advantage on the basis of differing distributions of worker characteristics.

2.1. **Wage inequality.** Andersson, Haltiwanger, Freedman, Lane, and Shaw (2006) use employer-employee matched data to study product specific payoffs and superstar wages in the software industry. They find that firms with high potential payoffs for selecting the right products (a task assisted by worker talent) pay higher starting salaries and select superstars who have a history of success. In particular, the highest talent workers are paid much more than those marginally less skilled, as implied by a submodular production technology. Martins (2008) also uses matched employer-employee data to tackle competing theories of the relationship between wage dispersion on firm performance, finding a positive relationship which becomes negative once firm and worker fixed effects are considered. Martins points out there could be unobserved traits of firms that simultaneously increase wage dispersion and firm performance as is implied by skill substitutability in production. Mamoon and Murshed (2008) find that developing countries with a higher level of average schooling experience less increases in wage inequality following trade. The theoretical implications for wage inequality and the linkages of superstar wages with trade due to the absence of factor price equalization are particularly striking and have been considered separately by the author, see Morrow (2008).

2.2. **Trade.** Skill heterogeneity can produce comparative advantage on the basis of differing distributions of worker characteristics and the pattern of trade reflects specialization toward goods which best utilize the curvature of a country's skill distribution. Such predictions for the pattern of trade have been established in different ways, depending on the mechanism: Grossman and Maggi (2000) consider a two good, two country, single factor (2x1x2) model where pairs of workers sort in either supermodular or submodular production. Here a mean preserving spread in skill for one country will cause it to specialize in submodular production. Bougheas and Riezman (2007) provide a 2x1x2 model where single workers can employ human capital either as effective labor units towards one good or in production where human capital is irrelevant to output. In this case both first order stochastic dominance and mean preserving spreads can predict a pattern of trade. Ohnsorge and Trefler (2004) consider a multisector model where heterogeneous workers have two attributes which enter production in a Cobb-Douglas fashion and workers individually sort into the sector which pays them their highest product. In this case a high correlation between worker attributes amounts to a relative abundance of one of the factors, resulting in a pattern of trade based on a second moment of the skill distribution.

3. Estimation Methodology

In order to uncover production technologies which would imply a ranking of skill diversity across sectors, we require functional forms which allow a clear interpretation of estimated parameters. As developed above, the CES form allows a clear interpretation of productivity differences arising from skill complementarity or substitutability. As the theory section shows, other specifications satisfying the Sector Ranking conditions would also be viable candidates for estimation. It is worth remarking that the often used Cobb-Douglas form for skill inputs cannot distinguish skill inputs as being supermodular or submodular since the cross partials are always positive, implying a supermodular form.[6] As pointed out by Hong and Page (2001), the original Cobb-Douglas specification for production was based on empirical regularities. As the CES form generates reasonable results, I leave other specifications for future work. In this section I first develop a simple, but novel, specification and then incorporate controls for differences in foreign and domestic markups and input costs. I then discuss the econometric approach and identification assumptions.

3.1. **Specification.** In order to motivate our empirical specification to uncover the role of skill diversity in production, I begin with a general form $Y_i = G(K_i, L_i, \psi_i)$ which relates value added output Y_i for a firm i to capital K_i, labor L_i and a $k-$dimensional distribution of skill levels employed $\psi_i = \begin{pmatrix} \psi_{1,i} & \dots & \psi_{k,i} \end{pmatrix}$ measured in percentage terms. Modeling the effect of ψ_i as a labor augmenting factor $\phi(\psi_i)$, we rewrite the production function using a neo-classical production function F

$$Y_i = G(K_i, L_i, \psi_i) = F(K_i, \phi(\psi_i) \cdot L_i) \tag{3.1}$$

Letting F be the standard Cobb-Douglas form $F(K, L) = AK^{\alpha}L^{\beta}$ and allowing both F and ϕ to be specific to each sector S, denoted F_S and ϕ_S, value added output Y_i for a firm i in sector S is given by Equation (3.2).

$$Y_i = F_S(K_i, \phi_S(\psi_i) \cdot L_i) = A_S K_i^{\alpha_S} L_i^{\beta_S} \phi_S(\psi_i)^{\beta_S} \tag{3.2}$$

In Equation (3.2), the contributions of capital and labor are assumed to be sector specific, with both sector specific and firm idiosyncratic productivity terms A_S and $\phi_S(\psi_i)^{\beta_S}$.

[6] For instance, Ohnsorge and Trefler (2004) model heterogeneous workers with "human capital" and "brawn" attributes which enter production in a Cobb-Douglas fashion, implying complementarity between the attributes across all sectors.

I now connect the productivity term $\phi_S(\psi_i)^{\beta_S}$ of Equation (3.2) to the composition of skills employed in the firm affects labor productivity via supermodularity and submodularity in skill inputs. This is done by assuming ϕ_S be the CES form, with a sector specific substitution parameter ρ_S. Specifically, I assume ϕ_S takes the form

$$\phi_S(\psi_i) = \left(\psi_{1,i}^{\rho_S} + \psi_{2,i}^{\rho_S} + \ldots + \psi_{k,i}^{\rho_S}\right)^{1/\rho_S} \tag{3.3}$$

The CES specification (3.3) implies ϕ_S is supermodular in ψ_i for $\rho_S < 1$ and submodular in ψ_i for $\rho_S > 1$. To help fix ideas about the meaning of $\rho_S \gtrless 1$, consider the limiting cases as $\rho_S \to \infty$ and $\rho_S \to -\infty$. As is well known, these limiting cases of the CES are

$$\lim_{\rho_S \to \infty} \phi_S(\psi_i) = \max\{\psi_{1,i}, \psi_{2,i}, \ldots, \psi_{k,i}\} \qquad \lim_{\rho_S \to -\infty} \phi_S(\psi_i) = \min\{\psi_{1,i}, \psi_{2,i}, \ldots, \psi_{k,i}\}$$

Therefore in a sector with $\rho_S > 1$, we can expect a high productivity firm (as measured by ϕ_S) to choose a ψ_i which maximizes $\max\{\psi_{1,i}, \psi_{2,i}, \ldots, \psi_{k,i}\}$. Such a choice of ψ_i would be typified by vectors of the form $\begin{pmatrix} 1 & 0 & 0 & 0 \end{pmatrix}$, $\begin{pmatrix} 0 & 1 & 0 & 0 \end{pmatrix}$, etc. which is to say a mix of workers with similar skill levels. Thus firms in a sector with $\rho_S > 1$ benefit from skill similarity. Conversely, in a sector with $\rho_S < 1$ we can expect a productive firm to pick a ψ_i which roughly maximizes $\min\{\psi_{1,i}, \psi_{2,i}, \ldots, \psi_{k,i}\}$, typical choices being ψ_i close to $\begin{pmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix}$. This implies a mix of workers with diverse skills. Finally, at $\rho_S = 1$, $\phi_S(\psi_i)$ collapses to $\sum \psi_i = 1$ implying that differences in skill mix have no influence on productivity, thus ϕ_S nests the null hypothesis that skill mix is irrelevant for productivity at $\rho_S = 1$. To summarize, for sectors where $\rho_S < 1$, increases in diversity as measured by ϕ_S increase productivity and conversely for $\rho_S > 1$.

Combining the specification (3.2) with the basic production Equation (3.2) and adding an idiosyncratic productivity term ϵ_i for estimation, we arrive at (3.4).

$$Y_i = F_S(K_i, \phi_S(\psi_i) \cdot L_i)\epsilon_i = \underbrace{A_S K_i^{\alpha_S} L_i^{\beta_S}}_{\text{Cobb-Douglas}} \cdot \underbrace{\left(\sum \psi_{e,i}^{\rho_S}\right)^{\beta_S/\rho_S}}_{\text{Explained Productivity}} \epsilon_i \tag{3.4}$$

The specification (3.4) allows identification of super/submodularity through estimation of ρ_S. In addition, the specification allows for testing against the null hypothesis $\rho_S = 1$ which implies $\left(\sum \psi_{e,i}^{\rho_S}\right)^{1/\rho_S} = 1$ so Equation (3.4) shows that the null hypothesis $\rho_S = 1$ corresponds to a standard neo-classical form with no labor augmentation from skill mix. We will be most concerned with using the term $\phi_S(\psi_i)^{\beta_S} = \left(\sum \psi_{e,i}^{\rho_S}\right)^{\beta_S/\rho_S}$ of (3.4) to explain within sector heterogeneity and later, export propensity.

3.2. **Controlling for the sales effects of exporting.** In my data, I observe the value of sales generated by a firm instead of the direct quantities of different goods produced. Fernandes and Pakes (2008) have also used a similar data set and emphasize that the data allows for estimation of the "sales generating function" rather than the production function (for simplicity we will stick to the label "production function") but refer the reader to Section 3.1 of their paper for a discussion of the distinction.[7] Since sales are what are observed, of immediate concern from our standpoint is controlling for the sales effects of producing for both the domestic and foreign market. Ideally, we would like to observe production information that differentiates (to the greatest extent possible) the use of inputs for domestic and foreign use, although of course many inputs cannot be differentiated so the true counterfactuals of exporting are not directly observable. We must therefore impose some structure on the domestic and foreign decomposition of revenues if we wish to control what we can with the data available. The decomposition is simple and of an accounting nature, although more involved derivations are possible.[8]

Suppose firm i produces a quality adjusted quantity q_i of which a fraction X_i is sold to foreign markets at price p_i^X and the remainder is sold domestically at price p_i^D. We then have that value added sales, Y_i is given by Equation (3.5).

$$Y_i = X_i \cdot [p_i^X - c_i^X]q_i + (1 - X_i) \cdot [p_i^D - c_i^D]q_i \tag{3.5}$$

Defining the foreign (M_i^X) and domestic (M_i^D) markups in the usual way by $M_i^X \equiv (p_i^X - c_i^X)/c_i^X$ and $M_i^D \equiv (p_i^D - c_i^D)/c_i^D$, we may rewrite Equation (3.5) as Equation (3.6):

[7] Fernandes and Pakes (2008) are primarily concerned with institutional constraints and productivity in Indian firms. Accordingly, they use data on corruption, electricity outages, and receiving loans as controls of which only the latter two are feasible in terms of attrition for my sample. I have not included them in this draft. They also incorporate industry specific constants to control for cross sector price differentials as I do.

[8] Depending on the focus and data available, various methods can be used. For instance, Melitz (2000) is primarily concerned with washing out biases in measuring firm productivity for differentiated product firms. After imposing a particular demand structure, Melitz (2000) provides an estimation method based on Levinsohn and Petrin (2003) to recover the "true" firm productivities. In a similar vein, De Loecker (2007) estimates productivity gains from liberalization using an explicit demand system which implies constant markups, the latter being an assumption I impose below.

$$(3.6) \qquad Y_i = \underbrace{(p_i^D - c_i^D)q_i}_{\substack{\text{Value added sales at} \\ \text{domestic prices and input costs}}} \cdot \underbrace{1 + \frac{M_i^X(c_i^X/c_i^D) - M_i^D}{M_i^D} X_i}_{\substack{\text{Export weight to account for} \\ \text{foreign markups and input costs}}}$$

so that value added sales may be decomposed into VA sales at current quantities if sold domestically times an export weighted quantity that depends on foreign and domestic markups and input costs.

In practice, logs are used for estimation, which is where the decomposition (3.6) is of particular use. After taking logs, (3.6) becomes

$$\ln Y_i \approx \ln(p_i^D - c_i^D)q_i + \frac{M_i^X(c_i^X/c_i^D) - M_i^D}{M_i^D} X_i$$

where the approximation is the commonly used fact that $\ln(1+x) \approx x$ for small values of x, or in our case, small values of $\frac{M_i^X(c_i^X/c_i^D)-M_i^D}{M_i^D}X_i$. We will use this approximation below, which in practice is very close, as this halves the number of non-linear parameters we must recover. Although we cannot identify the individual elements of $\frac{M_i^X(c_i^X/c_i^D)-M_i^D}{M_i^D}X_i$, X_i is observed so that assuming that the term $\frac{M_i^X(c_i^X/c_i^D)-M_i^D}{M_i^D}$ does not vary across some grouping (as would be implied by constant markups within the grouping and c_i^X/c_i^D fixed, say to one), we may identify $\frac{M_i^X(c_i^X/c_i^D)-M_i^D}{M_i^D}$ to use it as a control for the sales effects of exporting. In what follows we will assume $\frac{M_i^X(c_i^X/c_i^D)-M_i^D}{M_i^D} = \frac{M_S^X(c_S^X/c_S^D)-M_S^D}{M_S^D} \equiv M_S$ for all firms i in sector S in order to focus on within-sector differences.[9] Since the firms we are considering produce in developing countries, we generally should expect $M_S \geq 0$ both because of the volume being exported to the economic North leading us to expect $M_S^X \geq M_S^D$ (see Oecd (2006)) and because of the potentially higher costs for "export quality" goods ($c_S^X \geq c_S^D$).

3.3. **Econometric considerations.** After a transformation of (3.4) by logs, letting lower case letters represent log-values, $\tilde{\epsilon}_i \equiv \ln \epsilon_i$ and incorporating the control for the effect of exports on sales, $M_S X_i$ we arrive at Equation (3.7)

$$(3.7) \qquad y_i = M_S X_i + \frac{\beta_S}{\rho_S} \ln \sum_{e=1}^{4} \psi_{e,i}^{\rho_S} + a_S + \alpha_S k_i + \beta_S L_i + \tilde{\epsilon}_i$$

[9] Constant markups for both exporting and domestic production are, for example, consistent with Melitz (2003), but no longer hold once that model is modified to allow for scale effects as in Melitz and Ottaviano (2008). For a concise summary and comparison of these models see Dhingra and Morrow (2008).

In our case, K_i and L_i are measured by expenditures on capital and labor. Here we have specialized the complementarity or substitutability term $\left(\sum \psi_{e,i}^{\rho_S}\right)^{\beta_S/\rho_S}$ to reflect our data which has the percentage of workers within four educational bins by firm. Equation (3.7) is non-linear in the CES coefficients ρ_S which leads us to some choices about the estimation method.

Estimation of CES production technologies goes back at least to Kmenta (1967) who surmounts computational issues by using a second order approximation to the production function, which subsequently became a popular technique, e.g. Klump, Mcadam, and Willman (2007). However, subsequent simulation work indicates that Kmenta's approximation suffers from efficiency problems, resulting in "unacceptable standard errors" (Hansen and Knowles, 1998; Tsang and Persky, 1975; White, 1980). The most closely related paper in approach is (Iranzo, Schivardi, and Tosetti, 2006) who estimate the a linearized CES version which allows the use of techniques to control for firm level fixed effects and other endogeneity issues (for a brief overview of such techniques see Arnold (2005)). In comparison to my approach, Iranzo et al. have a larger sample across time and so suffers from fewer endogeneity issues although concerns about the the consistency and efficiency of the linearized CES in their estimates remain. In this respect, the current data availability of cross-country firm level panels is a limitation to controlling for endogeneity issues in my approach, but as the data becomes available and techniques for non-linear production estimation are better developed I expect these issues will be overcome.[10] However, while endogeneity is a problem for estimates of α_S and β_S, it is less important for our main parameters of interest, namely ρ_S. This is because while unexpected shocks in productivity ϵ_i might influence labor choices L_i if capital is fixed before the shock, the term $\left(\sum \psi_{e,i}^{\rho_S}\right)^{\beta_S/\rho_S}$ is Hicks neutral and should not be affected by ϵ_i if the firm faces competitive input markets. Consequently I estimate Equation (3.7) via non-linear least squares using feasible generalized least squares to control for heteroskedasticity across all extant country-sector pairs. Techniques for this method are outlined in (Cameron and Trivedi, 2005) and (Amemiya, 1983). Issues of identification for this form are discussed in Appendix B.

[10]Although there is a large literature on production function estimation, the techniques beginning with Olley and Pakes (1996) have been developed using panel data and assuming Cobb-Douglas forms, continuing on through Levinsohn and Petrin (2003) and more recently Ackerberg, Caves, and Frazer (2006). A different approach allowing CES forms has been advanced by Gandhi, Navarro, and Rivers (2008) but the technique still requires panel data.

4. Data and Production Estimates

I begin this section with a very brief description of the data used, moving quickly to a discussion of the production estimation results.[11] As far as I am aware, this paper is unique in the breadth of developing country firms examined ($\approx$ 6300 firms across 32 countries). With estimates of controls such as worker training in hand, I then focus on the economic magnitude of skill complementarity and substitutability within sectors.

4.1. **Data Description and Variable Construction.** The main data set consisting of firm level data comes from Enterprise Surveys conducted by the World Bank. The country/year pairs in the survey which reported the necessary information estimation are a subset of those available, consisting of thirty two countries in the year range of 2002-2005 as tallied in Table 6, found in the Appendix. The percentage of firms and sales by sector are presented in Table 1.[12] Monetary values have been converted to 2004 US Dollars (CPI adjusted) based on the 2008 International Financial Statistics published by the IMF.[13]

Table 1. Observations and Sales Percentages in Sample by Sector

	Agroindustry	**Autos/ Components**	**Beverages**	**Chemicals/ Pharma**	**Electronics**	**Food**	**Garments**
Observation %	1.732	2.034	5.370	6.435	1.668	13.060	17.207
Sales %	0.226	0.035	0.038	5.521	0.030	87.263	0.553
Value Added %	0.217	0.034	0.037	7.456	0.024	85.084	0.910
	Leather	**Metals/ Machinery**	**Non-metal/ Plastics**	**Other manufact.**	**Paper**	**Textiles**	**Wood/ Furniture**
Observation %	4.210	16.635	7.166	3.273	2.256	8.405	10.550
Sales %	0.018	3.020	0.139	0.073	2.040	0.104	0.940
Value Added %	0.015	3.239	0.148	0.054	1.976	0.099	0.708

I now briefly discuss variable construction. Value added sales were constructed as total sales reported, less raw material costs and energy costs, with the caveat that energy costs are only available for about 70% of observations. Four controls, indicators for product line and technology upgrading, ISO certification and internal worker training are used to capture productivity differences associated with these activities. ISO certification in particular has been found to be associated with increases in exports, quality upgrading and higher productivity firms; for evidence and a theoretical

[11]For a detailed discussion of issues and findings regarding manufacturing firms in developing countries see Tybout (2000).

[12]At present, there is some concern about the currency calculations done in the individual country surveys and this data is not presently available. I emphasize this does not effect any estimate throughout the paper and only statements regarding the percentage of sales by sector.

[13]For some countries, this publication simultaneously provides market and official exchange rates. The market rate was preferred when available.

mechanism see Verhoogen (2008). Finally, the fraction of inputs which are imported are used as a control for quality and technology differences of processes and inputs which may be associated with their use.

4.2. **Production Estimates.** The production estimates are provided in Table 2 and the parameter estimates have been segmented into three groups: Controls, Production and Markups, and the CES skill parameter by sector. Beyond Sector controls as provided for in the specification, Country controls are included to pick up a variety of country/time specific and currency measurement differences. The association of firm level value-added with ISO certification and training have the expected positive and significant signs, explaining productivity differences of roughly 13% and 2%. I also find a productivity difference of roughly 8% if a firm has upgraded their product line in the last three years, while a similar question regarding new production technologies is surprisingly insignificant. Also as expected, the percentage of inputs which are imported has a significant positive sign but is very modest, showing that roughly a 17% increase in imported inputs is associated with a 1% increase in productivity. The next group of estimates for production and markups shows highly significant capital and labor production parameters which have a sum slightly less than one for each sector, suggesting slight decreasing returns to scale in capital and labor in each sector. The controls for the effects of markups ($\hat{M_S}$) are generally insignificant with the notable exceptions of Garments and Textiles where they are positive as expected.

The final group of estimates characterizes sectors as "diverse skill loving" ($\rho_S < 1$) or "similar skill loving" ($\rho_S > 1$). Here tests of significance that $\rho_S \neq 1$ (so the estimates do not collapse to the usual Cobb-Douglas formulation) are good and actually have even more coverage than Table 2 suggests: ten of fourteen sectors have a significant characterization that skill mix explains productivity differences, comprising 68.5% of the firms in the sample and 99% of all sales in the sample. The high proportion of sales accounted for is largely driven by Food which comprises the lions share of both Sales and Value Added Sales. However, it would be safe to say that in terms of the value added sales, over two-thirds are generated in sectors where skill mix helps explain productivity differences.

Table 2. Non-linear FGLS production function estimates

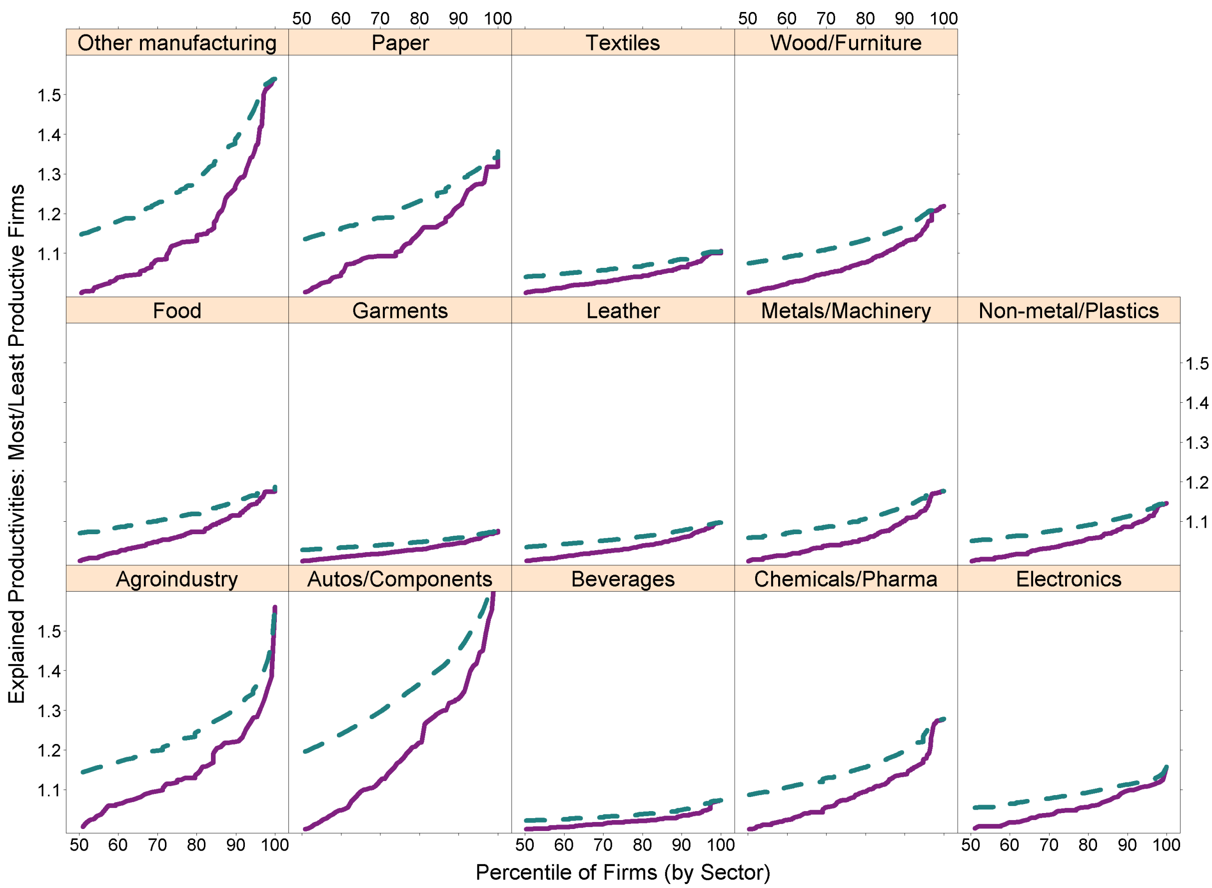
Controls	**Estimate**	**SE**	p-value	**Other Controls**		
Upgraded Product Line	0.0815***	(0.0136)	0.0000	*Sector Dummies:*		
New Production Tech	-0.0105	(0.013)	0.2096	13 of 14 Significant at $\alpha = .01$		
ISO Certification	0.1284***	(0.0154)	0.0000	*Country Dummies:*		
Worker Training	0.0202**	(0.0118)	0.0437	21 of 31 Significant at $\alpha = .05$		
% Imported Inputs	0.0626***	(0.0181)	3e-040			
Production and Markups	**Capital** (α_S)	**Labor** (β_S)	**Markup** (M_S)	**CES Parameter** (ρ_S) **Estimate**	**SE**	p-value
Agroindustry	0.3658***	0.5664***	-0.2207	0.6325**	(0.2008)	0.0336
Autos and components	0.2474***	0.7543***	-0.013	0.6324***	(0.1243)	0.0015
Beverages	0.8225***	0.1494***	-0.0385	0.7461*	(0.1876)	0.0880
Chemicals/Pharmaceutics	0.4505***	0.5328***	0.0353	0.7498***	(0.101)	0.0066
Electronics	0.3245***	0.6441***	0.1019	0.8577	(0.2065)	0.2454
Food	0.3728***	0.6115***	0.0850	1.2559***	(0.0848)	0.0013
Garments	0.4147***	0.5612***	0.0771**	1.1042	(0.1141)	0.1805
Leather	0.2493***	0.7782***	0.0187	0.9206	(0.1231)	0.2594
Metals and machinery	0.4853***	0.5071***	0.0523	0.8112***	(0.0703)	0.0036
Non-metallics/Plastics	0.3598***	0.6271***	0.0430	0.8635*	(0.1039)	0.0945
Other manufacturing	0.3581***	0.5744***	0.0152	0.6457***	(0.0852)	0.0000
Paper	0.5516***	0.4692***	0.0649	1.9495*	(0.5792)	0.0506
Textiles	0.3520***	0.5952***	0.2212***	1.1412	(0.1259)	0.1311
Wood and furniture	0.2434***	0.7421***	0.0606	0.8376***	(0.0609)	0.0038

*/**/*** denote .1/.05/.01 Significance levels

4.3. **Interpretation of Explained Productivities.** We now turn to detailed examination of the within sector productivity differences explained by the labor augmenting productivity terms $\phi_S(\psi_i)^{\beta_S} = \left(\sum \psi_{e,i}^{\rho_S}\right)^{\beta_S/\rho_S}$. The terms $\phi_S(\psi_i)^{\beta_S}$ can explain within sector variation, but the $\phi_S(\psi_i)^{\beta_S}$ terms are not directly comparable across sectors because, as shown in Lemma **??** of the Appendix, $\phi_S(\psi_i)^{\beta_S}$ is decreasing in ρ_S. Therefore, while ρ_S can pick up the submodularity and supermodularity within a sector, this is inherently a sector specific measure. The dispersion of $\phi_S(\psi_i)^{\beta_S}$ within each sector is captured by Z-scores in Figure 3, found in the Appendix.

More importantly, we wish to gage the magnitude of productivity differences explained by skill mix. For example, consider the interquartile range: is the productivity difference between the most productive 25% and least productive 25% of firms (as accounted for by skill mix) comparable to that associated with ISO certification, training and imported inputs? In order to answer this question for a particular sector, I first introduce the shorthand $P_i^S \equiv \phi_S(\psi_i)^{\beta_S}$ and we can examine the ratio $P_{(75)}^S/P_{(25)}^S$ where $P_{(x)}^S$ denotes the x^{th} percentile of explained productivities. This forms a measure of productivity differences. If $P^S_{(75)}/P^S_{(25)}$ is equal to say, 1.17 then any firm H picked from the top 25% of explained productivity and any firm L picked from the bottom 25% must have a the ratio of productivities P^S_H/P^S_L of at least 1.17. This translates into at least a 17% productivity difference between the firms H and L. Accordingly, the productivity ratios $P^S_{(x)}/P^S_{(1-x)}$ for $x \geq$50% are graphed in Figure 1 by a solid line. Considering the sector as a whole, I also calculate the average "Kuznet" ratios $R^S(x) \equiv \sum_{y \geq x} P^S_{(y)}/\sum_{y \leq 1-x} P^S_{(y)}$ representing the average productivity of the top x% or firms over the average productivity of the bottom x% of firms displayed as a dashed line in Figure 1.

FIGURE 1. Productivity Ratios and Mean Productivity Ratios by Percentile



In interpreting Figure 1, consider the patterns we should expect of the productivity ratios. First, sectors with ρ_S terms close to unity, especially if they are insignificant, imply that the estimates are very close to a production model which ignores skill mix, so that skill mix has little to no role in explaining productivity differences. Therefore the estimated productivity ratios accounted for by skill mix should be close to unity. In our case these are the Electronics, Garments, Leather and Textiles sectors (due to insignificance) and possibly the Beverages sector which is significant but stands out as being exceedingly capital intensive so labor based skill mix does not amount to large differences. Second, with regard to significant sectors (excluding Beverages), differences in productivity of, say, at least 4-7% at the interquartile range would imply that skill mix is as least as important as training or imported inputs. In fact, referring to Table 3 we see interquartile productivity differences of 4-17% under the individual firm measure $P^S_{(75)}/P^S_{(25)}$ and 8-33% under the "Kuznets" ratio measure $R^S(x)$ for significant sectors. Thus, under the Kuznets measure, productivity differences explained by skill mix are comparable to the magnitude of training and imported inputs combined, and for four sectors comparable to training, imported inputs and ISO combined. These results are emphasized in Table 3. By comparison, the interquartile Kuznets measure in the capital intensive Beverage sector is roughly comparable to the effect of training. Of course, all of these differences become more pronounced if we consider the 90%/10% firm and Kuznets measures in Table 3. These results support Iranzo, Schivardi, and Tosetti (2006) who find that firms in the last productivity decile have dispersion almost 35% higher than those in the first decile.

Table 3. Interquartile and 90/10 Productivity Ratios

Sector	**Skill Mix Estimate**	**Diverse/Similar Skill Mix**	**75%/25% Firm Ratio**	**75%/25% Avg Ratio**	**90%/10% Firm Ratio**	**90%/10% Avg Ratio**
Agroindustry	0.6325**	Diverse	1.1239	1.2233	1.2215	1.3067
Autos/Components	0.6324***	Diverse	1.1755	1.3339	1.3321	1.4539
Beverages	0.7461*	Diverse	1.0184	1.0345	1.0345	1.0495
Chemicals/Pharma	0.7498***	Diverse	1.0736	1.1428	1.1382	1.1987
Electronics	0.8577	–	1.0489	1.0858	1.0978	1.1133
Food	1.2559***	Similar	1.0608	1.1114	1.1179	1.1502
Garments	1.1042	–	1.0246	1.0441	1.0460	1.0591
Leather	0.9206	–	1.0302	1.0566	1.0596	1.0773
Metals/Machinery	0.8112***	Diverse	1.0452	1.0953	1.1021	1.1378
Non-metal/Plastics	0.8635*	Diverse	1.0434	1.0824	1.0864	1.1126
Other manufacturing	0.6457***	Diverse	1.1245	1.2555	1.2752	1.3907
Paper	1.9495*	Similar	1.1094	1.2122	1.2252	1.2849
Textiles	1.1412	–	1.0365	1.0634	1.0663	1.0855
Wood/Furniture	0.8376***	Diverse	1.0633	1.1210	1.1276	1.1682

*/**/*** denote .1/.05/.01 Significance levels

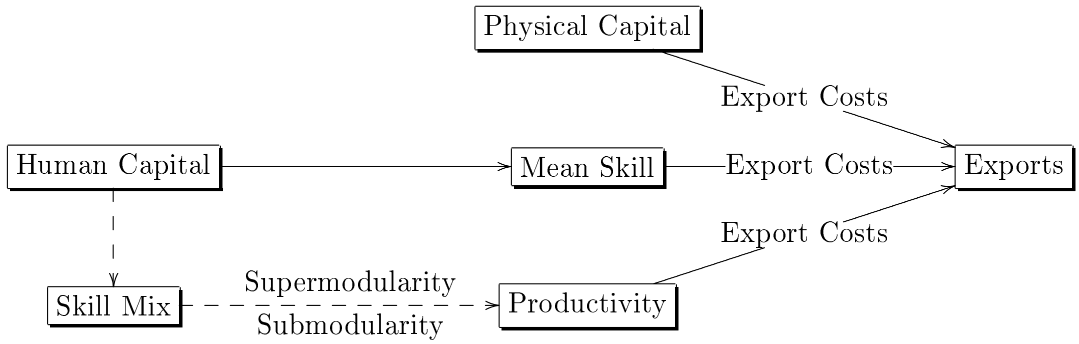
Referring to Table 3, we see that the majority of sectors best utilize diverse skills. However, since the largest sector by sales is Food and best utilizes similarly skilled workers, we cannot conclude that sectors in developing countries are either diverse or similar with regard to optimal choice of skill mix. Rather, depending on the stage of development or export orientation into sectors beyond Food a particular country likely transitions into an increasing percentage of GDP in manufacturing which allows for specialized jobs that encourage employment of a diverse workforce. If theory implying a convex structure of wages in diverse sectors is correct (i.e. Grossman and Maggi (2000) and Morrow (2008)) then the expansion of the manufacturing sector caused by growth and trade implies a widening wage gap between workers employed in diverse sectors. This suggests further work looking at the link between inequality and the growth of diverse sectors as enumerated in Table 3.

5. Export Propensity and Productivity From Diversity

We now return to the trade question of the first section, namely is diversity a basis for exports? Having seen appreciable evidence for the role of skill mix in productivity differences, namely that skill diversity is positively related to productivity in sectors with $\rho_S < 1$ sectors and vice-versa for $\rho_S > 1$ sectors, can we find evidence of increased exports for more productive firms? In this section I first frame the question and quickly proceed to our specification of explaining exports through skill mix after controlling for overall level of skill and capital intensity. I then present the results, showing a positive linkage between productivity explained through skill mix and exporting.

5.1. **Productivity-Export Linkage.** While there are many questions of endogeneity of the relationship between skill mix and the propensity to export, I frame the question by considering a basic selection mechanism caused by incurred exporting costs. In the presence of trade frictions, we should expect that only the most productive firms export. Higher productivity should assist in amortizing trade frictions, as should higher physical and human capital intensities. These relationships are depicted with solid lines in Figure 2. Provided these positive relationships between productivity and exporting, we can expect that productivity differences arising from skill diversity will increase exports, by increasing productivity in sectors whose sub/supermodular technologies match the skill endowment available in an advantageous way. These relationships are depicted with dashed lines in Figure 2 as well.

Figure 2. Effects of Endowments and Diversity on Firm Level Exporting



5.2. **Specification.** With this potential channel for productivity differences explained by skill diversity to have an effect on exports, we now use the firm level explained productivities $\phi_S(\psi_i)^{\beta_S}$ to capture the effect of productivity differences through skill diversity. Since the percentage of exports is between zero and one, any linear model examining determinants of exporting is necessarily truncated so our basic specification is that of a two-tailed tobit as given in Equation (5.1).

$$
\begin{aligned}
\text{(5.1)} \qquad \text{Export \% of Sales}_i = \text{Sector Effects} + \text{Country Effects} + \alpha \cdot \frac{K_i}{L_i} + \beta \cdot \text{Skill}_i \\
+ \gamma \cdot \text{Productivity(Skill Mix)}_i + \delta \cdot \text{Unexplained Productivity}_i
\end{aligned}
$$

The heuristic specification in Equation (5.1) is simple by design, aimed to address the simple question, "Can productivity explained by skill mix predict exports after controlling for average skill and capital intensity?" However, in order to operationalize Equation (5.1) using the firm productivities $\phi_S(\psi_i)^{\beta_S}$ we need to address the fact as discussed above that $\phi_S(\psi_i)^{\beta_S}$ is a measure relative to each sector S. Accordingly, we define the Z-score for each $\phi_S(\psi_i)^{\beta_S}$ within a sector by $Z_i^S \equiv (\phi_S(\psi_i)^{\beta_S} - \mu^S)/\sigma^S$ where μ^S and σ^S are the estimated mean and standard deviation of $\phi_S(\psi_i)^{\beta_S}$. Z_i^S has the added relevance of interpretation since a one unit increase in Z_i^S is precisely an increase of one standard deviation. For example, since Z_i^S is approximately normal the interquartile difference $Z_{(75)}^S - Z_{(25)}^S \approx 1.35$ and $Z_{(90)}^S - Z_{(10)}^S \approx 2.56$ which allows us to gage the magnitude of our estimates. Finally, Z_i^S increases in productivity so positive estimates of γ show a positive relationship between exports and productivity explained by skill mix.

5.3. **Results.** The results of estimating Equation (5.1) are reported in Table 4, with and without controls such as ISO certification which have been found to be linked to exports.

TABLE 4. Skill Determinants of Export Sales (two sided Tobit)

	Firm Export %			**Firm Export %**		
Controls						
Sector Effects	14 of 14 Significant at $\alpha = .1$			13 of 14 Significant at $\alpha = .1$		
Country Effects	24 of 31 Significant at $\alpha = .1$			22 of 31 Significant at $\alpha = .1$		
Trade Variables	**Estimate**	**SE**	p-value	**Estimate**	**SE**	p-value
K/L	0.2026**	(0.095)	0.0330	0.1280	(0.0933)	0.1701
Mean Skill	1.1774*	(0.6173)	0.0565	-0.298	(0.6101)	0.6253
Skill Mix Z-Score	5.0146***	(1.1022)	0.0000	4.5365***	(1.0822)	0.0000
Unexplained Prod Z-Score	-1.1566	(1.1763)	0.3255	-0.6112	(1.1303)	0.5887
Trade Dummies	**Estimate**	**SE**	p-value	**Estimate**	**SE**	p-value
ISO Certification	-	-	-	31.4044***	(2.7822)	0.0000
Worker Training	-	-	-	18.0411***	(2.4963)	0.0000
Upgraded Product Line	-	-	-	12.8468***	(2.7237)	0.0000
New Production Tech	-	-	-	5.9156**	(2.3765)	0.0128

*/**/*** denote .1/.05/.01 Significance levels

With regard to magnitude of the skill mix effects, we appeal to our "rule of thumb" interquartile and 90/10 figures $Z^S_{(75)} - Z^S_{(25)} \approx 1.35$ and $Z^S_{(90)} - Z^S_{(10)} \approx 2.56$, suggesting the difference in export percentage explained by interquartile skill mix differences is 6-7%. In contrast, the remaining unexplained productivity from the production estimates does not explain exports, supporting the claim that skill mix is an especially important determinant of trade. Furthermore, the skill mix is robust in predicting exports even under the inclusion of controls, unlike physical and human capital. In order to compare the magnitudes of the predictive power of skill mix to physical and human capital, I provide the interquartile and 90/10 firm differences by sector in Table 5. Considering the significant estimate for the effect of physical capital on exporting, we find an implied export propensity range of .7-2.45%, very small compared to the magnitude explained by skill mix. Similarly, examining mean skill shows interquartile differences of 2.1-4.2%. Therefore interquartile differences of exporting due to skill mix are more than the differences accounted for by physical and human capital combined. Having seen that skill mix can explain export propensity better than physical and human capital (after controlling for sector and country effects) I conclude that skill diversity is relatively good determinant of exports, through its effects on firm productivity.

Table 5. Interquartile and 90/10 differences by sector

	K/L		*Mean Skill*		*Skill Mix*	
Sector	**75%/25% Difference**	**90%/10% Difference**	**75%/25% Difference**	**90%/10% Difference**	**75%/25% Difference**	**90%/10% Difference**
Agroindustry	12.2614	25.3163	3.6125	6.2200	1.5358	2.4724
Autos/Components	7.0875	15.0275	2.5702	4.3720	1.5554	2.6317
Beverages	7.6896	17.7951	2.0500	3.5000	1.3177	2.4483
Chemicals/Pharma	10.5233	22.9614	2.9792	5.5026	1.3694	2.5177
Electronics	6.3304	13.4774	2.3195	4.3055	1.4856	2.8906
Food	10.6009	28.3263	2.7750	5.1473	1.3966	2.6739
Garments	3.4948	9.4443	2.8594	6.3244	1.4303	2.6621
Leather	5.4098	12.0238	2.9750	6.0866	1.3847	2.6765
Metals/Machinery	6.2643	15.1582	2.2500	4.0193	1.2387	2.7009
Non-metal/Plastics	9.5591	24.6690	2.4633	5.1974	1.3850	2.6736
Other manufacturing	7.2083	14.8269	1.7780	3.3194	1.3464	2.7292
Paper	9.2050	18.9207	1.9500	4.3250	1.3315	2.7022
Textiles	8.2421	19.5441	3.0940	6.2716	1.4646	2.6396
Wood/Furniture	5.3022	13.3502	2.3875	4.7786	1.3924	2.6920

6. Conclusion and Directions for Further Work

In this paper I have characterized developing country manufacturing sectors by whether skill mix (diversity or similarity) helps explain productivity. I have found that greater than two thirds of firms a very large cross country sample belong to sectors where skill mix is an important determinant of productivity. Interquartile productivity differences explained by skill mix are comparable to the magnitude of training and imported inputs combined, and the magnitude in four sectors is comparable to training, imported inputs and ISO combined. Furthermore, the majority of sectors best utilize diverse skills which theory suggests are associated with higher wage inequality through "superstar" wage effects. This suggests growth and trade can have differing outcomes with respect to inequality, depending on a particular developing country's stage of development or export orientation across sectors. Therefore this paper empirically establishes facts about the structure of production which have implications for inequality, among other themes in the theoretical literature. This suggests further work looking at the link between inequality and changes in the size of "skill diversity loving" sectors through growth and trade.

Having established a linkage from skill mix to productivity, this paper also evaluates the effects of productivity differences on exports. I find that interquartile differences in skill mix explain intersector variation in exporting more than the variation accounted for by physical and human capital combined. I conclude that skill diversity is relatively good determinant of exports, through its effects on firm productivity. This result clearly has implications for the human capital *content* of traded goods, where patterns exist that have not been explained. Put together, the results of this paper show that a more detailed view of human capital, beyond that of a simple average, yields insights into both productivity and export patterns.

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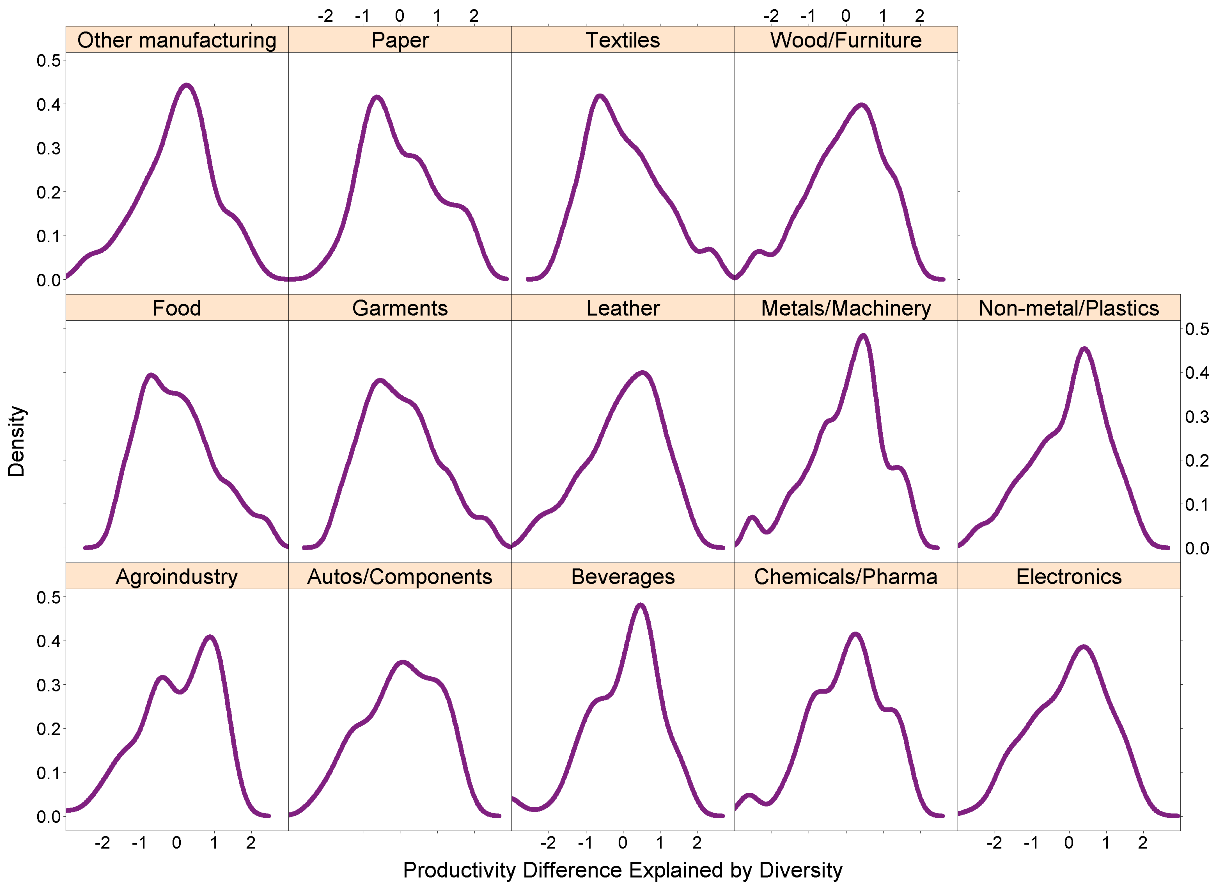
Appendix A. Supplemental Empirical Results

A.1. **Dispersion of firm productivity accounted for by skill diversity.** Taking the explained components of productivity, $P_i^S \equiv \left(\sum \psi_{e,i}^{\rho_S}\right)^{\beta_S/\rho_S}$ we define the Z-score for each P_i^S within a sector by $Z_i^S \equiv (P_i^S - \mu^S)/\sigma^S$ where μ^S and σ^S are the estimated mean and standard deviation of P_i^S following production estimation. Kernel density plots of Z_i^S for each sector are presented in Figure 3.

Figure 3. Distribution of Productivity Explained by Diversity



A.2. **Firm distribution by Sector and Country.** The distribution of firms by sector and country is presented in Table 6. In order to facilitate feasible generalized least squares estimations, sector/country pairs containing exactly one observation were dropped from the sample, making the minimum number of observations two for each pair.

Table 6. Distribution of Firms by Country and Sector

Country	**Year**	**Agroindustry**	**Autos/Components**	**Beverages**	**Chemicals/Pharma**	**Electronics**	**Food**	**Garments**	**Leather**	**Metals/Machinery**	**Non-metal/Plastics**	**Other Manufacturing**	**Paper**	**Textiles**	**Wood/Furniture**	**Country Totals**
Albania	2005	0	0	8	3	0	5	5	0	4	2	0	0	0	4	31
Armenia	2005	0	0	70	3	0	13	9	0	23	6	0	4	3	5	136
Belarus	2005	0	0	0	0	0	0	0	0	5	4	0	0	0	3	12
Brazil	2003	0	120	0	67	55	101	377	145	155	0	0	0	94	273	1387
Bulgaria	2005	0	0	6	2	0	2	3	0	7	2	0	0	5	3	30
Chile	2004	38	0	16	86	0	136	0	0	122	0	0	41	0	72	511
CostaRica	2005	0	0	4	0	2	16	8	2	19	40	19	2	10	12	134
Croatia	2005	0	0	3	2	0	0	0	0	6	4	0	2	0	2	19
Egypt	2004	0	8	0	47	0	93	80	20	107	120	25	0	85	31	616
ElSalvador	2003	0	0	0	3	0	5	2	0	5	0	0	0	0	0	15
Estonia	2005	0	0	3	0	0	0	4	0	4	2	0	3	2	4	22
FYROM	2005	0	0	5	0	0	2	0	0	5	0	0	0	0	2	14
Georgia	2005	0	0	8	0	0	2	0	0	2	0	0	0	2	0	14
Guyana	2004	0	0	0	3	0	52	6	0	0	0	0	0	5	28	94
Kazakhstan	2005	0	0	85	0	0	3	16	0	46	4	0	4	0	0	158
Kyrgyzstan	2003	0	0	16	3	0	14	12	0	4	6	0	0	7	2	64
Lithuania	2004	0	0	0	0	0	20	0	0	0	0	0	0	11	9	40
Madagascar	2005	0	0	0	5	0	10	8	0	4	4	12	2	4	10	59
Mauritius	2005	0	0	3	5	0	10	0	0	4	0	2	7	14	4	49
Moldova	2005	0	0	38	0	0	5	16	0	16	2	3	2	0	5	87
Morocco	2004	0	0	0	56	30	60	316	76	17	70	0	3	150	3	781
Oman	2003	0	0	0	3	0	5	0	0	9	12	4	2	0	2	37
Poland	2005	0	0	8	0	0	32	46	0	78	3	0	4	4	3	178
Romania	2005	0	0	36	8	0	26	64	0	61	4	0	5	5	5	214
Russia	2005	0	0	9	3	0	2	3	0	13	9	0	4	3	14	60
Serb&Mont	2005	0	0	6	0	0	2	0	0	5	0	0	2	2	0	17
SouthAfrica	2003	0	0	0	35	7	42	19	6	99	38	71	11	16	69	413
Turkey	2005	0	0	0	27	6	74	40	4	104	34	3	2	53	6	353
Ukraine	2005	0	0	12	3	0	3	9	4	13	4	11	6	4	8	77
Uzbekistan	2003	0	0	0	0	0	8	9	0	0	0	0	0	0	0	17
Vietnam	2005	0	0	2	23	5	79	31	8	91	81	56	29	33	81	519
Zambia	2002	71	0	0	18	0	0	0	0	19	0	0	7	17	4	136
Sector Totals		109	128	338	405	105	822	1083	265	1047	451	206	142	529	664	6294

Appendix B. Estimation: Identification and Significance

B.1. **Consistency.** There are a variety of "assumption bundles" we might choose to establish consistency of the NLS estimator. See for instance Cameron and Trivedi (2005); Jennrich (1969). I have settled on those presented in Malinvaud (1970) as stated in the below claim. I briefly discuss the content of the functionally important Conditions 2-4. Condition 2 implies data is essentially being draw from an (unknown) population distribution (say, of all firms). Condition 3 is an identification type assumption that within the "true" population, different population parameters always distinguish outcomes for some positive mass of the population. Condition 4 assures that parameter values sufficiently far away from the true parameters will cause the sum of squares to be large (see the following remark for an alternative condition which makes this relationship more apparent).

Claim (Consistency). Consider the econometric specification above, namely for $\gamma_0 = (\rho_0, \alpha_0, \beta_0)$ we have

$$y_i = f_i(w_i, \gamma_0) + \epsilon_i = \ln \left(\sum_j e_{ij}^{\rho_0} \right)^{\alpha_0/\rho_0} + x_i\alpha_0 + z_i\beta_0 + \epsilon_i$$

where ϵ_i are iid with mean zero and variance σ^2. Then the NLS estimator $\hat{\gamma}$ is consistent provided the following conditions:

(1) $\{w_i\}$ are contained in a compact set K.
(2) The Borel measure $\mu_T(B) \equiv \frac{1}{T}\sum_{i=1}^T \mathbf{1}_B(w_i)$ converges weakly to a measure μ.
(3) For any $\gamma \neq \tilde{\gamma}$ we have $\mu(\{w : \quad f(w,\gamma) \neq f(w,\tilde{\gamma})\}) > 0$.
(4) There is some $B > 0$ and T_0 such that for all $T \geq T_0$ the sets $\{\gamma : \quad \frac{1}{T}\sum_{i=1}^T f(w_i,\gamma)^2 \leq B\}$ are bounded uniformly in T.

Remark. Following Theorem 3 of Malinvaud (1970), we need to verify Malivaud's assumptions 1,5,6,7 and 8 hold. Assumptions 1,5,7 and 8 we have assumed directly while Assumption 6 clearly holds given our specification. Alternatively Condition 4 above can be replaced with (see Assumption 4(i) of Malivaud):

Condition. There exists a compact set G containing γ_0 and

$$\lim_{T\to\infty} \inf \inf_{\gamma \in G^c} \frac{1}{T} \sum_{i=1}^{T} [\frac{f(w_i,\gamma) - f(w_i,\gamma_0)}{2\sigma}]^2 > 1$$

B.2. **Significance of the parameter estimates.** Here we need to establish a distribution theory for the parameter estimates: again there are many possibilities, see for instance the review of Amemiya (1983), where a joint parameter test may be found.