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Abstract: This article combines data on trade flows with a novel construction of the distribution of skill in the population, based on the results from the International Adult Literacy Survey of the OECD, to evaluate the empirical importance of the distribution of talent as a determinant of the sectoral pattern of trade. It is found that both the mean and standard deviation of the distribution of skills are significant determinants of the pattern of trade. According to the results, cross-country differences in the distribution of skills explain more of the sectoral pattern of trade than differences in capital stocks and differences in indicators of a country's institutional framework.
Keywords: comparative advantage; labor force composition; factor endowments; human capital.
JEL Classification: F12, F14, F16, J82.

Resumen: Este artículo combina datos de flujos en comercio internacional con una construcción novedosa de la distribución de habilidades en la población, con base en los resultados de la International Adult Literacy Survey de la OCDE, con el objetivo de evaluar de manera empírica la importancia de la distribución de talento como un determinante del patrón sectorial del comercio. Se encuentra que tanto la media como la desviación estándar de la distribución de habilidades son determinantes significativos del patrón de comercio. De acuerdo a los resultados, diferencias en la distribución de habilidades entre países explica más del patrón sectorial de comercio que diferencias en acervos de capital físico y que diferencias en indicadores del marco institucional de un país.
Palabras Clave: ventaja comparativa; composición de la fuerza laboral; dotación de factores; capital humano.

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1 Introduction

In this paper I investigate the implications of the distribution of talent across workers on a country's pattern of trade. In particular, I test whether higher moments of a country's skill distribution are an empirically important determinant of comparative advantage by combining data on trade flows with data from the International Adult Literacy Survey (IALS) which provides a direct measure of the educational capital relevant for workplace productivity held by a country's working-age population. In contrast to previous work, I do not rely on measures of educational attainment to proxy for the distribution of talent in the population, instead I use IALS test scores to obtain a more direct measure of skills that can be used to construct a continuous distribution of talent, providing a more precise picture of the cross-country differences in endowments of workers at all skill levels.

Theories that emphasize relative factor differences as a source of comparative advantage are central to the classical theory of international trade. However, classical factor proportions models fell out of favor given the lack of compelling empirical evidence to support them, and due to the disproportionately high amount of international trade that takes place among industrialized countries. This last observation contradicts what would be expected from factor proportions theory, since these countries share similar factor endowments and incomes per capita (see Deardorff [1984]).

Recent theoretical work has emphasized the role that worker heterogeneity can play in determining comparative advantage. By focusing on subtler aspects of the cross-country differences in factor supplies, models that emphasize the role of the distribution of talent on comparative advantage can help rationalize both the large *volume* of trade observed between developed countries, without appealing to returns to scale, and the systematic *pattern* observed in these trade flows. As pointed out by Grossman and Maggi [2000]

> *"It is well established that a country's endowment of human capital is an important determinant of the pattern of trade, but given that there are systematic differences in the trading patterns of economies with similar levels of development, physical capital, and human capital endowments it is of interest to investigate whether the distribution of talent in the workforce can play a role in the determination of the pattern of trade."*

There are two basic mechanisms through which higher moments of the skill distribution matter for comparative advantage: worker *sorting* and *matching*. Models of sorting, such as

Ohnsorge and Trefler [2007] and Costinot and Vogel [2010], are based on Roy-like assignment models (see Heckman and Honoré [1991], Sattinger [1993], and Costinot and Vogel [2014]) in which workers are endogenously specific to the industry that values their talent the most. In equilibrium, workers sort uniquely into the industry in which their income is maximized. Differences in the relative endowments of workers at different talent levels across two countries determine the efficient division of production as in standard factor proportions models, here with the notable difference that there is a continuum of factors of production. In this case, if country A's distribution of talent is more dispersed than country B's, then country A enjoys a relative abundance of both high and low skill workers, conferring to it a comparative advantage in those industries into which these type of workers sort into.

In models of matching, such as Grossman and Maggi [2000], workers produce output in teams, and industries vary by the degree of complementarity (or substitutability) that exists between the talent levels of the members who constitute a production team.[1] In this type of model, the production technology is specified so as to emphasize the idea that the output of a production team depends on how talent is distributed across its members, rather than on the overall talent level of the production team. The distribution of talent across the workforce determines the relative supply of different production teams, and in this case if country A has a more dispersed skill distribution than country B, then country A has a relative abundance of production teams comprised of low and high talent levels, and thus should have a comparative advantage in industries where these type of production teams are relatively most productive.

So far, little to no attention has been paid to the empirical content of these theories. A notable exception is Bombardini et al. [2012] which also provides evidence supporting the empirical relevance of the dispersion of skill in the working population as a source of comparative advantage. These authors focus on the theoretical mechanism linking a country's skill distribution to the pattern of trade first outlined by Grossman and Maggi [2000]. However, the theoretical analysis of Bombardini et al. differs from that in Grossman and Maggi in at least two important dimensions: 1. the focus is on the set of skills that are not easily observable ex-ante, so that *random matching* prevails along this dimension, and 2. all sectors are assumed to be supermodular, albeit to different degrees, so that all sectors benefit from assortative matching. These authors present evidence supporting the prediction that if (i) workers and

[1] Grossman and Maggi [2000] define complementarity in terms of "submodular" and "supermodular" production technologies. Supermodularity applies when workers are complementary in creating value, while submodularity applies when workers are substitutable in creating value. For supermodular technologies, the efficient assignment of workers implies *self-matching* (i.e.production teams with members of similar talent levels). On the other hand, for submodular technologies, the efficient assignment of workers implies *cross-matching* (i.e. production teams whose members possess disparate talent levels).

firms randomly match along the unobservable component of skill, and (ii) industries vary in the degree in which they can substitute workers of different skills across production tasks, then firms in sectors with higher complementarity are relatively more productive in countries with lower skill dispersion.[2]

In contrast to Bombardini et al. [2012], the focus of this study is on the comparative advantage predictions implied by the equilibrium *sorting* of workers of disparate talent levels into industries of varying skill intensity since this provides a natural generalization of standard factor proportions models (see Costinot and Vogel [2010]). The assignment model of Costinot and Vogel is a generalized factor endowments model and many of their results are generalizations of the standard trade theorems of the two-by-two Hechscher-Ohlin model.[3] While the emphasis in Costinot and Vogel is on income distribution, factor allocations determine patterns of specialization and thus, patterns of trade. Their equation (20) implies that, if Home is skill abundant relative to Foreign, then the employment share of tasks with high skill intensities increase at Home, while the employment share of tasks with low skill intensities increase abroad. Since in their model the free-trade equilibrium replicates the integrated equilibrium, Home will export in sectors that are skill intensive, while Foreign will export in sectors that are skill un-intensive. Similarly, if Home is skill diverse relative to Foreign, then their equations (24) and (25) imply that following trade integration the employment share of both low and high skill intensity sectors increases in Home, and the employment share of intermediate skill intensity sectors increases in Foreign, implying that the skill diverse country exports in both the high and low skill intensity sectors.

The results outlined above are presented in greater generality in Costinot [2009], where in the context of a generalized factor endowments model it is shown that a country will produce relatively more -compared to other countries- in sectors in which a relatively higher share of its factors select into. The selection of factors of production into tasks/sectors determines the pattern of specialization, and in turn the pattern of specialization of aggregate output determines the pattern of specialization in exports (see Corollaries 2 and 3 in Costinot [2009]). Thus, based on the results of Costinot [2009] and Costinot and Vogel [2010] regarding gen-

[2]Under random matching the equilibrium distribution of workers within each firm is the same as the economy wide skill distribution. Since production functions are supermodular, mismatches between the talent levels of hired workers are costly in terms of productivity, and more so in those industries in which complementarity between the talent levels of the workforce are more important. More dispersed skill distributions result in a higher number of mismatches to prevail in equilibrium, and thus countries with dispersed talent distributions will have a comparative advantage in industries where complementarities are less important since mismatches will be relatively less costly in terms of forgone productivity.

[3]See Feenstra [2004] or Dixit and Norman [1980] for a textbook treatment of the standard theorems of neoclassical trade theory.

eralized factor endowment model, the two fundamental comparative advantage predictions investigated here are: (i) *skill abundant* countries should export relatively more in skill intensive industries since they are relatively well endowed with higher skill workers, and (ii) *skill diverse* countries should export relatively more in both low ans high skill intensive industries since they are relatively well endowed with both low and high skilled workers.[4]

A final comment on the difference between the study of Bombardini et al. [2012] and the present study is in order. The fact that the former focus on a different channel through which skill dispersion can shape trade flows than the one under scrutiny in this study leads to important differences in the specification of the estimation framework used to test the relevant hypotheses. First, the measure of skill dispersion necessitated by their approach refers to the dispersion of the "unobservable" component of skills. Thus, their empirical counterpart of unobservable skills is approximated by purging IALS scores from the effect of a variety of observable individual characteristics to create a measure of "residual" skill dispersion. Secondly, the relevant industry characteristic for these authors is not *skill intensity*, as it is here, but rather *skill complementarity* (i.e. the degree of complementarity between the skill of workers across production tasks). Finally, the comparative advantage prediction studied by Bombardini et al. can be easily tested by specifying a covariate that is the interaction between skill dispersion (the exporter characteristic of interest) and skill complementarity (the relevant industry characteristic), while in the present case the estimation framework *must* specify a marginal effect of skill dispersion on trade flows that is non-linear as a function of skill intensity, since one of the comparative advantage predictions under consideration states that skill diverse countries will tend to specialize in both low-skill *and* high-skill intensive industries.

The two most challenging issues for the empirical analysis of the relationship between trade flows and worker heterogeneity that are the focus of this paper are: (a) the limited availability of internationally comparable data on the distribution of skills at the country level, and (b) constructing an index that adequately ranks industries in terms of skill intensity. Regarding the former, I use data from the IALS to proxy for the distribution of skills at the country level.[5]

[4]These two correlations rest on the assumption that equilibrium in the labor market entails *positive assortative matching*. Positive assortative matching implies that in equilibrium the most skilled workers are going to be found in the more skill intensive industries. Costinot and Vogel [2010] assume that the profile of sector-specific productivities of a worker with skill level s, $\{A(s,z) : z \in Z\}$, is log-supermodular which is a sufficient condition for positive assortative matching to prevail in competitive equilibrium. Shimer [2005] and Atakan [2006] show that positive assortative matching is attained in the labor market even under certain labor market frictions such as costly search or coordination frictions.

[5]International Adult Literacy Survey (IALS): http://www5.statcan.gc.ca

This survey tests the working age population aged 16-65 on three key dimensions of literacy, which are meant to capture attributes relevant to productivity in the workplace. The advantage of this source of data over other literacy attainment surveys is that the data is continuous (test scores are reported in a scale ranging from 0 to 500) and the data is internationally comparable (see the Appendix for details). Regarding the latter issue, I use data from the BLS's National Employment Matrix to obtain employment shares and average industry wages of Standard Occupation Classification (SOC) occupations, and the O*NET v.14 database to obtain data regarding the skill requirements of employed occupations.[6] I use these two sources of data to construct a measure of skill intensity at the industry level.[7]

The results presented in section 4 lend support to the empirical validity of a generalized version of the standard $2 \times 2 \times 2$ Heckscher-Ohlin Theorem: countries will tend to export goods that use relatively intensively their relatively abundant factors of production. According to my estimates, the endowment of human capital (i.e. the endowment of workers of varying degrees of skill) explains more of the pattern of trade than countries' endowment of capital and institutional features combined, at least for the set of exporters under consideration. The result may seem surprising given the set of exporters under consideration, most of which are at similar stages of development and for which factor endowments had been previously argued to not be a significant determinant of the pattern of trade (see Deardorff [1984]). Thus, my estimates suggest that human capital remains a key determinant of comparative advantage, even for trade among industrialized countries, once the rich heterogeneity in the skills embedded in the labor endowement are taken into account. The results also suggest that estimates found elsewhere in the literature (see, for example, Romalis [2004], Levchenko [2007] and Cuñat and Melitz [2010]) which find support for the hypothesis that capital abundant countries tend to specialize in capital intensive industries are sensitive to controlling for the effect of the distribution of talent on the pattern of trade.

The paper is organized as follows. Section 2 describes the estimation framework. Section 3 describes the data and explains the classification of industries by skill intensity and the construction of the skill distribution at the country level. Section 4 reports the results from regression analysis, and section 5 concludes.

[6] O*NET: http://www.onetonline.org/

[7] One might consider looking directly at the education levels of the workers employed by an industry to attempt to determine the industry's skill intensity. However, looking directly at the education levels of people actually found in an industry is an endogenous outcome that could be the result of various economic mechanisms. By looking at the skill requirements of occupations, as determined by O*NET, the goal is to elicit the *technological need* for skill as much as possible.

2 Background and Estimation Framework

The theoretical importance of worker heterogeneity for comparative advantage has been well developed in the literature (see Grossman and Maggi [2000], Grossman [2004], Ohnsorge and Trefler [2007], Costinot and Vogel [2010], and Grossman et al. [2014]). Grossman [2013] provides a recent survey of the theoretical literature that incorporates heterogeneous labor into models of international trade. The way in which the distribution of skill across workers matters for comparative advantage through the sorting of workers into industries is an extension of the insights of the standard factor proportions model. The objective of this paper is the empirical quantification of the generalized $2\times2\times2$ Heckscher-Ohlin predictions outlined in Costinot [2009] and Costinot and Vogel [2010].

To fix ideas, let $f(s)$ and $h(s)$ denote the distribution of skills in countries A and B, respectively, so that the supply of workers at any skill level is given by $f(s)L_A$ in country A and $h(s)L_B$ in country B. For simplicity, assume that $L_A = L_B$, so that all differences in factor supplies are captured through the ratio $f(s)/h(s)$. Figure 2.1 depicts a situation in which the ratio$f(s)/h(s)$ is monotone decreasing in s. This implies that country B has a higher endowment of high-skill levels relative to A. Because country B is relatively well endowed with high-skilled workers, the cost of producing goods which use these type of workers should be low relative to A, and because whenever there is positive assortative matching high-skill workers sort into skill intensive sectors, country B should have a comparative advantage in these sectors.

On the other hand, Figure 2.2 depicts a situation in which the ratio $f(s)/h(s)$ is initially monotone increasing, but after some point $\hat{s}$ the ratio is monotone decreasing. This situation corresponds to the case in which country B is relatively well endowed with both very low and very high-skilled workers. If positive assortative matching prevails in equilibrium, the cost of producing goods in the extreme sectors is relatively low for country B, and this should confer to it a comparative advantage in both low-skill and high-skill intensity industries relative to country A.

To assess the merits of these comparative advantage predictions I consider the estimation framework specified by

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + g\left(s_z, \mu_j, \sigma_j\right) + \varepsilon_{ijz},$$

where x_{ijz} is the log of average exports from j to i in industry z over the period 1996-2000;

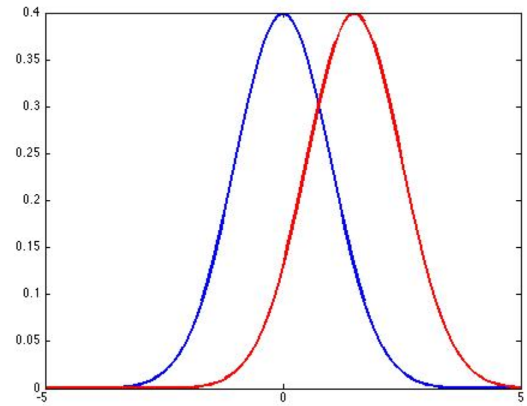


Figure 2.1: Differences in Skill Abundance

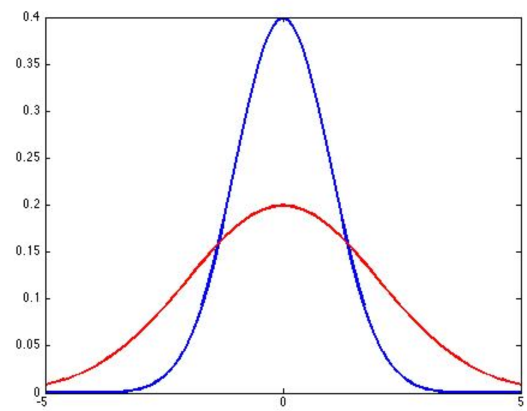


Figure 2.2: Differences in Skill Diversity

σ_j is the log of the standard deviation of the skill distribution in j; μ_j is the log of the mean of the skill distribution in j; s_z is a measure of the skill intensity of sector z; W_{jz} is a set of covariates that could potentially affect trade flows differentially across exporter-industry pairs (for example, alternative sources of comparative advantage), and the $\lambda' s$ are importer, exporter, and industry fixed effects. The left-hand side variable is taken as the average trade flow over a 5 year window, rather than for a specific year, to smooth out the effects of any year-to-year fluctuations in the distribution of exports across sectors.

This formulation explains exports through the interaction of industry-level characteristics and country-level characteristics. The effect of exporter characteristics on the volume of trade across all industries is captured by the exporter fixed effect. The terms $W_{jz}\delta$ and $g\left(s_z, \mu_j, \sigma_j\right)$ capture the effect of exporter characteristics on the *pattern*, but not the *volume*, of trade. The aim of the empirical framework is to identify whether a given correlation, derived in the context of a two-country model, is present in the data. The estimating equation is specified in such a way that it tests whether the correlation of interest holds when comparing the relative exports of two exporters into a third market. Conditions under which such a test would be theoretically justified are outlined in the online Appendix.

To gain further insight into the logic behind the estimation framework and the way it is related to the comparative advantage predictions derived from theoretical models, suppose that we assume $g(s, \mu, \sigma) = \gamma(\mu \times s) + \sigma \cdot \tilde{g}(s)$ and consider two exporters which are identical except for the mean of their skill distributions. Then, the estimating equation implies

$$\mathbb{E}\left[\left(x_{ijz} - x_{ijz'}\right) - \left(x_{ij'z} - x_{ij'z'}\right) | W_{jz} = W_{j'z'}, \sigma_j = \sigma_{j'}\right] = \gamma\left(\mu_j - \mu_{j'}\right)\left(s_z - s_{z'}\right).$$

The expression above relates the exports of exporters j and j', in industries z and z', to a common destination i. If j is more skill abundant than j' ($\mu_j > \mu_{j'}$), and z is more skill intense than z' ($s_z > s_{z'}$), then theory suggests that we should expect to see $\gamma > 0$ (i.e. the positive coefficient would indicate that countries more abundant in high-skill workers should export relatively more in skill intensive industries).

On the other hand, consider two exporters which are identical except for the standard deviation of their skill distributions. Then, the estimating equation readily implies

$$\mathbb{E}\left[x_{ijz} - x_{ij'z} | W_{jz} = W_{jz'}, \mu_j = \mu_{j'}\right] = \left(\lambda_j - \lambda_{j'}\right) + \left(\sigma_j - \sigma_{j'}\right) \cdot \tilde{g}\left(s_z\right).$$

This expression makes it clear that the exporter fixed effects capture differences in the volume of trade common to all sectors, and that variation across industries in relative exports between j and j' to export destination i is captured through the function $\tilde{g}\left(s_z\right)$. The discussion preceding Figure 2.2 suggests that if j is more skill diverse than j' (i.e. $\sigma_j > \sigma_{j'}$), then $\tilde{g}(\cdot)$ should be a $U-$shaped function (opening upward). That is, conditional on both j and j' exporting to i, then the more skill diverse country should command a higher share of country $i's$ expenditures in both low-skill and high-skill intensive industries.

This estimation framework has become standard in the international trade literature. Romalis [2004] uses a version of this estimation framework to test for the importance of capital endowments, both physical and human, in the determination of the pattern of trade. More recently, Levchenko [2007] has used this framework to show that countries with better institutions have a comparative advantage in goods that are institutionally dependent; Nunn [2007] has also used this framework to show that exporters with better contract enforcement specialize in the production of goods for which relationship-specific investments are important, while Cuñat and Melitz [2010] have used it to assess the importance of labor market institutions as a source of comparative advantage. These reduced form estimation frameworks contrast with the approach developed by Chor [2010]. While the estimating equation in the latter is similar to the estimating equation here, Chor [2010] is able to give a structural interpretation to his estimates by deriving his estimating equation within the context of a multi-industry version of Eaton and Kortum [2002].[8]

Before proceeding to the discussion of the results from regression analysis, section 3 describes the data and explains the construction of the measure of skill intensity at the industry level and the construction of the distribution of skills at the country level.

3 The Data

Data on bilateral trade flows are taken from Feenstra et.al. [2005]. I convert the original trade data which are classified by 4-digit SITC Rev.2 codes to the NAICS 1997 4-digit classification. The final data comprise 84 industries that include both manufacturing and non-manufacturing industries. The 84 industries included in the sample are those for which the BLS's National Employment Matrix accounts for at least 80% of industry employment. While this threshold of 80% is arbitrary, for reasons that will become apparent shortly, it is necessary to restrict attention to industries where most of the division of employment across occupations is accounted for. Within this set of industries the employment coverage ranges from a minimum of 80% to a maximum of 98% of industry employment, and the median employment coverage is 93.5% of industry employment. 729 SOC occupations are represented within these 84 industries.

As alternative determinants of the pattern of trade, I control for standard factor proportions as in Romalis [2004], and institutional sources of comparative advantage as in Cuñat and Melitz [2010] and Nunn [2007]. Data on contract enforcement quality and relationship-specificity at the industry level are from Nunn [2007]. Data on the flexibility of labor markets and industry volatility are taken from Cuñat and Melitz [2010]. Data on countries' stock of physical capital

[8] In the appendix, the estimating equation is motivated in terms of a model similar to Romalis [2004] and Helpman et al. [2008].

are from the Penn World Tables, and I use the natural log of the average capital endowment over the period 1997-2000 as my measure of capital abundance. Because data on capital endowments are not available for either the Czech Republic or Slovenia, when I control for this source of comparative advantage the number of exporters in the sample falls from 19 to 17. Data on capital intensities are from the NBER CES Manufacturing Database for the year 2000. Because this source of data only covers manufacturing industries, the number of industries falls from 84 to 76 when I control for the effect of capital abundance on the pattern of trade. Further details can be found in the Appendix.

The novel exporter characteristic under investigation here is the distribution of skills at the country level. I define the variable "skill" as

$$\text{Skill} = \omega_p \text{Prose} + \omega_d \text{Document} + \omega_q \text{Quantitative},$$

which is a weighted average of three dimensions of literacy assessed by the International Adult Literacy Survey (IALS). This survey reports scores, ranging from 0 to 500, on three dimensions of literacy: prose literacy, document literacy, and quantitative literacy.

The weights $\left(\omega_p, \omega_d, \omega_q\right)$ are chosen through principal components analysis (PCA) and my variable "skill" corresponds to the first component of PCA, which accounts for roughly 80% of the variation in the IALS data. Further details regarding the IALS data, its summary statistics and the construction of the distribution of skills and its cross-country differences are available in the online Appendix. Table 1 reports the first two moments of the skill distribution for the 19 exporters in the sample.

A cursory examination of this data reveals that Anglo-Saxon countries are typically low-mean-high-dispersion countries, while Scandinavian countries are typically high-mean-low-dispersion countries. Table 1 also indicates that countries at similar stages of development exhibit differences in the degree of skill dispersion amongst its workforce: the USA and Canada display a more dispersed skill distribution than, for example, Germany and Denmark. The last row of Table 1 reports the coefficient of variation for the exporter characteristic of interest, and it can be readily seen that for the set of exporters under consideration, differences in the distribution of human capital are more pronounced for dispersion measures of the distribution than for the mean which has traditionally been the focus of the empirical trade literature.

The reasons why the distribution of skill in the workforce differs across countries at similar stages of development falls beyond the scope of this study. I take this country characteristic as given, and investigate *how* it shapes the pattern of trade at a given point in time. Unfortunately, the sensitivity of the results to alternative measures of the distribution of skills cannot be easily checked, as other sources of data on literacy attainment suffer from limitations that make them inadequate for the purposes of this paper.

Country	μ	σ	σ/μ
Belgium	287.6	50.64	0.18
Canada	258.8	65.01	0.25
Chile	207.6	58.74	0.28
Czech Rep.	287.6	46.07	0.16
Denmark	291.7	40.29	0.13
Finland	289.6	47.37	0.16
Germany	283.8	42.74	0.15
Hungary	251.9	48.39	0.19
Ireland	261.6	57.06	0.22
Italy	252.8	57.94	0.23
Netherlands	284.4	45.23	0.16
New Zealand	277.8	51.51	0.19
Norway	295.9	46.57	0.16
Poland	228.6	64.84	0.28
Slovenia	234.9	62.05	0.26
Sweden	297.6	52.74	0.18
Switzerland	273.2	55.52	0.20
UK	266.5	62.04114	0.23
USA	258.7	71.13	0.27
Coefficient of Variation	0.09	0.16	0.24

μ denotes mean and σ denotes standard deviation

Table 1: Summary Statistics for Skill Distribution

The standard source in the literature for measures of skill at the country level has been the Barro-Lee database on international data on educational attainment (see Barro and Lee [2001]). There are at least two reasons why the measure of skill based on the IALS data proposed here is preferable to the data available from the Barro-Lee database. First, years of schooling is a noisy measurement of a person's underlying productivity in the workforce. As Barro and Lee [2001] note themselves

> "Although the test scores of students reflect the quality of schooling and, hence, indicate the quality of the labor force, they do not directly measure the educational capital held by a country's working-age population. Knowledge can

> be gained or lost after the completion of formal education. Ideally, tests of cognitive ability would be administered to adults, as well as to students."

The IALS is aimed precisely at addressing this shortcoming in measures of educational attainment, since it is designed to elicit certain work-related skills in the adult population. As previously mentioned, the IALS data contains three measures of literacy, thus recognizing the multifaceted nature of literacy and has made great efforts to measure skills directly in the adult population. In addition, the IALS has strived to minimize measurement error by having each test subject take the exam on multiple occasions. The final score that I use for each of these subjects is his or her average score across replications, which should provide a more accurate measurement of an individual's underlying skill level.

Second, the IALS initiative has gone to great lengths to ensure that administered tests are consistent across countries so that cross-country comparisons of these measures of skill are meaningful. A drawback of measuring skill through educational attainment is that a year of schooling may not be easily comparable across countries and may not adequately reflect the level of skills that a worker is bringing to the workplace. This limitation of educational attainment data would be problematic for goals of the empirical analysis to be carried out here. Of course, the shortcoming of the IALS data, in contrast to the Barro-Lee data, is the limited availability of data given that only 20 countries currently participate in the survey, most of which are OECD countries, and only 19 of them make their data publicly available. This severely limits the set of exporters that can be included in the sample.

3.1 Constructing Measures of Skill Intensity

The final variable of interest to estimate the effect of skill abundance and skill diversity on the pattern of trade is a measure of skill intensity at the industry level. To construct this measure I use data from the National Employment Matrix for 2006, available from the Bureau of Labor Statistics, and the O*NET database on occupational descriptors. The National Employment Matrix provides detailed employment information for 4-digit NAICS industries. This matrix provides a breakdown of industry employment across Standard Occupation Classification (SOC) occupations, as well as industry wage data for these occupations. The O*NET database provides information on occupational descriptors, which include skill requirements for over 800 SOC occupations. For several of these occupational descriptors the O*NET database reports *importance* and *level ratings.* As the names suggests, the "importance" dimension rates whether a particular worker attribute is important in a given occupation, while the "level" dimension rates the level of this attribute required to perform the occupation.[9]

For each of the 729 SOC occupations represented in the sample, I obtain standardized scores from the O*NET v.14 database for occupational descriptors concerning an occupation's skill requirements that closely resemble the dimensions of literacy elicited in the IALS data:

1. **Speaking**: Talking to others to convey information effectively.
2. **Writing**: Communicating effectively in writing as appropriate for the needs of the audience.
3. **Mathematics**: Using mathematics to solve problems.
4. **Reading Comprehension**: Understanding written sentences and paragraphs in work related documents.

Using these descriptors, for each occupation I calculate a *skill relevance* score as

$$\begin{aligned} R^{skill} &= \omega_s R_s + \omega_w R_w + \omega_m R_m + \omega_{rc} R_{rc} \\ R_k &= \frac{\text{Importance}_k \times \text{Level}_k}{10,000}, \end{aligned}$$

where the weights $(\omega_s, \omega_w, \omega_m, \omega_{rc})$ are chosen using principal components analysis.[10] This skill relevance score is an index between 0 and 1 that summarizes the skill level that a worker must have to perform efficiently in a given occupation. For each descriptor k, the score R_k is an index between 0 and 1, with $R_k = 1$ if and only if *both* the importance *and* level ratings are scored at their maximum level, and $R_k = 0$ if and only if the descriptor k is deemed "Not Relevant" for the occupation.[11] Table 2 reports the bottom ten occupations (in ascending order of skill relevance score), and the top ten occupations (in descending order of skill relevance score) that result from this construction.

Based on these skill relevance scores for SOC occupations, I measure skill intensity at the industry level as

[9]For example, both lawyers and legal clerks are given the same importance rating for the skill attribute "reading comprehension". However, they differ in that lawyers are required to have a higher level of this skill than legal clerks do.

[10]The results do not vary significantly if equal weights are given to each descriptor.

[11]This property provides the rationale behind the definition of R_k in terms of the interaction of the level and importance ratings.

Bottom 10 Occupations	Top 10 Occupations
Models	Anthropology and Archaeology Teachers (p.s.)*
Crossing Guards	Environmental Science Teachers (p.s.)
Graders and Sorters, Agricultural Products	Engineering Teachers (p.s.)
Sewing Machine Operators	Nursing Instructors and Teachers (p.s.)
Logging Equipment Operators	Atmospheric, Earth, Marine, and Space Sciences Teachers (p.s.)
Cleaners of Vehicles and Equipment	Forestry and Conservation Science Teachers (p.s.)
Locomotive Firers	Criminal Justice and Law Enforcement Teachers (p.s.)
Pressers, Textile, Garment, and Related Materials	Health Specialties Teachers (p.s.)
Meat, Poultry, and Fish Cutters and Trimmers	Sociologists
Earth Drillers, Except Oil and Gas	Area, Ethnic, and Cultural Studies Teachers (p.s.)

*(p.s.)=Post-secondary

Table 2: Skill Requirement Ranking of SOC Occupations

$$\begin{aligned} s_z &= \prod_{i \in \mathcal{O}_z} R_i^{\alpha_{iz}} \\ \alpha_{iz} &= \frac{w_{iz} L_{iz}}{\sum_{j \in \mathcal{O}_z} w_{jz} L_{jz}}, \end{aligned}$$

where R_i is occupation $i's$ skill relevance score, $\mathcal{O}_z$ is the set of occupations employed in industry z, and α_{iz} is occupation $i's$ share in labor costs in industry z, where w_{iz} is occupation $i's$ average yearly wage in industry z and L_{iz} is employment of occupation i in industry z. Both w_{iz} and L_{iz} are taken from the BLS National Employment Matrix for the year 2006. This measure is a geometric average of the skill levels of those occupations employed in the industry, weighted by their "factor intensity" or cost share.[12] Table 3 reports the bottom five and top five ranked industries in terms of this measure of skill intensity.[13]

The measure proposed here for skill intensity at the industry level is novel in that it is constructed from detailed employment data and skill requirements at the occupation level. In the literature it is standard to proxy a sector's skill intensity by the ratio of non-production worker wages to total payroll, and it might be of interest to compare s_z to this more standard measure of a sector's skill intensity. Let h_z denote the standard measure of skill intensity. Then, the correlation between these two measures is 0.72.[14] A potential advantage of the measure s_z

[12]Results are not affected if skill intensity is defined as the arithmetic average $s_z = \sum_{i \in \mathcal{O}_z} \alpha_{iz} R_i$.

[13]A higher rank number corresponds to a lower skill intensity (i.e. the number 1 ranked industry is the most skill intensive industry, while the number 84 ranked industry is the least skill intensive industry).

[14]The high correlation between these two proxies for skill intensity indicates that both measures roughly order

Industry Name	Rank
Computer and Peripheral Equipment Manufacturing	1
Pharmaceutical and Medicine Manufacturing	2
Communications Equipment Manufacturing	3
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	4
Oil and Gas Extraction	5
Other Textile Product Mills	80
Cut and Sew Apparel Manufacturing	81
Animal Slaughtering and Processing	82
Apparel Accessories and Other Apparel Manufacturing	83
Logging	84

Table 3: Ranking of Industries by Skill Intensity

is that it does not a priori assume that non-production occupations require more skill than production occupations, but rather directly looks at who is employed in a sector and what are the skill requirements of those workers.[15]

Table 4 below presents correlations between the rankings for different industry characteristics. The skill intensity ranking s_z is positively correlated with all other industry characteristics, and in particular exhibits a relatively strong positive correlation with capital intensity. The correlations between capital intensity, volatility, and relationship specificity are of the same sign and of comparable magnitude to those reported elsewhere (see Cuñat and Melitz [2010] and Nunn [2007]).

Industry Characteristic	Capital Intensity	Volatility	Rel. Specificity
Skill Intensity	0.54	0.18	0.11
Capital Intensity	-	-0.02	-0.34
Volatility	-	-	0.17

Table 4: Correlations Between Industry Characteristics

I assume that industry-specific characteristics computed for the United States also apply to

industries in the same manner. If we were to think of these two measures as independent and noisy estimates of the true skill intensity of the sector, then we may calculate the reliability ratio of each of them. The reliability ratio for s_z is 0.91, while the reliability ratio for h_z is 0.66. These numbers have the following interpretation: only 9% of the variability in s_z can be attributed to measurement error, while 34% of variability in h_z can be attributed to measurement error. This would suggest that the proxy for skill intensity proposed here is preferable to the one commonly used in the literature.

[15] Another commonly used proxy for sectoral skill intensity relies on industry wages. The skill intensity measure s_z is positively and statistically significantly correlated with average industry wages, a commonly used proxy for skill intensity. Further details regarding the relationship between the skill intensity measure s_z and industry wages can be found in the appendix.

industries in other countries. This assumption is standard in the recent empirical trade literature on comparative advantage (see, for example, Cuñat and Melitz [2010] and Nunn [2007]), and is justified to the extent that countries have access to the same technologies.[16] For the set of exporters under consideration this assumption does not seem unreasonable. However, this claim is not easily verified due to the lack of publicly available data with similar sector classification from countries other than the United States, and I must rely on the commonly used assumption that the ranking of measures does not vary across countries.

4 Empirical Results

4.1 Examining the Raw Data

Before turning to the results from regression analysis, in this section I give an overview of the raw data. Table 5 reports the distribution of exports across low-skill intensity sectors, medium-skill intensity sectors, and high-skill intensity sectors. Theory suggests that the relative exports of a skill diverse country, vis-‘a-vis a less diverse country, should be concentrated in the low and high-skill intensity sectors, while the relative exports of the less diverse country should be concentrated in the medium-skill intensity sectors. That is, relative exports should display a U-shaped pattern as we move from low to high-skill intensity sectors.

The type of exercise I am interested in relates the quantity

$$\frac{X_{iHz}/X_{iFz}}{X_{iHz'}/X_{iFz'}},$$

where X_{ijz} are exports from j to i in industry z, to exporter and industry characteristics. Figure 4.1 compares the distribution of exports between selected exporter pairs. The selected pairs, which are all comparable in size in terms of GDP per capita, present the U-shaped pattern predicted by theory for exporters who differ in terms of skill diversity. However, as can be discerned from Table 5, this pattern is not evident in the raw data for all exporter pairs in the sample.

[16] Even with access to the same technologies, if factor prices vary across countries, then factor intensities measured as cost shares will vary across countries (see Davis and Weinstein [2001]). However, Davis and Weinstein also point out that the observed differences in input usage by industry across countries may result from the aggregation of goods of heterogeneous factor content within industry categories, rather than a failure of factor price equalization. Here, as in other empirical studies on the determinants of the pattern of trade (i.e. Romalis [2004], Levchenko [2007], Nunn [2007]), I do not address this issue and acknowledge that my findings

Country	Low Skill	Medium Skill	High Skill
Belgium	0.27	0.22	0.51
Canada	0.39	0.19	0.42
Chile	0.41	0.48	0.11
Czech Rep.	0.36	0.31	0.33
Denmark	0.28	0.26	0.46
Finland	0.42	0.2	0.38
Germany	0.23	0.24	0.53
Hungary	0.35	0.21	0.44
Ireland	0.11	0.11	0.78
Italy	0.26	0.36	0.38
Netherlands	0.20	0.18	0.62
New Zealand	0.59	0.23	0.18
Norway	0.16	0.10	0.74
Poland	0.42	0.35	0.23
Slovenia	0.40	0.29	0.31
Sweden	0.37	0.20	0.43
Switzerland	0.09	0.17	0.74
UK	0.14	0.20	0.66
USA	0.18	0.18	0.64

Table 5: Distribution of Exports

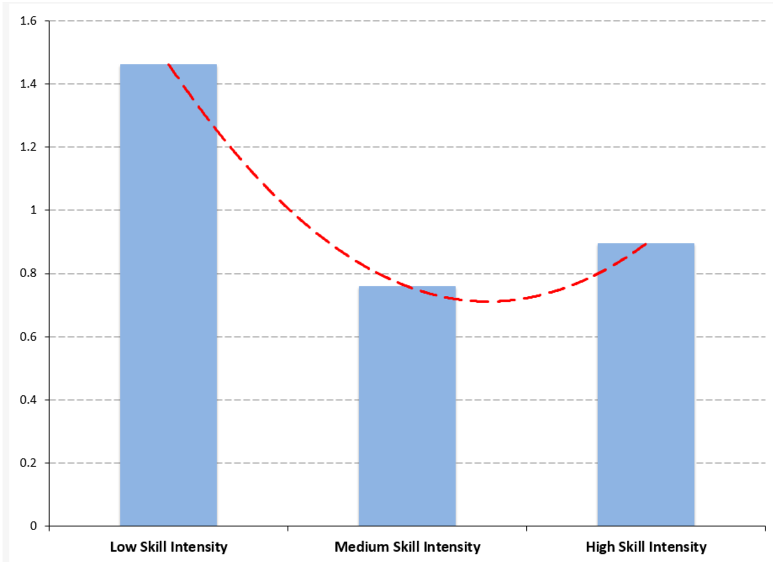
Closer inspection of the export shares in Table 5 suggests that "richer" countries have larger export shares in high skill intensity sectors. Indeed, in the sample the correlation between the share of high-skill intensity exports and the level of development (measured by the log of the average GDP per capita between 1998-2000) is 0.75. If high-quality goods are characterized by skill-intensive technologies, then the recent literature suggesting a positive association between per capita income and the quality of exports (see, for example, Fajgelbaum et al. [2011]) can account for this observed correlation. This also suggests that controlling for the way in which the level of development affects the pattern of trade may prove important for the empirical exercise considered here.

4.2 Estimation Results

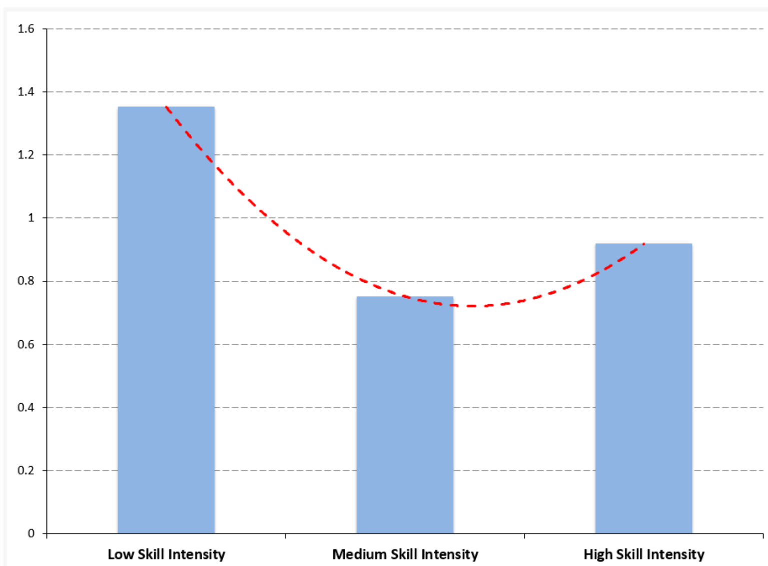
I now turn to the results from regression analysis. Recall that the estimation framework is given by

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + g\left(s_z, \mu_j, \sigma_j\right) + \varepsilon_{ijz}.$$

may be affected if this proves to be a significant issue for the sample under consideration.



(a) Finland (high σ) vs Denmark (low σ)



(b) Canada (high σ) vs Denmark (low σ)
Relative export shares are compared across three bins: low, medium, and high skill intensity.

Figure 4.1: Relative Exports: High versus Low Skill Dispersion

In this section I will discuss the results from different modeling assumptions regarding the term $g\left(s_z, \mu_j, \sigma_j\right)$, which captures the effect of skill abundance (through the mean skill level) and of skill diversity (through the standard deviation of the skill distribution) on the pattern of trade across industries that vary in their skill intensity. Because I do not include observations where no exports are recorded for a given exporter-importer-industry triplet, the results that follow should be interpreted as capturing the pattern of comparative advantage for countries across all of its export sectors, and not the effect of comparative advantage on the country-level decision to export in a particular sector. That is, the exclusion of observations that record zero trade flows implies that the analysis is focused on the pattern of comparative advantage *conditional* on exporting.

The vector W_{jz} controls for alternative sources of variation in the pattern of trade. It includes the interaction term $K_j \times k_z$ to control for the effects of capital abundance on the pattern of trade. Here K_j is the natural log of the average capital stock per worker over the period 1998-2000 and capital intensity k_z is proxied by one minus the ratio of total payroll to value added.[17] Also included are the interaction terms $F_j \times v_z$ and $F_j \times k_z$, where F_j and v_z are labor market flexibility and industry volatility as in Cuñat and Melitz [2010], that control for labor market flexibility as a source of comparative advantage, and the interaction term $CE_j \times rs_z$, where CE_j is a measure of contract enforcement and rs_z is relationship-specificity, that controls for institutional determinants of the pattern of trade as in Nunn [2007]. Finally, in some of the specifications to be discussed, the vector W_{jz} also includes controls for the effect of the level of development on the pattern of trade.

My baseline specification for the estimating equation is

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + \beta_0 \left(\mu_j \times s_z\right) + \beta_1 \left(\sigma_j \times s_z\right) + \beta_2 \left(\sigma_j \times s_z^2\right) + \varepsilon_{ijz}.$$

This specification is parsimonious in the way that it controls for the effects of skill abundance and skill diversity on the pattern of trade. The interaction $\mu_j \times s_z$ specifies a linear marginal effect , where we would expect $\beta_0 > 0$, capturing the intuition that increases in skill abundance should have larger marginal effects on skill intensive industries. The interactions $\sigma_j \times s_z$ and $\sigma_j \times s_z^2$ specify a non-linear marginal effect of skill diversity on exports:

$$\frac{\partial \mathbb{E}\left[x_{ijz}\right]}{\partial \sigma_j} = \beta_1 s_z + \beta_2 s_z^2,$$

where, according to theory, we should expect $\beta_2 > 0$. A positive coefficient on β_2 would reflect that increases in skill diversity should benefit low skill intensive and high skill intensive sectors relatively more.

[17] This measure of capital intensity is used by Romalis [2004] and Nunn [2007]. Results do not vary significantly if alternative measures of capital intensity are use such as the log of of the ratio of the real capital stock to number of production workers.

As is common in practice I consider a series of short and long regressions. First, I estimate the short regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \beta_0 \left(\mu_j \times s_z\right) + \beta_1 \left(\sigma_j \times s_z\right) + \beta_2 \left(\sigma_j \times s_z^2\right) + \varepsilon_{ijz},$$

and then proceed to a series of long regressions. OLS estimates are reported in Table 6.

Column (1) estimates the short regression on the full sample. In this specification data are available for 84 industries, and 19 exporters that export to 185 destinations. The estimated coefficients $\hat{\beta}_0$ and $\hat{\beta}_2$ are positive, and statistically significant. These estimates provide evidence in favor of the hypotheses that: (a) skill abundant countries specialize in skill intensive industries, and (b) skill diversity confers a comparative advantage in both low and high-skill intensity industries.

Next, I control for capital endowments and institutional sources of comparative advantage. Because capital endowment data is unavailable for Slovenia and the Czech Republic, and because capital intensities are only available for manufacturing industries, the sub-sample on which the long-regression is estimated includes 76 industries, and 17 exporters which export to 184 export destinations. In column (2) of Table 6, I first re-estimate the short-regression using this smaller sample of exporters and industries. The coefficient on the interaction $\mu_j \times s_z$ is of roughly the same magnitude, and retains its statistical significance. On the other hand, the coefficient on the interaction $\sigma_j \times s_z^2$ looses much of its magnitude, and all of its statistical significance.

In column (3) of Table 6 I control for the effect of capital endowments by introducing the interaction term $K_j \times k_z$, and for the institutional sources of comparative advantage by introducing the interaction terms $F_j \times v_z$, $F_j \times K_z$ and $CE_j \times rs_z$, where the former control for the effect of labor market flexibility on the pattern of trade, and the latter controls for contract enforcement as a source of comparative advantage. The estimate for β_0 is of similar magnitude to that in column (2), and of the same statistical significance. Notice that after controlling for alternative sources of comparative advantage, the estimate for β_1 gains in magnitude *and* statistical significance. The estimate for β_2 remains statistically insignificant.

Finally, I add two sets of controls that if omitted may bias the estimated importance of the distribution of talent for comparative advantage. One set includes the interaction of country capital abundance K_j with sector factor intensity s_z. This controls for the possibility that capital abundance, through its effect on factor prices, affects specialization differentially across industries varying in terms of skill intensity. The other is a set of interaction terms $y_j \times D_z$,

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\mu_j \times s_z$	5.93^{***}	6.15^{***}	6.25^{***}	4.40^{***}	1.95^{***}	1.79^{***}
	(0.25)	(0.27)	(0.28)	(0.34)	(0.51)	(0.51)
$\sigma_j \times s_z$	0.52	$0.80^{\star}$	1.06^{*}	0.99^{*}	0.18	-0.17
	(0.45)	(0.48)	(0.48)	(0.48)	(1.11)	(1.14)
$\sigma_j \times s_z^2$	0.93^{*}	0.65	0.28	0.17	0.22	0.30
	(0.44)	(0.46)	(0.47)	(0.47)	(0.86)	(0.87)
$K_j \times k_z$	-	-	-0.68^{***}	-0.94^{***}	-1.90^{***}	-1.50^{***}
			(0.09)	(0.10)	(0.06)	(0.07)
$F_j \times v_z$	-	-	0.24^{***}	0.25^{***}	0.20^{***}	0.17^{***}
			(0.04)	(0.04)	(0.02)	(0.021)
$F_j \times k_z$	-	-	0.23^{***}	0.23^{***}	0.05	0.07
			(0.04)	(0.04)	(0.01)	(0.01)
$CE_j \times rs_z$	-	-	0.10^{***}	0.08^{***}	-0.002	-0.01
			(0.02)	(0.02)	(0.01)	(0.01)
$K_j \times s_z$	-	-	-	1.16^{***}	-	-1.34^{***}
				(0.12)		(0.07)
$y_j \times D_z$	NO	NO	NO	NO	YES	YES
$\bar{R}^2$	0.967	0.969	0.969	0.969	0.969	0.969
No. observations	109400	98703	98703	98703	98703	98703

Beta coefficients reported. Heteroskedasticity robust standard errors in parentheses. $\star$, *, **, and *** denote significance at the 10, 5, 1, and 0.1 percent levels, respectively.

Table 6: The Determinants of Comparative Advantage

where D_z is an industry dummy and y_j is the log of average GDP per capita over the period 1998-2000 in country j. These interaction terms allow for the level of development to affect trade in each individual sector differentially in an unrestricted way. This specification is more general than, for example, adding interaction terms between y_j and individual sector characteristics such as value added, TFP growth, input variety, etc. as done by some authors (see, for example, Nunn[2007]). These additional interactions control for other country-level determinants of the pattern of trade.

These last set of results are reported in columns $(4)-(6)$ in Table 6. The addition of the interaction term $K_j \times s_z$, as can be seen in column (4), does not affect the statistical significance of the estimates for β_0 or β_1, although the estimate for β_0 observes a substantial drop in its magnitude. The estimate for β_2, although positive, remains statistically insignificant. The estimates in column (5) show that controlling for the effect of the level of development on the pattern of trade strongly affects the magnitude of the predictions for the distribution of talent as a source of comparative advantage: the estimates for $\beta = (\beta_0, \beta_1, \beta_2)'$ drop substantially. In particular, the estimate for β_0 drops significantly as compared to its estimate in column (3), although it loses none of its statistical significance. However, notice that the estimate for β_1 does lose all of its statistical significance.

Because I report standardized beta coefficients, one can directly compare the relative magnitude of the effects of the distribution of skills on the pattern of trade with those of alternative determinants of comparative advantage. According to the estimates in column (3), the effect that the distribution of talent has on the pattern of trade is greater than the combined effects of both capital and institutional sources of comparative advantage. Of particular significance, notice that skill abundance is an economically significant determinant of the pattern of trade: a one standard deviation increase in the interaction term $\mu_j \times s_z$ increases the dependent variable by 6.24 standard deviations, while a simultaneous one standard deviation increase in the interaction terms $F_j \times v_z$, $F_j \times k_z$, and $CE_j \times rs_z$, that correspond to institutional sources of comparative advantage, only increase the dependent variable by 0.78 standard deviations. Observe also, that increasing the interaction term $\sigma_j \times s_z$ by one standard deviation has a greater impact on the dependent variable than the combined effect of institutional determinants of comparative advantage. Thus, both skill abundance and skill diversity appear to be economically significant determinants of the pattern of trade.

An interesting issue arises concerning the estimates of the coefficient on the interaction term $K_j \times k_z$. Notice from columns (3) – (6) in Table 6, that the estimated coefficient on the interaction term $K_j \times k_z$, although highly statistically significant, is of a sign opposite to what would be expected from the traditional comparative advantage prediction based on capital abundance and capital intensity. That is, while it would be expected that more capital abundant countries should export relatively more in capital intensive industries, the estimate here suggests otherwise. This is at odds with findings elsewhere in the literature. [18]

I explore this result by running the short-regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \beta_0 \left(K_j \times k_z\right) + \beta_1 \left(F_j \times v_z\right) + \beta_2 \left(F_j \times k_z\right) + \beta_3 \left(CE_j \times rs_z\right) + \varepsilon_{ijz}.$$

The standardized coefficient on the interaction $K_j \times k_z$ is $\hat{\delta}_0 = -0.13$, which is negative but not statistically significant at any of the conventional levels. That β_0 is not statistically different from zero might not be surprising considering that the sample under consideration includes only 17 exporters, most of which are OECD countries and most of which are classified as "Northern" countries by Romalis [2004].[19] For these subset of countries, differences in endowments of physical capital have been argued to play no significant role in the deter-

[18]See, for example, Romalis [2004], Levchenko [2007], Nunn [2007], and Cuñat and Melitz [2010], who all find a positive estimated coefficient for this covariate.

[19]Romalis classifies a country as belonging to the "North" if its GDP per capita, at purchasing power parity, is at least 50 percent of the U.S. level. 14 out of the 17 exporters under consideration in this estimation belong to the "North" under this classification.

mination of the pattern of trade (see Deardorff [1984]) and this is consistent with β_0 is not being statistically different from zero for the sample of exporters used here. Therefore, it is interesting to note that once I control for the effect of the distribution of talent on the pattern of trade, the coefficient on the interaction $K_j \times k_z$ remains negative, but gains in statistical significance.[20]This anomalous result is hard to interpret and possibly suggests that more attention needs to be paid to the modeling of the complementarity relationships that may exist between physical capital and workers of heterogeneous talent levels.[21]

The estimates reported in Table 6 provide support for both the hypotheses that skill abundance and skill diversity are economically, and statistically, significant determinants of the pattern of trade. However, the estimates from Table 6 find weak support to the hypothesis that skill diverse countries tend to export relatively more in both low and high-skill intensive sectors. Although the estimate for β_2 is in all cases positive, it is not statistically significant at any of the conventional levels. There is, however, strong evidence for a hypothesis that would posit that skill diversity induces specialization in skill intensive industries. These estimates suggest that, within this group of exporters, the endowment of human capital, understood as an endowment of labor that is heterogeneous in terms of the skill level embedded in a worker, is a more economically substantial determinant of the pattern of trade than institutional factors or more traditional determinants of comparative advantage such as endowments of physical capital .

4.2.1 "Accounting" for the Variation in Trade Flows

The reported standardized coefficients of Table 6 provide information regarding the relative importance of each of the determinants of the pattern of trade, to the extent that they quantify the impact of changing a specific covariate on the dependent variable. However, it is also of interest to assess how much of the variation in the dependent variable can be attributed to each of the independent variables of interest. In this section I discuss a number of results whose aim is to provide some understanding of which of the determinants of the pattern of trade account for more of the observed variation in trade flows.

I begin by considering the construction of R^2 increments for each explanatory variable. The h^{th}´s variable R^2 increment is defined as $R^2 - R_h^2$, where R_h^2 is the coefficient of determination from the regression with the h^{th} variable omitted, and R^2 is the coefficient of determination

[20]In columns (3) – (6) in Table 6, the estimated coefficient on this covariate is statistically significant at the 0.1 percent level.

[21]See Costinot and Vogel [2015] for recent efforts in this direction.

from the full regression. It can be shown that the R^2 increment for the h^{th} variable may be expressed as

$$R^2 - R_h^2 = r_h^2 \left(1 - R_h^2\right),$$

where r_h is the sample correlation between the h^{th} variable and the dependent variable (see Theil [1971] for details). The above expression states that the incremental contribution of the h^{th} variable in accounting for the variation in the dependent variable increases as the absolute value of the partial correlation between the dependent and h^{th} variable increases. However, the contribution of the h^{th} variable decreases when the other $k-1$ variables account for a larger proportion of the variation of the dependent variable.

Column (2) in Table 7 presents the percent increase[22] in R^2 for the regression

$$\hat{x}_{ijz} = \hat{W}_{jz}\delta + \beta_0 \left(\widehat{\mu_j \times s_z}\right) + \beta_1 \left(\widehat{\sigma_j \times s_z}\right) + \beta_2 \left(\widehat{\sigma_j \times s_z^2}\right) + \varepsilon_{ijz},$$

where hatted variables are the residuals from the regression of the original variable on the fixed effects $\left(\lambda_i, \lambda_j, \lambda_z\right)$.[23] The results show that accounting for skill abundance does much in terms of explaining the variation in trade flows that is not accounted for by the fixed effects. In fact, it is this dependent variable which has the greatest effect on model fit from the variables under consideration.

The next exercise I consider relies on the following decomposition of the coefficient of de-

[22]Since the level increases in R^2 are very small, given that a significant amount of the variation in the dependent variable is accounted for through the various fixed effects included in the regression, rather than reporting the R^2 increment $R^2 - R_h^2$, table 9 reports

$$\left(\frac{R^2 - R_h^2}{R_h^2}\right) \times 100,$$

so that the reader can more easily identify which explanatory variables have a greater impact in terms of increasing the goodness of fit of the model.

[23]For example, $\hat{x}_{ijz}$ is the residual variation in trade flows that cannot be accounted for by importer, exporter, and industry fixed effects and the level of development. Therefore, I report R^2 for a regression purged from the variation that can be accounted for by the fixed effects. This approach is advantageous, relative to reporting R^2 increments for the original regression, for two reasons: 1. I am interested in determining the relative merits of different sources of comparative advantage, and as mentioned in section 2 the fixed effects account for the volume of trade, not the pattern of trade. Therefore, purging variables from these fixed effects makes sense in order that we may have a more accurate picture of the contribution of each of the other covariates in accounting for the distribution of relative exports across industries, and 2. Fixed effects alone account for most of R^2 in the original regression. The R^2 for the regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \varepsilon_{ijz}$$

is 0.9684, which implies that the *combined* R^2 increment of *all* determinants of the pattern of trade is in the order of 0.0003. Thus, in the original regression the presence of the fix effects mask any contribution in terms of fit made by any of the other covariates.

h^{th} explanatory variable	% Increase in R^2	Decomposition of R^2
$\mu_j \times s_z$	331.8	73.7%
$\sigma_j \times s_z$	0.58	7.4%
$\sigma_j \times s_z^2$	0.04	2.1%
$K_j \times k_z$	7.95	3.1%
$F_j \times v_z$	72.72	4.2%
$F_j \times k_z$	3.26	5.3%
$CE_j \times rs_z$	2.15	4.2%

Table 7: Accounting for the Variation in Trade Flows

termination that holds in linear regression models:

$$R^2 = \sum_{h=1}^{p} \delta_h r_h,$$

where δ_h is the standardized (beta) regression coefficient of the h^{th} explanatory variable and r_h is the sample correlation between the dependent variable and the h^{th} explanatory variable. The quantity $\delta_h r_h$ is the *contribution* of the h^{th} explanatory variable to the explanation of the variance of the dependent variable (see Theil [1971] for details).

The third column in Table 7 reports the contribution of each explanatory variable in the regression

$$\hat{x}_{ijz} = \hat{W}_{jz}\delta + \beta_0 \left(\widehat{\mu_j \times s_z}\right) + \beta_1 \left(\widehat{\sigma_j \times s_z}\right) + \beta_2 \left(\widehat{\sigma_j \times s_z^2}\right) + \varepsilon_{ijz},$$

where, once again, hatted variables denote residuals from the regression of the original variable on the fixed effects $\left(\lambda_i, \lambda_j, \lambda_z\right)$. It is clear from these estimates, that the endowment of human capital, as captured through the mean and standard deviation of the skill distribution, accounts for more of the variation in residual trade flows than any of the other determinants of the pattern of trade. In particular, skill abundance has the highest contribution in terms of accounting for the unexplained variation in the dependent variable. These estimates also suggest that both physical and human capital play a more significant role than institutional determinants of the pattern of trade in accounting for the residual variation in trade flows. Factor endowments account for 86.3% of the explained variation in residual trade flows, while institutional endowments only account for 13.7%.

In fact, the distribution of skill among the working age population alone accounts for 81% of the explained variation in residual trade flows, while the dispersion of skill accounts for 9.5%. The results discussed in this section lend further support to the hypothesis that the distribution of talent is in fact an empirically significant determinant of the pattern of trade. The results of this section are complementary to the estimates presented in Table 6. Taken together these results also suggest that classical determinants of the pattern of trade (i.e. factor endowments) still play an important role in explaining the sectoral distribution of trade flows, even for a set of exporters at similar levels of development.

5 Robustness Analysis and Alternative Specifications

In this section I test the sensitivity and robustness of my baseline estimates to various forms of misspecification in the estimating equation of section 4. I begin by considering a specification that allows for the mean and standard deviation to affect each individual sector differentially by interacting these determinants of the pattern of trade with industry dummies:

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \mu_j \times D_z + \sigma_j \times D_z + W_{jz}\delta + \varepsilon_{ijz}.$$

This specification allows these country-level characteristics to affect trade flows differentially across sectors in a completely unrestricted manner. This specification captures the effect that μ and σ have on the pattern of trade, without specifying the mechanism through which this occurs. The estimated coefficients from this regression allow us to broach the following question: what is the effect of marginal changes in skill moments (mean or standard deviation) on the relative exports of any two manufacturing industries? These estimates serve as an important robustness test to assess whether the first two moments of the distribution of skill are empirically significant determinants of the pattern of trade or not, although they reveal nothing about the underlying mechanism driving the result.

Because a full set of exporter and industry dummies have been included, the full set of interactions $\mu_j \times D_z$ and $\sigma_j \times D_z$ cannot be included. For $\mu_j \times D_z$ I normalized against $z =$ NAICS_3159, which has the lowest average skill level for its workforce (within manufacturing industries), while for $\sigma_j \times D_z$ I normalize against $z =$ NAICS_3324, which has the median skill level for its workforce (within the 76 manufacturing industries under consideration).

The first substantial result from this estimation is that out of the 75 coefficients estimated for the interaction term $\mu_j \times D_z$, 59 are statistically significant at the 10 percent level and this number only drops to 58 if I consider significance at the 5 percent level. This lends support to the claim that mean skills are an important determinant of the pattern of trade. Since I am normalizing against the industry with the lowest skilled workforce, theory suggests that the coefficients estimated on the interactions $\mu_j \times D_z$ should all be positive and increasing as the skill intensity of the industry increases. This sign restriction is violated in only three cases, all of which are not statistically significant at conventional levels. The estimated coefficients, as a function of the skill intensity of the industry to which the coefficient belongs, are not monotonically increasing as theory would suggest. However, it is apparent from Figure 5.1 that industries with a higher skill intensity benefit relatively more from an increase in the abundance of skills.[24] These results provide further evidence that skill abundant countries tend to export relatively more in skill intensive industries.

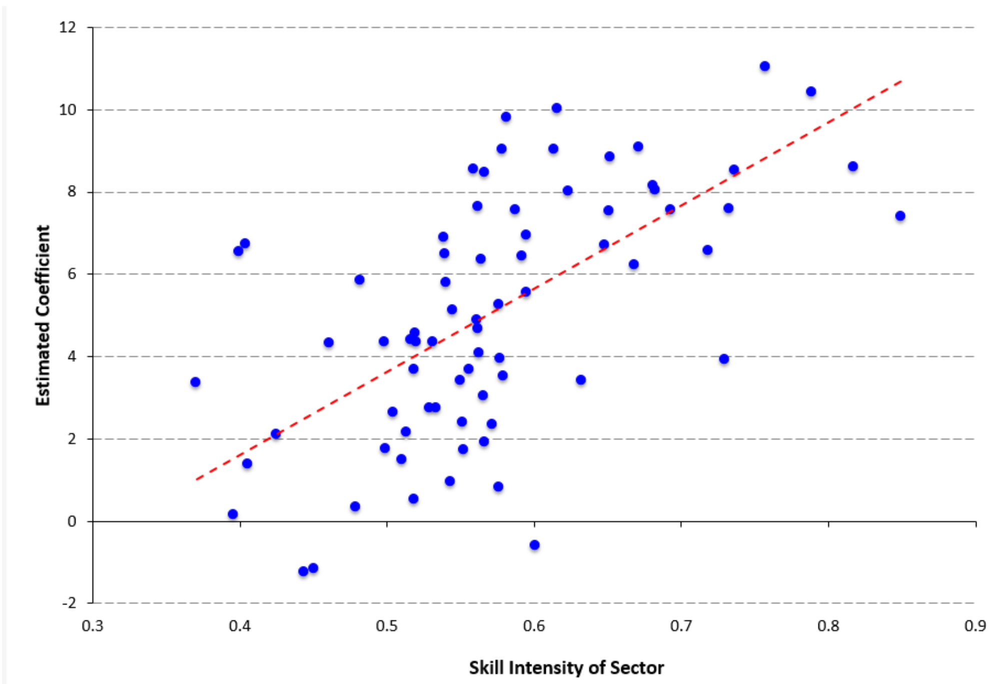


Figure 5.1: Mean Coefficients Ordered by Increasing s_z

For the case of the interaction term $\sigma_j \times D_z$, only 37 out of the 75 estimated coefficients are statistically significant at the 10 percent level. This lends limited support to the claim that skill dispersion is an important determinant of the pattern of trade. Figure 5.2 shows that the effect of increasing skill diversity is increasing in the skill intensity of an industry. This corroborates the positive and statistically significant coefficient estimated on the interaction term $\sigma_j \times s_z$ reported in Table 6, and the more limited role of a non-linear effect of σ on the determination of the pattern of trade. The estimated coefficients on the interactions which control

[24]Ordering the estimated coefficients from lowest to highest, and using this ordering to provide a ranking of industries in terms of skill intensity, produces a ranking whose correlation with s_z is 0.67.

for alternative sources of comparative advantage remain highly statistically significant.[25]

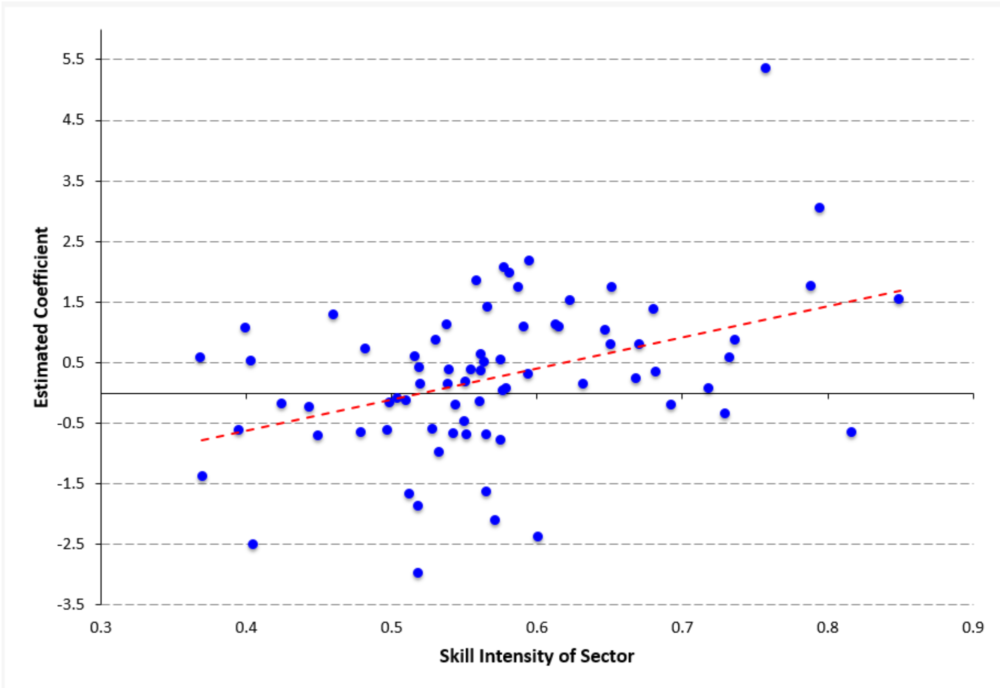


Figure 5.2: Dispersion Coefficients Ordered by Increasing s_z

Next, I consider robustness to the presence of non-linearities in the effect that alternative sources of comparative advantage may have on the pattern of trade. That is, I look for evidence that might suggest that the results reported in Table 6 regarding the effects of the skill distribution on trade flows where, in fact, driven by unmodeled non-linearities in alternative determinants of the trade pattern. To address this issue, rather than controlling for the effect of capital endowments and institutional factors on the pattern of trade through interaction terms of the form $K_j \times k_z$, I now introduce interaction terms of the form $K_j \times g_K(k_z)$, where $g_K(\cdot)$ is a second-degree polynomial. This allows for some degree of non-linearity of the effect of alternative sources of comparative advantage on the trade pattern. Thus, the estimating equation becomes

$$\begin{aligned} x_{ijz} &= \lambda_i + \lambda_j + \lambda_z + \mu_j \times s_z + \sigma_j \times g_\sigma(s_z) + \\ &\quad K_j \times g_k(k_z) + F_j \times g_f(v_z) + F_j \times g_{fk}(k_z) + CE_j \times g_c(rs_z) + \varepsilon_{ijz}, \end{aligned}$$

[25] All estimated coefficients on these interactions are statistically significant at the 0.1 percent level. However, the puzzling result of a negative estimated coefficient for the interaction term $K_j \times k_z$ remains. This provides further evidence that the estimates found elsewhere in the literature for the effects of capital endowments on the pattern of trade are sensitive to controlling for the effect of the distribution of talent on trade flows.

where the g_i are second-degree polynomials.

Table 8 reports the results of this specification. It is confirmed that the positive, and statistically significant, estimate for the coefficient on the interaction terms $\mu_j \times s_z$ and $\sigma_j \times s_z$ remains even after controlling for possible non-linearities in the effects of capital and institutional endowments. In fact, the magnitude of the estimate for these coefficients reported in column (1) of Table 8 are much the same as those reported in column (3) of Table 6. The estimate for the coefficient on the interaction term $\sigma_j \times s_z^2$ remains statistically insignificant.

Explanatory Variable	(1)	(2)
$\mu_j \times s_z$	6.18^{***} (0.29)	4.31^{***} (0.34)
$\sigma_j \times s_z$	1.07^{*} (0.48)	1.36^{**} (0.51)
$\sigma_j \times s_z^2$	0.25 (0.47)	-0.21 (0.50)
$K_j \times k_z$	-0.69 (1.11)	-1.33 (1.12)
$K_j \times k_z^2$	0.004 (1.10)	0.41 (1.11)
$F_j \times v_z$	1.34^{***} (0.31)	1.39^{***} (0.31)
$F_j \times v_z^2$	-1.08^{***} (0.31)	-1.11^{***} (0.31)
$F_j \times k_z$	-2.35^{***} (0.52)	-2.34^{***} (0.52)
$F_j \times k_z^2$	2.50^{***} (0.49)	2.51^{***} (0.49)
$CE_j \times rs_z$	-0.004 (0.11)	-0.010 (0.11)
$CE_j \times rs_z^2$	0.11 (0.11)	0.10 (0.11)
$K_j \times s_z$	-	2.99^{***} (0.80)
$K_j \times s_z^2$	-	-1.84^{**} (0.79)
$\bar{R}^2$	0.97	0.97

Beta coefficients reported. Heteroskedasticity consistent standard errors in parentheses. *, **, and *** denote significance at the 5, 1, and 0.1 levels, respectively.

Table 8: Controlling for Non-linearities in Alternative Sources of Comparative Advantage

Another possible source of misspecification concerns the issue of whether μ and σ have independent effects on the pattern of trade. Table 1 suggests that the mean and standard deviation of the skill distribution may be related in a systematic manner. In particular, there is a negative relationship between these two variables.[26] It is then possible that the interaction

[26]For my construction of the distribution of skills using the IALS data, there is an estimated 4 percent decrease

terms $\sigma_j \times s_z$ and $\sigma_j \times s_z^2$ are simply picking up unmodeled non-linearities of the effect of skill abundance on the pattern of trade. To this end, I consider a specification in which instead of introducing the simple interaction term $\mu_j \times s_z$ to control for the effects of mean skill on trade flows, I control for the mean with the interaction $q\left(\mu_j\right) \times \tau\left(s_z\right)$, where both $q\left(\cdot\right)$ and $\tau\left(\cdot\right)$ are second-degree polynomials.

Table 9 reports the results from this estimation. Notice that all of the estimates for the interaction $q\left(\mu_j\right) \times \tau\left(s_z\right)$ are highly statistically significant, but more importantly, the estimate for the coefficient on the interaction $\sigma_j \times s_z$ remains positive and highly statistically significant. Furthermore, after controlling for possible non-linearities in the effect of skill abundance on the pattern of trade, the estimate on the interaction $\sigma_j \times s_z^2$ gains in statistical significance, suggesting a non-linear effect of skill diversity on trade flows *after* controlling for non-linear effects of skill abundance on the pattern of trade. More importantly, it is confirmed that the mean and the standard deviation of the distribution of skill have independent and statistically significant effects in the determination of the pattern of trade.

This subsection carried out a series of robustness tests to address possible misspecifications in the estimating equation of section 4.[27] The results presented here corroborate my earlier findings regarding the empirical relevance of the distribution of talent in the workforce as a determinant of the pattern of trade. Skill abundance confers comparative advantage in skill intensive industries, while it is found that greater dispersion in the skill distribution induces specialization in skill intensive industries as well. The evidence, however, does not support the hypothesis that skill diversity also confers a comparative advantage in low-skill intensity industries. The effect on the pattern of trade of these country level characteristics is robust to controlling for non-linearities in the effects of alternative sources of comparative advantage. Both the mean *and* the standard deviation of the skill distribution are important country-level characteristics in the determination of the observed pattern of trade and they have independent effects on the distribution of exports across industries.

5.1 Extensions

In section 4.2 it was found that, while the dispersion in skills is an important determinant of the pattern of trade, the evidence did not lend support for the kind of non-linearity implied

in the mean skill level for a 10 percent increase in the standard deviation of the distribution of skill. Brown et al. [2007] find that this negative relationship between mean and standard deviation is a robust feature of educational attainment surveys.

[27] Additional robustness results can be found in the appendix.

Explanatory Variable	(1)	(2)
$\mu_j \times s_z$	-1108.70^{***}	-1125.47^{***}
	(187.73)	(186.73)
$\mu_j \times s_z^2$	1319.78^{***}	1307.60^{***}
	(187.25)	(186.27)
$\mu_j^2 \times s_z$	568.06^{***}	575.81^{***}
	(95.71)	(95.21)
$\mu_j^2 \times s_z^2$	-667.70^{***}	-661.49^{***}
	(94.72)	(94.25)
$\sigma_j \times s_z$	2.65^{***}	2.60^{***}
	(0.71)	(0.71)
$\sigma_j \times s_z^2$	-1.68^{*}	-1.71^{**}
	(0.70)	(0.70)
$K_j \times k_z$	-0.72^{***}	-0.94^{***}
	(0.09)	(0.10)
$F_j \times v_z$	0.26^{***}	0.27^{***}
	(0.04)	(0.04)
$F_j \times k_z$	0.25^{***}	0.25^{***}
	(0.04)	(0.04)
$CE_j \times rs_z$	0.10^{***}	0.08^{***}
	(0.02)	(0.02)
$K_j \times s_z$	-	0.98^{***}
		(0.12)
$\bar{R}^2$	0.97	0.97

Beta coefficients reported. Heteroskedasticity consistent standard errors in parentheses. *, **, and *** denote significance at the 5, 1 and 0.1 levels, respectively.

Table 9: Independent Effect of μ and σ on Trade Flows?

by the theory (i.e. that skill diversity confers a comparative advantage in both low-skill and high-skill intensive industries). The estimates from section 4 implied that differences in skill diversity, as captured by differences in the standard deviation of the skill distribution, induce specialization in high-skill intensive industries, but not in low-skill intensive industries.

The apparent lack of evidence favoring the prediction that skill diversity implies a comparative advantage in the most extreme skill-intense industries may derive from the fact that cross-country differences in skill diversity that are relevant for shaping comparative advantage are poorly summarized by differences in the standard deviation of the skill distribution. In the work of Grossman and Maggi [2000] and Costinot and Vogel [2010], skill diversity is defined in terms of either stochastic-dominance or likelihood-ratio dominance. Differences in standard deviations do not necessarily imply either of these kind of relationships. As such, it would seem desirable to use more of the information regarding the underlying skill distributions to characterize differences in factor endowments and their effects on shaping trade flows.

In this subsection I address this issue by considering a specification that attempts to incorporate more information regarding the underlying labor heterogeneity that is relevant in shaping trade flows, rather than collapsing this information into a summary statistic. In order that I may include more information regarding the full distribution of skills into the estimating equation, I define the following (relative) composite labor inputs:

$$\begin{aligned} Q_j^1 &= \frac{\hat{F}_j(100)}{\hat{F}_j(300)-\hat{F}_j(200)} \\ Q_j^2 &= \frac{\hat{F}_j(200)-\hat{F}_j(100)}{\hat{F}_j(300)-\hat{F}_j(200)} \\ Q_j^4 &= \frac{\hat{F}_j(400)-\hat{F}_j(300)}{\hat{F}_j(300)-\hat{F}_j(200)} \\ Q_j^5 &= \frac{1-\hat{F}_j(400)}{\hat{F}_j(300)-\hat{F}_j(200)}, \end{aligned}$$

where $\hat{F}_j(\cdot)$ is the empirical cumulative distribution function of skills in country j.[28]

Here, rather than dividing the labor pool into two classes of workers, skilled and unskilled as is common elsewhere in the literature[29], I divide the labor pool into 5 groups of workers, and with the Q_j^s's measure the relative endowment of these groups with respect to the middle group (i.e. those workers with a skill level between 200 and 300, which is the group that contains the mean and median skill level in all countries). Countries which are skill diverse should be expected to have relatively high values of Q^1 and Q^5, which are the groups with the most extreme skilled workers, while countries which are not skill diverse should be expected to have relatively higher values of Q^2 and Q^4, which are those workers with skill levels closer to the mean skill level. Finally, let $q_j^k = \ln\left(e+Q_j^k\right)$ for $k=1,2,4,5$.[30]

[28]Recall that the $\tau-th$ quantile of a random variable X_i solves

$$F\left(q_\tau(X_i)\right)=\tau,$$

where $F(\cdot)$ is the cdf of X. This implies that a fraction τ of the observations are below q_τ, while a fraction $1-\tau$ of the observations are above q_τ. The distribution of X is fully characterized by the set of $q_\tau(X_i)$ for $\tau\in[0,1]$.

[29]One may consider the case in which the labor pool is divided into low and high skill workers as the case in which we define the relative supply of high-skilled workers

$$\frac{L_s}{L_u}=\frac{1-\hat{F}(\tau)}{\hat{F}(\tau)}$$

for some τ in the support of the skill distribution.

[30]Notice that q_j^k is being normalized to unity for those cases in which $Q_j^k=0$.

Correspondingly, I divide occupations into 5 groups according to their skill relevance scores and define factor intensities in industry z as

$$q_z^k = \omega_{kz} \times \left(\frac{\text{Total Payroll}_z}{\text{Value Added}_z} \right)$$

where ω_{kz} is the employment share in industry z of occupations in group $k = 1,2,3,4,5$.

I now consider the following estimating equation

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + \sum_k \beta_k \left(q_j^k \times q_z^k \right) + \varepsilon_{ijz}.$$

The results from this estimation may prove useful in understanding how the distribution of talent shapes trade flows to the extent that: (a) workers with a skill level in group $[0,100]$, roughly, sort into the set of occupations with the lowest skill relevance scores, workers with a skill level in group $[100,200]$ sort into the set of occupations in group two with the second lowest range of skill relevance scores, and so on; and (b) these aggregate labor inputs are complementary in production, and not perfect substitutes, as they would be in a Cobb-Douglas production function that utilizes different types of labor inputs.[31]

As in section 4.2, I proceed by estimating first the short regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \sum_k \beta_k \left(q_j^k \times q_z^k \right) + \varepsilon_{ijz},$$

and then consider a series of long-regressions to control for alternative determinants of the pattern of trade. Results are reported in Table 10

Column (1) in Table 10 reports the results for the short-regression. Consistent with the predictions of standard factor proportions theory, the estimate for $\beta = (\beta_1, \beta_2, \beta_4, \beta_5)'$ is positive, and except for β_2, highly statistically significant. Next I control for institutional determinants of the pattern of trade, and for capital endowments as a source of comparative advantage; the results are reported in column (2) of Table 10. The estimates for β_1, β_2, and β_5 are all positive and statistically significant. The estimate for β_4 is negative, but not statistically significant at conventional levels. Finally, I control for the effect of the level of development on trade flows, and for the possibility that capital abundance, through its effect on factor prices, affects specialization differentially across industries varying in terms of the factor intensities

[31] This is the case in Romalis [2004] for a production function that uses two types of labor input: skilled and unskilled labor.

of the composite labor inputs. The results of the estimation with these additional controls are presented in column (3) of Table 10. The estimates for β_1, β_2, and β_5 remain positive and highly statistically significant. Notice however, that the estimate for β_4 is negative, and statistically different from zero.

Explanatory Variable	(1)	(2)	(3)
$q_j^1 \times q_z^1$	2.47*** (0.36)	5.02*** (0.42)	3.89*** (0.48)
$q_j^2 \times q_z^2$	0.04 (0.07)	0.32*** (0.07)	0.45*** (0.08)
$q_j^4 \times q_z^4$	0.19*** (0.04)	-0.001 (0.04)	-0.412*** (0.05)
$q_j^5 \times q_z^5$	23.32*** (1.94)	24.89*** (1.97)	18.01*** (1.86)
$K_j \times k_z$	-	-0.83*** (0.11)	1.73⋆ (0.99)
$F_j \times v_z$	-	0.30*** (0.04)	0.18*** (0.04)
$F_j \times k_z$	-	0.59*** (0.05)	0.21*** (0.05)
$CE_j \times rs_z$	-	0.17*** (0.02)	0.04 (0.03)
$K_j \times q_z^1$	-	-	3.80*** (0.73)
$K_j \times q_z^2$	-	-	2.82*** (0.40)
$K_j \times q_z^4$	-	-	-0.18 (0.47)
$K_j \times q_z^5$	-	-	1.76*** (0.29)
$y_j \times D_z$	-	-	YES
$\bar{R}^2$	0.97	0.97	0.97
No.Observations	98703	98703	98703

Beta coefficients reported. Heteroskedasticity robust standard errors in parentheses.⋆,*, **, and *** denote significance at the 10, 5, 1 and 0.1 percent levels, respectively.

Table 10: The Determinants of Comparative Advantage

The estimates presented in Table 10 attest to the importance of relative factor endowments in shaping trade flows. In particular, they point to the importance of taking into account the heterogeneity in the labor input when accounting for the determinants of comparative advantage. Because standardized coefficients are reported, they can be compared directly in terms of there impact on the dependent variable. Notice that within this group of exporters, a one standard deviation change in either $q_j^1 \times q_z^1$ or $q_j^5 \times q_z^5$ has a more substantial impact on trade flows than a one standard deviation change in any of the other covariates. These results suggest that the endowment of workers at the low and high end of the skill distribution are empirically significant determinants of the pattern of trade.

These results lend support to the hypothesis that accounting for the heterogeneity in the labor input is important in assessing the determination of trade flows. In particular, they offer evidence in favor of the hypothesis that relative factor differences at the low and high end of the skill distribution are important in accounting for the pattern of trade among exporters at a similar level of development.

6 Conclusions

What goods do countries trade? This is a central question in many theories of international trade, and my results have something to say in this regard. I have tested whether the distribution of talent in the workforce is a source of comparative advantage and found that both the mean and standard deviation of the skill distribution are economically, and statistically, significant determinants of the pattern of trade. While care should be taken in interpreting and generalizing my results as data limitations regarding IALS scores preclude me from incorporating more exporters into the sample, my results present strong evidence to support the hypothesis that skill abundant countries possess a comparative advantage in skill intensive sectors.

The data also provides strong evidence that countries characterized by more dispersed skill distributions tend to specialize in skill intensive industries. However, the hypothesis that skill diversity would also confer a comparative advantage in low-skill intensity industries finds weak support in the data. It is possible that I am not able to accurately identify the comparative advantage prediction related to this higher moment of the skill distribution because there is insufficient variation along this dimension for the group of exporters under consideration. When skill abundance and skill dispersion are defined in terms of stochastic dominance rather than by comparing summary statistics of the distribution (see the online Appendix for details), out of the 171 possible pairwise comparisons of skill distributions only 43 correspond to cases in which we can say that one distribution is more skill diverse than the other. Thus, for the group of exporters under consideration, most cross-country differences in skill distributions are characterized by differences in skill abundance, rather than by differences in skill diversity. This may help shed some light as to why I find such a strong effect for the mean skill level on the pattern of trade, but a more limited role for the standard deviation.

The estimates presented in section 5 are indicative of the importance of including more detailed information regarding the full extent of the underlying heterogeneity in skills, rather than collapsing this information into a couple of summary statistics, to accurately determine the importance of the distribution of talent in the population in shaping trade flows. Once this is done, the evidence is more favorable to the comparative advantage prediction that suggests that countries which are skill diverse, and thus relatively abundant in both low and high-skill workers, will export relatively more in low and high-skill intensity sectors. In particular, the results of section 5 suggest that the endowments of skills at the high and low ends of the distribution are particularly important for the determination of the pattern of trade.

According to my estimates, factor proportions theory is still clearly favored as the most successful theory explaining the pattern of trade, once it is recognized that labor is a highly heterogeneous input in production. The distribution of talent has a more significant impact on trade flows, and explains more of the pattern of trade, than capital endowments and institutional determinants of comparative advantage for the set of exporters under consideration.

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Appendix A: Data Description

IALS Data

The data regarding a country's skill distribution is obtained from the International Adult Literacy Survey (IALS), which provides the first internationally comparable data on literacy attainment for the working age population aged 16-65. This survey was implemented in 20 countries[32], which account for over 50 percent of the world's entire gross domestic product. Of these 20 countries, all except Australia have made their survey results publicly available.

The IALS data provides *reliable* and *comparable* estimates of the *levels* and *distribution* of literacy skills in the adult population.[33] Most previous studies have defined literacy in a binary way: either the person was literate or not. Furthermore, many of these surveys suffer from the unfortunate drawback that testing procedures are not standardized across countries, making it difficult to make cross-country comparisons.

In the IALS dataset, proficiency levels are measured along a continuum (test scores range from 0 to 500) and denote how well adults use information to function in society and the economy. That is, literacy is defined as

> " the ability to understand and employ printed information in daily activities, at home, at work, and in the community - to achieve one's goals, and to develop one's knowledge and potential" - *Literacy in the Information Age -Final Report of the International Adult Literacy Survey*, OECD Publications.

The IALS collects data on three dimensions of literacy that can be used to approximate skills:

1. *Prose Literacy*: represents the knowledge and skills needed to understand and use information from texts. In this domain, subjects where tested on three aspects relevant to information processing: *locating*, *integrating*, and *generating*. Locating tasks ask the subject to find information in the text based on conditions or features specified in the question or directive. Integrating tasks ask the subject to pull together two or more pieces of information in the text. Finally, generating tasks require the subject

[32]The participating countries are: Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, Switzerland, United Kingdom, and the United States.

[33]The number of survey participants in each country ranges from 2062 to 6718, with the average number of participants being 3378.

to produce a written response by processing information from the text and by making text-based inferences or drawing on their own background knowledge.

2. *Document Literacy*: represents the knowledge and skills required to locate and use information contained in various formats. Within this domain, subjects are tested on four aspects relevant to the processing of information contained in documents: *locating*, *cycling*, *integrating* and *generating*. Locating tasks require the reader to match one or more features of information stated in the question to either identical or synonymous information given in the document. Cycling tasks ask the reader to locate and match one or more features of information, but differ from locating tasks in that they require the reader to engage in a series of feature matches to satisfy conditions given in the question. The integrating tasks typically require the reader to compare and contrast information in adjacent parts of the document. In the generating tasks, readers must produce a written response by processing information found in the document and by making text-based inferences or drawing on their own background knowledge.

3. *Quantitative Literacy*: represents the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a checkbook, figuring out a tip, completing an order from or determining the amount of interest on a loan from an advertisement.

The IALS also goes to great lengths to minimize measurement error in order to obtain a more accurate assessment of a subject's underlying capabilities. Each text subject is administered the IALS exam five times. For each test subject I will work with the average score across these five observations. However, to get a sense of the variation in test scores present in the data, for each test subject I compute the standard deviation of test scores in each of the three dimensions of literacy being assessed. Table 15 presents summary statistics for this measure of variability in test scores. As can be seen, for some text subject there is no variation in test scores across the five replications of the test.

	Mean	min	max
$sd\,(Prose)$	16.64	0	87.06
$sd\,(Document)$	17.57	0	96.08
$sd\,(Quantitative)$	17.83	0	95.23

Table 11: Variability in test score for IALS

Further details concerning the IALS data and the construction of the distribution of skills at the country level can be found in the online Appendix.

Other Sources of Data

Data on total exports from exporter j to importer i in industry z are taken from the World Trade Flows Database 1962-2000 (see Feenstra et. al [2005]). The data are from the period 1996-2000 and are measured in thousands of U.S. dollars. The data is originally classified according to the 4-digit SITC Rev. 2 system. I map the data to the 4-digit NAICS 1997 classification using the SITC to NAICS concordance available at the NBER website.[34]

Capital endowment data is taken from the Penn World Tables (PWT). The relevant variable is KAPW, which measures "total capital stock per worker". Data is for the period 1997-2000 and it is measured in 2000 prices in international dollars. The international dollar is a currency created for the PWT data, where an international dollar has the purchasing power over all of GDP (but not the components) of a US dollar in current prices of the benchmark year. KAPW is not available for the the Czech Republic or Slovenia.[35]Real per capita GDP data is also taken from PWT. The relevant variable is CGDP and the data is for the period 1998-2000.

The measure of contract enforcement CE_j is from Nunn [2007]. The contract enforcement variable is an index which ranges from 0 to 1, with a higher number indicating greater contract enforcement. This variable is derived from a "rule of law" index which measures the extent to which agents have confidence in and abide by the rules of society.

The measure of labor market flexibility F_j is from Cuñat and Melitz [2010]. This variable is an index which ranges from 0 to 100, with a higher number indicating a greater extent of labor market flexibility. The measure is derived from a summary index produced by the World Bank which combines different dimensions of labor market rigidity such as hiring costs, firing costs, and restriction on changing the number of working hours.

Contract intensity (or relationship-specificity) rs_z is the variable z^{rs1} from Nunn [2007], which measures the proportion of an industry's inputs, weighted by value, that require relationship-specific investments. Nunn's variable is classified according to the I-O classification. I map the data to the 4-digit NAICS classification using the concordance available from the BEA.

[34]http://www.nber.org/lipsey/sitc22naics97/

[35]OECD does not provide any estimates for the capital endowment of the these two countries either.

The 4-digit NAICS contract intensity used is constructed as $z_k = \sum \omega_i z_i$, where the sum is over the set of I-O industries which map into a 4-digit NAICS industry, and $\omega_i \equiv u_i / \sum u_j$ where u_i is the total value of inputs used in i.

The industry volatility variable v_z is the variable VOL_s from Cuñat and Melitz [2010]. This variable measures industry volatility as the standard deviation of the growth rate of firm sales. This variable is classified according to the US SIC classification, and I map this data into the 4-digit NAICS classification using the concordance available from the BEA. The variable v_z corresponds to the average volatility of the I-O industries which map into a 6-digit NAICS industry encompassed by the 4-digit industry.

Data on capital intensities across industries are from NBER-CES Manufacturing Industry Database (see Bartelsman et. al. [2009]). Capital intensity k_z is measured as

$$1 - \frac{\text{Total Payroll}}{\text{Value Added}}$$

for industry z in the United States in the year 2000. The original data is classified according to the NAICS 1997 classification, but reported at the more disaggregated 6-digit level. I aggregate 6-digit categories up to the 4-digit level.

The construction of the variable s_z, which measures skill intensity at the industry level, is described in section 3. Construction of this variable makes use of employment and wage data from the National Employment Matrix, available from the Bureau of Labor Statistics, and the O*NET v.14 database on occupational descriptors. The O*NET database contains several hundred variables that represent descriptors of work and worker characteristics, including skill requirements for over 800 SOC occupations. For several of these occupational descriptors the O*NET database reports **importance** and **level ratings** of these descriptors for a particular occupation. The importance rating indicates the degree of importance a particular descriptor is to the occupation. The possible ratings range from "Not Important" (1) to "Extremely Important" (5). The level rating indicates the degree, or point along a continuum, to which a particular descriptor is required or needed to perform the occupation[36]. These ratings are derived, primarily, from the ratings of job incumbents and to a lesser degree from the ratings provided by occupational analysts. Because different descriptors utilize different

[36]The level rating for an item is identified as "not relevant" for a particular occupation when a majority (75% or more) of the incumbents or occupational analysts rate the corresponding importance item as "not important".

rating scales, all ratings are reported as standardized scores:

$$r = \left(\frac{O-L}{H-L}\right) \times 100$$

where

$$\begin{aligned} O &= \text{original score on the rating scale} \\ L &= \text{lowest possible score on the rating scale} \\ H &= \text{highest possible score on the rating scale.} \end{aligned}$$

The National Employment Matrix provides detailed employment information for 4-digit NAICS 1997 industries. This matrix contains employment shares (and levels) for SOC occupations, as well as average industry wage data for these occupations.

Tables 16 and 17 present summary statistics for the industry-level and country-level characteristics of interest. Those summary statistics are calculated based on the subsample of industries and exporters for which there is data available for all variables.

	Mean	Standard Deviation	Minimum	Maximum	Coefficient Variation
Skill Intensity	0.57	0.10	0.37	0.85	0.18
Capital Intensity	4.95	0.82	3.03	7.26	0.17
Volatility	0.18	0.04	0.11	0.29	0.21
Rel. Specificity	0.51	0.21	0.06	0.94	0.42

Table 12: Industry-level Characteristics

	Mean	Standard Deviation	Minimum	Maximum	Coefficient Variation
Mean Skill	5.59	0.10	5.34	5.70	0.02
Std. Deviation Skill	3.98	0.16	3.70	4.26	0.04
Capital Stock	11.60	0.42	10.59	12.03	0.04
Labor Market Flexibility	4.25	0.23	3.81	4.57	0.05
Contract Enforcement	0.84	0.11	0.61	0.97	0.12
log(GDP per capita)	9.96	0.38	9.11	10.41	0.04

Table 13: Country-level Characteristics

Appendix B: Other Supplementary Material

Relationship between Theory and the Estimation Framework

The estimation framework of section 4 is given by

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + g\left(s_z, \mu_j, \sigma_j\right) + \varepsilon_{ijz}$$

It is reasonable to wonder whether this specification is theoretically justified. As Deardorff [1984] points out

> "The major obstacle to the testing of trade theories has been the difficulty of constructing tests that all would agree were theoretically sound. The intuitive content of most trade theories is quite simple and straightforward. But empirical tests of the theories are often faulted on the grounds that they test propositions that do not derive rigorously from the theories."

In this appendix I provide an informal derivation of a relationship between trade flows and importer, exporter, and industry characteristics such as the one specified in the estimation framework. This derivation clearly lays out the manner in which the empirical framework is linked to the theory.

Assume that preferences are given by a two-tier CES structure:

$$\begin{aligned} U &= \sum_{z \in \mathscr{Z}} \alpha(z) \ln\left[Q(z)\right] \\ Q(z) &= \left(\int_{\omega_z \in \Omega_z} q(\omega_z)^{\frac{\sigma-1}{\sigma}} d\omega_z\right)^{\frac{\sigma}{\sigma-1}} \end{aligned}$$

with $\sum_{z \in \mathscr{Z}} \alpha(z) = 1$. Here, the first tier is a Cobb-Douglas utility index over consumption bundles $Q(z)$ from different sectors, indexed $z \in \mathscr{Z}$, and the second tier is a CES aggregator over different varieties within each sector. The parameter $\sigma > 1$, is the elasticity of substitution across varieties, assumed common across sectors, and Ω_z is the set of available varieties in sector z.

This demand system is standard in the international trade literature and leads to the following expression for the expenditures of country i on a variety from sector z

$$e_i(\omega_z) = D_{iz} p_i(\omega_z)^{1-\sigma}.$$

Here, $p_i(\omega_z)$ is the price paid in i for a variety in sector z, and D_{iz} captures the *strength of demand* in country i for varieties in sector z and depends on: (a) the CES ideal price index for sector z in country i, $P_{iz} = \left(\int_{\omega_z \in \Omega_z} p_i(\omega_z)^{1-\sigma} d\omega_z\right)^{\frac{1}{1-\sigma}}$; (b) the share of income spent on goods from sector z, $\alpha(z)$, and (c) the income of country i.

On the production side, assume that final goods are produced by monopolistically competitive firms. The unique factor of production for these firms is a sector specific composite input that is assumed to be non-traded and produced competitively by a constant returns to scale technology. Firms face fixed production costs so that in equilibrium each firm chooses to produce a unique variety.This cost structure is similar to that assumed in Bernard et al. [2007]. Given the demand structure outlined above, optimal pricing by final good producers results in a constant markup over marginal cost:

$$p_{ijz} = \left(\frac{\sigma}{\sigma-1}\right)\tau_{ijz}c_{jz},$$

where c_{jz} is the cost of the sector specific composite in country j, and τ_{ijz} are the trade barriers faced by country j in sector z when serving demand from country i.

Given the expression for expenditures and the fact that each firm supplies a unique differentiated variety, trade volumes are given by the following expression

$$X_{ijz} = M_{jz}D_{iz}p_{ijz}^{1-\sigma},$$

where X_{ijz} are the imports of country i, from country j, in sector z; p_{ijz} is the price paid by consumers in i for a variety from country j in sector z, and M_{jz} is the mass of firms in the exporting country in industry z.

Finally, assume that $\tau_{ijz}^{1-\sigma} = (T_{ij} \cdot T_{iz}) e^{-u_{ijz}}$, where $u_{ijz} \sim N(0, \sigma^2)$ are i.i.d. unobserved/unmeasured trade barriers. Given this assumption, and the optimal pricing strategy of final good producers, trade flows may be expressed as

$$\begin{aligned} X_{ijz} &= M_{jz}D_{iz}p_{ijz}^{1-\sigma} \\ &= M_{jz}D_{iz}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} c_{jz}^{1-\sigma}\left(T_{ij} \cdot T_{iz}\right)^{-1} e^{u_{ijz}}. \end{aligned}$$

Taking logs on both sides of this expression yields

$$\log\left(X_{ijz}\right) = \log\left[\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\right] + \left[\log\left(D_{iz}\right) - \log\left(T_{iz}\right)\right] - \log\left(T_{ij}\right) + \log\left(M_{jz}c_{jz}^{1-\sigma}\right) + u_{ijz},$$

which suggests the expression

$$\log\left(X_{ijz}\right) = \lambda_{iz} + \lambda_{ij} + \log\left(M_{jz}c_{jz}^{1-\sigma}\right) + u_{ijz},$$

where λ_{iz} is an importer-industry specific term, and λ_{ij} is an importer-exporter specific term.

Notice that this expression has the following implication for the distribution of relative exports across sectors for the exports of countries j and k into the common destination i:

$$\begin{aligned}\mathbb{E}\left[\log\left(\frac{X_{ijz}}{X_{ikz}}\right) - \log\left(\frac{X_{ijz'}}{X_{ikz'}}\right)\right] &= (\sigma-1)\left[\log\left(\frac{c_{jz'}}{c_{kz'}}\right) - \log\left(\frac{c_{jz}}{c_{kz}}\right)\right] \\ &\quad + \left[\log\left(\frac{M_{jz}}{M_{kz}}\right) - \log\left(\frac{M_{jz'}}{M_{kz'}}\right)\right].\end{aligned}$$

This expression relates the distribution of relative exports to two terms: the first, which refers only to relative costs of production, is tied to comparative advantage, while the second term comes from the endogenous adjustment in the entry and exit of firms to achieve equilibrium.

In two-country models of international trade it can be shown that

$$\log\left(\frac{c_{jz'}}{c_{kz'}}\right) - \log\left(\frac{c_{jz}}{c_{kz}}\right) > 0 \Rightarrow \log\left(\frac{M_{jz}}{M_{kz}}\right) - \log\left(\frac{M_{jz'}}{M_{kz'}}\right) > 0.$$

That is, there is relatively more entry into the comparative advantage sectors.[37] The intuition is that the equilibrium distribution of firms across countries and sectors is such that there remains no further possibility for profitable entry.Thus, in a two-country model of international trade these two forces both point in the same direction.This result is not easily extended to a multi-country model, specially when countries are asymmetric. As Behrens et al. [2009] show, in a multi-country setup third country effects crucially affect production patterns. Therefore, the results that the relative mass of firms M_{jz}/M_{kz} is decreasing in relative costs c_{jz}/c_{kz} is not generally valid and must either be assumed or derived under stringent

[37] See, for example, Romalis [2004]. Although this author considers a multi-country model, in his setup the world is divided into North and South countries with all countries homogeneous within each block. Thus, the model is essentially a two-country model of international trade. See also Bernard, Redding, and Schott [2007].

conditions. Implicit in the estimation framework is the assumption that entry is relatively higher in comparative advantage sectors.

A fully specified general equilibrium model will provide a mapping from exporter and industry characteristics to the mass of firms and the cost of the industry specific composite input. That is,

$$\log\left(M_{jz}c_{jz}^{1-\sigma}\right) = f\left(\text{characteristics of exporter } j, \text{characterisitics of sector } z\right).$$

For example, in the model of Romalis [2004], c_{jz} is given by

$$c_{jz} = \left(\omega_j\right)^z$$

where ω_j is the relative price of skilled to unskilled labor, and z is the cost share of skilled labor in the sector (i.e. z is the sector's skill intensity). Because of transport costs, there is a failure of factor price equalization (FPE) and in equilibrium $\omega_j = \omega\left(L_j^s/L_j^u\right)$, where L^s/L^u is the relative endowment of skilled to unskilled labor. In this way, Romalis is able to derive the three way relationship between trade, factor endowments, and factor intensities necessary to test the trade implications of a standard factor proportions model.

It should be clear that the most important part in deriving the estimating equation of interest is the way in which the term $\log\left(M_{jz}c_{jz}^{1-\sigma}\right)$ is modeled, since this is the term that is germane to the theory of comparative advantage. I do not specify a full general equilibrium model, but given the previous discussion, here I have chosen to model the term of interest as

$$\log\left(M_{jz}c_{jz}^{1-\sigma}\right) = W_{jz}\delta + g\left(s_z, \mu_j, \sigma_j\right) + \varepsilon_{jz},$$

so that the expression for trade flows is given as

$$\log\left(X_{ijz}\right) = \lambda_{iz} + \lambda_{ij} + W_{jz}\delta + g\left(s_z, \mu_j, \sigma_j\right) + \varepsilon_{ijz},$$

where $\varepsilon_{ijz} = \varepsilon_{jz} + u_{ijz}$.

This specification is parsimonious in the way in which alternative sources of comparative advantage affect trade flows. In a fully specified general equilibrium model the term $\log\left(M_{jz}c_{jz}^{1-\sigma}\right)$ might be a complicated, nonlinear function of exporter and sectoral characteristics so it is worth emphasizing that the estimated coefficients reported in section 4 should be interpreted as those for the best approximation to the true CDF $\mathbb{E}\left[\log\left(M_{jz}c_{jz}^{1-\sigma}\right)|\mathbb{X}\right]$ within a given class of functions (see Goldberger [1991]).

The above derivation suggests that the estimating equation should have importer-industry and importer-exporter fixed effects, rather than separate industry, importer, and exporter fixed effects. The reason why I adopt the latter specification instead of the former, is that the computational costs of including importer-industry and importer-exporter fixed effects is too high.[38]Therefore, by replacing importer-industry and exporter-importer fixed effects with separate industry, importer, and exporter fixed effects, the expression relating trade flows to exporter and industry characteristics becomes

$$\log\left(X_{ijz}\right) = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + g\left(s_z, \mu_j, \sigma_j\right) + \varepsilon_{ijz}.$$

Construction of Skill Distribution

In this section I describe the construction of the skill distribution for each exporter in the sample, and document the properties of these distributions. Due to the novelty of the construction of the distribution of skills using test scores rather than educational attainment, it is of interest in its own right to study the statistical properties of these distributions and the cross country comparison amongst them.

Table 14 summarizes the IALS data. The last three columns display the correlations across the three dimensions of literacy tested by the IALS. As can be observed, all of these dimensions of literacy are highly correlated with each other.

To gain further insight into the relationship between these different dimensions of literacy, I consider simple regressions of one of these variables on the other two. The results are presented in Table 15 and suggest that any of these three dimensions of literacy is well explained by the other two, and that there is a positive and statistically significant relationship between any of these three dimensions of literacy and the other two.

The sample correlations presented in Table 14 , and the results from simple regression analysis, suggest that these three dimensions of literacy in fact contain much redundant information. Therefore, it seems appropriate to consolidate these different literacy scores into a single variable which I will call “skill”.

[38]Estimating importer-industry and importer-exporter fixed effects would require close to 19,000 dummy variables given the number of exporters and industries included in the sample, while including separate importer, exporter, and industry fixed effects requires about 300 dummy variables only.

Country	μ_{prose}	$\mu_{doc.}$	$\mu_{quant.}$	σ_{prose}	$\sigma_{doc.}$	$\sigma_{quant.}$	$\rho_{prose,doc}$	$\rho_{prose,quant}$	$\rho_{doc,quant}$
Belgium	282.60	287.85	292.16	51.52	49.99	54.74	0.92	0.89	0.93
Canada	259.97	256.92	259.65	64.19	72.03	63.45	0.92	0.91	0.93
Chile	212.96	211.97	200.04	54.14	54.32	68.36	0.95	0.94	0.96
Czech Rep.	272.01	285.70	301.28	40.23	49.98	50.74	0.89	0.88	0.93
Denmark	276.61	295.66	299.66	35.27	44.56	43.07	0.93	0.88	0.93
Finland	290.20	290.99	287.45	47.46	52.33	46.02	0.93	0.87	0.93
Germany	275.41	284.50	291.78	44.93	44.57	42.69	0.91	0.90	0.92
Hungary	239.80	245.78	267.00	42.43	53.09	54.19	0.87	0.87	0.88
Ireland	264.48	257.68	262.81	55.34	57.26	61.58	0.94	0.93	0.96
Italy	254.53	247.12	256.66	58.67	58.68	60.17	0.93	0.92	0.96
Netherlands	281.77	284.59	286.69	44.52	46.90	47.32	0.94	0.90	0.95
New Zealand	282.06	275.12	276.48	50.97	54.09	52.89	0.94	0.91	0.95
Norway	290.44	298.02	298.53	43.55	51.47	47.55	0.93	0.89	0.94
Poland	228.83	222.99	234.22	58.68	70.48	67.62	0.93	0.92	0.97
Slovenia	229.72	231.93	242.29	57.56	64.79	66.33	0.94	0.93	0.96
Sweden	293.92	298.93	299.91	53.68	54.18	54.34	0.93	0.88	0.97
Switzerland	266.47	272.67	279.65	53.13	59.43	58.53	0.91	0.90	0.92
UK	266.16	265.15	268.05	59.93	64.28	64.79	0.96	0.93	0.96
USA	260.24	254.23	261.80	71.85	74.19	71.93	0.94	0.93	0.95
Pooled Sample	**264.40**	**265.94**	**270.56**	**57.90**	**63.50**	**63.44**	**0.93**	**0.91**	**0.95**

μ denotes mean, σ denotes standard deviation, and ρ denotes correlation.

Table 14: IALS Summary Statistics

I define the variable *"skill"* as

$$\text{Skill} = \omega_p \text{Prose} + \omega_d \text{Document} + \omega_q \text{Quantitative},$$

where the weights $\left(\omega_p, \omega_d, \omega_q\right)$ are chosen through principal component analysis (PCA). PCA is particularly appropriate when the original variables are highly correlated, suggesting a certain degree of redundancy in the information contained by these variables. From an initial set of m **correlated** variables, principal component analysis (PCA) creates **uncorrelated** indices or components, where each component is a linear weighted combination of the initial variables. Being uncorrelated, the indices measure different dimensions of the data. The components are ordered so that the first component (PC_1) explains the largest possible amount of variation in the original data. The weights $\left(\omega_p, \omega_d, \omega_q\right)$ are the weights corresponding to the first component from PCA performed on the IALS survey data and it accounts for roughly 80

Dependent Variable	Constant	$\hat{\beta}_{Prose}$	$\hat{\beta}_{Document}$	$\hat{\beta}_{Quantitative}$	R^2
Prose	33.58^{***} (0.35)	-	0.63^{***} (0.004)	0.23^{***} (0.004)	0.88
Document	-8.61^{***} (0.32)	0.46^{***} (0.003)	-	0.56^{***} (0.003)	0.93
Quantitative	10.56^{***} (0.37)	0.23^{***} (0.004)	0.75^{***} (0.003)	-	0.9

*** denotes statistical significance at the 0.1 percent level.

Table 15: Regression Analysis for Dimensions of Literacy in IALS Data

percent of the variation in the data for each of the countries under consideration.[39] Table 16 presents summary statistics for the skill distribution constructed in this fashion.

Country	μ	σ	median	$1^{st}qu.$	$3^{rd}qu.$	min	max
Belgium	287.6	50.64	295.5	263.1	322	29.81	413.5
Canada	258.8	65.01	269.2	219.9	305.9	14.18	445.1
Chile	207.6	58.74	213.5	169.6	250	45.77	380.5
Czech Rep.	287.6	46.072	292.7	260.1	318.9	70.41	475.7
Denmark	291.7	40.29	296.8	268.8	320.9	109.5	397.8
Finland	289.6	47.37	296	264.6	322	61.86	418.6
Germany	283.8	42.74	285	257.8	313.8	102.3	419
Hungary	251.9	48.39	255.7	223.4	284.2	102.2	431.1
Ireland	261.6	57.06	268.4	227.9	302.2	54.13	403.5
Italy	252.8	57.94	262.9	220.6	295.1	48.26	395
Netherlands	284.4	45.23	291	260.3	315.7	56.53	417.3
New Zealand	277.8	51.51	283	250.6	277.8	42.51	412
Norway	295.9	46.57	303.4	271	328.2	71.01	410.1
Poland	228.6	64.84	239.3	191.9	274.9	24.77	381.4
Slovenia	234.9	62.05	244.2	197.9	279.6	44.71	407.9
Sweden	297.6	52.74	303.2	269.5	333.8	50.76	421.9
Switzerland	273.2	55.52	283.5	250.2	310.2	58.75	404.2
UK	266.5	62.04	274	231.4	311.2	19.74	470
USA	258.7	71.13	271.5	218.7	310.9	40.93	437.9

Table 16: Summary Statistics for Skill Distribution

To further characterize the full distribution of skills I perform kernel density estimation to

[39]Actually, since the weights from principal component analysis do not sum to one - the sum of their squares does -, I normalize the weights so that they sum to unity. This, additionally, makes sure that the change of basis that is involved in PCA does not affect the range of potentially observable skill levels (i.e. the skill variable remains in the range $[0,500]$). Weights are chosen independently across countries. That is, I perform a principal components analysis on the data of each country individually. The weights across the three dimensions of literacy are roughly equal, with quantitative literacy typically receiving a slightly higher weight, and the weights on these three variables are roughly the same across countries.

obtain densities for the skill distribution of each country. The estimation is performed using the "Normal Reference Rule" (see Silverman [1998] and Wasserman [2006] for details). Selected results are presented in Figure 6.5. For four of the nineteen countries, the skill distribution is bi-modal. This suggests the possibility that for these countries the overall skill distribution is in fact the mixture of the skill distribution for two separate populations. The countries with the most dispersed skill distributions are Anglo-Saxon countries, while the countries with the highest mean skill levels are typically Scandinavian countries (who also have the most compressed distributions).

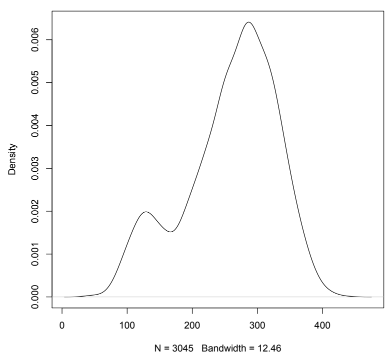

Figure 6.1: USA

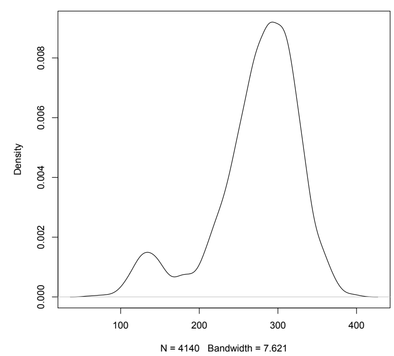

Figure 6.2: Switzerland

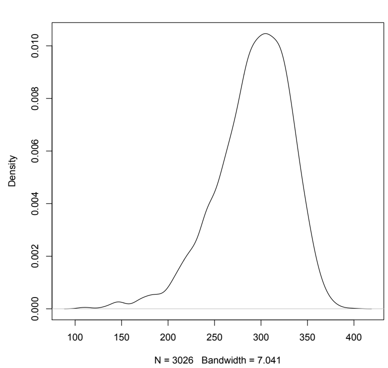

Figure 6.3: Denmark

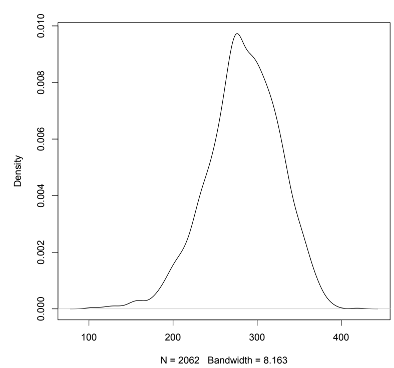

Figure 6.4: Germany

Figure 6.5: Kernel Density Estimates of Skill Distribution

In what follows I perform a series of hypotheses tests whose aim is to further our understanding of the cross-country differences that prevail for the skill distributions constructed in the manner outlined above. In particular, the focus is in testing whether there are true cross-country differences in the distribution of skills. While the number of participants in each country is relatively large in absolute terms, it is small compared to the country's population. Thus, it might be cause for concern that the observed differences in skill distributions are the result of sampling variability, rather than true underlying differences in the distribution of skills across countries.

I start by testing the null

$$\begin{aligned} H_0 &: F_i(z) = F_j(z) \ \forall z \\ H_1 &: F_i(z) \neq F_j(z) \text{ for some } z, \end{aligned}$$

for two countries $i \neq j$. That is, I test that null of equal distributions for a given pair of exporters.

To test H_0 I use the Rank-sum Test of Mann and Whitney (see Mood et. al. [1974]). There are 171 possible pairwise comparisons. Testing H_0 at the five percent level results in 159 rejections of the null of identical distributions. This suggests that it is safe to assume that skill distributions vary across countries. However, these differences may be subtle and may not be reflected in particular moments of interest.

To address this concern I consider the following hypotheses tests

$$\begin{aligned} H_0 &: \mu_i = \mu_j \\ H_1 &: \mu_i \neq \mu_j \end{aligned}$$

and

$$\begin{aligned} H_0 &: \sigma_i = \sigma_j \\ H_1 &: \sigma_i \neq \sigma_j. \end{aligned}$$

That is, I test whether there is cross-country variation in the first two moments of the distribution of skills. To test the first hypothesis I use Welch's t-test.[40]. Testing the null of equal means at the five percent level results in 162 (out of the 171 possible pairwise comparisons) rejections of the null. To test the null that standard deviations do not vary across country pairs, I use the Levene test (see Brown and Forsythe [1974]). Testing H_0 at the five percent level, I

[40]Welch's $t-$test is a variation on a Student $t-$test for the case in which it cannot be assumed that the two populations under consideration share the same variance, and the samples differ in size. See Welch [1947] for details on the test statistic and its asymptotic distribution.

can reject the null of equal variances of the skill distributions in 142 of the 171 possible cases to consider.

Finally, I consider comparisons of skill distributions in the spirit of the notions defining *skill abundance* and *skill diversity* in Grossman and Maggi [2000] and Costinot and Vogel [2010]. In particular, I look at the empirical cdf's of exporter pairs to define whether the bilateral difference in skill endowments is one that can be classified as a difference in the abundance of skills or a difference in the diversity of these. I define skill abundance in terms of *first-order stochastic dominance*: the distribution of exporter i is said to be more *skill abundant* than that of exporter j, if $\hat{F}_i$ first-order stochastically dominates $\hat{F}_j$, denoted by $F_i \succeq_A F_j$. A case of skill abundance is depicted in Figure 6.6, where the distribution of skills in Denmark is shown to first-order stochastically dominate that of Chile. On the other hand, exporter i is said to be more *skill diverse* than exporter j, denoted $F_i \succeq_D F_j$, if : (a) the ecdf's cross each other at most once, and (b) $\hat{F}_j$ first-order stochastically dominates $\hat{F}_i$ to the left of the crossing point, and $\hat{F}_i$ first-order stochastically dominates $\hat{F}_j$ to the right of the crossing point. Figure 6.7 depicts a case of two exporters who differ in terms of skill diversity defined in this way.

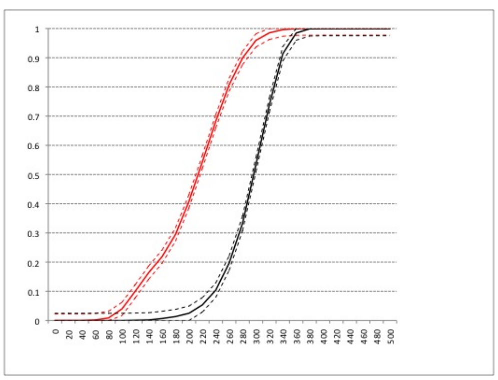

Figure 6.6: Denmark$\succeq_A$Chile

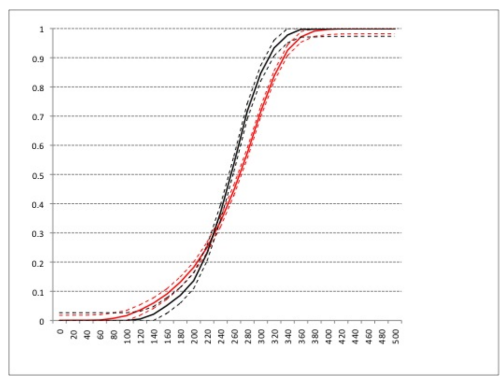

Figure 6.7: Canada$\succeq_D$Hungary

Using these definitions of skill abundance and skill diversity I look at all the possible exporter pairs in the sample to see which relationship holds. Out of the 171 pairwise comparisons possible, 43 correspond to cases where one distribution is said to be more skill diverse than the other; in only one case is no relation defined as the empirical cdf's cross each other more than once, and the rest are cases in which it is said that one distribution is more skill abundant than the other. For the cases in which a skill abundance relation is said to hold, I can formally test whether one distribution first-order stochastically dominates the other. It seems of interest to formally test this hypothesis as, by far, bilateral relationships where the main difference is in terms of skill abundance are the most pervasive in the IALS data set. [41]

To test the null

$$\begin{aligned} H_0 &: G(x) \leq F(x) \quad \forall x \\ H_1 &: G(x) > F(x) \quad \text{for some } x \end{aligned}$$

(i.e.that G first-order stochastically dominates F) I use the test proposed by Barrett and Donald [2003].[42] In all cases in which comparison of the ecdf's indicated the existence of a skill abundance relationship, I test H_0 at the five percent level, and in all cases the null of stochastic dominance cannot be rejected.

Together, these set of results help us understand the extent of cross-country differences in skill distributions. The results presented here suggest that observed differences in skill distributions across countries are not driven by sampling variability, bur rather reflect true differences in the underlying distributions.

Relationship Between Skill Intensity and Industry Wages

Given the novel construction of the proxy for skill intensity proposed here, it is of interest to ascertain whether it provides a reasonable classification of industries according to their skill intensity. In the main text it was shown that the measure of skill intensity proposed here, s_z, is highly correlated to the share of non-production wages in total payroll which is the standard measure of skill intensity used in the literature. Here I investigate the relationship between skill intensity s_z and industry wages, since a commonly used proxy for skill intensity at the sector level is the average wage in the sector.

[41] Formally testing the null hypothesis defining the skill diversity relationship is beyond the scope of standard testing procedures as the crossing point of the distributions is not known a priori and must be estimated.

[42] The test statistic for testing the hypothesis H_0 against H_1 is given by

$$\hat{S} = \left(\frac{nm}{n+m}\right)^{\frac{1}{2}} \sup_z \left(\hat{G}_m(z) - \hat{F}_n(z)\right),$$

where $\hat{G}_m$ and $\hat{F}_n$ are the empirical cdf's when the sample sizes are m and n, respectively. Barret and Donald [2003] show that, when testing for first-order stochastic dominance, $p-$values can be computed as $\exp\left\{-2\left(\hat{S}\right)^2\right\}$. These $p-$values are justified asymptotically by Proposition 1 and equation (3) in their paper. This testing procedure is similar to the more familiar Kolmogorov-Smirnov test, and is a consistent test for the complete set of restrictions implied by stochastic dominance (i.e. it tests the relevant inequality at all points in the support of the distributions).

Let $\bar{w}_z$ be the average wage in industry z. I consider a regression of average industry wage on skill intensity, allowing for a non-linear effect of skill intensity on average wages:

$$\ln(\bar{w}_z) = \underset{(0.22)}{10.18^{***}} - \underset{(0.77)}{.22}\, s_z + \underset{(0.08)}{1.58^{***}} s_z^2 \qquad \left(R^2 = 0.82\right).$$

The results show a positive, and statistically significant, relationship between average industry wages and skill intensity as measured by s_z.[43] This relationship is more clearly depicted in Figure 6.8.

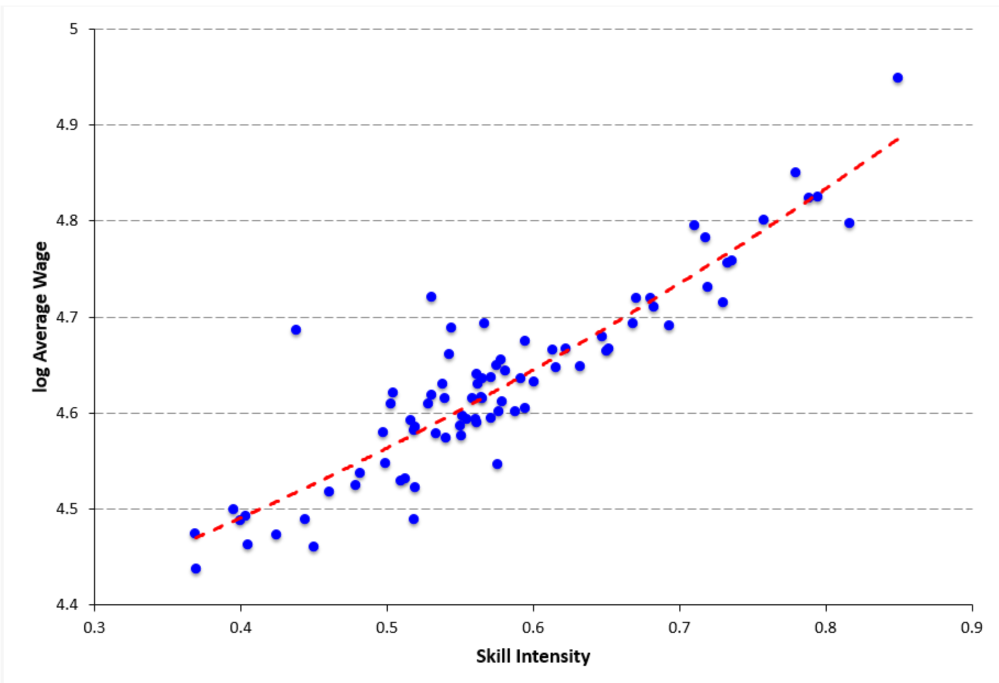

Figure 6.8: Relationship Between Skill Intensity and Average Industry Wages

Next, I consider the wage regression

$$w_{ij} = \lambda_i + \gamma_i \left(D_i \times \ln\left(R_j\right)\right) + \varepsilon_{ij},$$

where w_{ij} is the log average wage of occupation j in industry i, λ_i is an industry fixed effect, D_i is an industry dummy, and R_j is occupation $j's$ skill relevance score. This wage regression

[43] A similar exercise, but with the dependent variable being the coefficient of variation of industry wages, shows that there is no statistically significant relationship between wage dispersion and skill intensity as measured by s_z. If industries also varied by the degree of complementarity in production of different labor inputs, and we believed s_z to be possibly reflecting this varying degree of complementarity across industries, then we would expect to observe a relationship between s_z and industry wage dispersion.

implies that the marginal effect of an increase in skills varies by industry:

$$\frac{\partial w_{ij}}{\partial \ln\left(R_j\right)} = \gamma_i.$$

To gain intuition behind this wage regression, consider the model in Costinot and Vogel [2010] where the wage for a worker of skill level s in industry σ reflects his/her productivity in that sector: $w_{s\sigma} = p(\sigma)A(s,\sigma)$, where $p(\sigma)$ is the price of output in sector σ and $A(s,\sigma)$ is the productivity of a worker with skill s in sector σ. Suppose that $A(s,\sigma) = \exp(s\cdot\sigma)$, which is log-supermodular. Then,

$$\Delta\hat{w}_{\sigma_1} - \Delta\hat{w}_{\sigma_2} = (\sigma_1 - \sigma_2)(s_1 - s_2),$$

where $\Delta\hat{w}_{\sigma_i} = \log w_{s_1\sigma_i} - \log w_{s_2\sigma_i}$. If $s_1 > s_2$ and $\sigma_1 > \sigma_2$, then $\Delta\hat{w}_{\sigma_1} - \Delta\hat{w}_{\sigma_2} > 0$. That is, increases in skill observe a higher increase in wages in more skill intensive industries due to the complementarity between the worker's skill and the sector's skill intensity. Now, observe that for the wage regression under consideration we have

$$\Delta\hat{w}_j - \Delta\hat{w}_k = (\gamma_i - \gamma_{i'})\left(\ln\left(R_j\right) - \ln\left(R_k\right)\right),$$

where $\Delta\hat{w}_j = w_{ij} - w_{i'j}$. Thus, higher $\gamma's$ reflect higher returns to skill in an industry.

Therefore, we can think of the $\gamma's$ are reflecting an industries skill intensity.When the profile of sector-specific productivities of workers is log-supermodular, as in Costinot and Vogel [2010], more skill intensive industries will be more willing to pay for high skilled workers and we should expect to see a strong positive association between γ_z and s_z. Indeed this is the case, the correlation between the $\gamma's$ and the skill intensity s_z is equal to 0.68, confirming that skills are more highly rewarded in skill intensive industries. Table 17 reports the top 5 and bottom 5 ranked industries according to the γ's .

The results from these wage regressions suggest that the measure of skill s_z effectively captures the skill intensity of the different productive sectors in the economy.

Additional Robustness Checks

As mentioned in section 4.2 of the main text, the baseline estimating equation is deliberately parsimonious. In that section the effect of $\mu$and σ on trade flows were captured through the

Industry	Rank
Manufacturing and Reproducing Magnetic and Optical Media	1
Audio and Video Equipment Manufacturing	2
Computer and Peripheral Equipment Manufacturing	3
Communications Equipment Manufacturing	4
Semiconductor and Other Electronic Component Manufacturing	5

(a) Top 5 Industries

Industry	Rank
Grain and Oilseed Milling	80
Nonmetallic Mineral Mining and Quarrying	81
Metal Ore Mining	82
Coal Mining	83
Logging	84

(b) Bottom 5 Industries

Table 17: Industries by Skill Intensity

sum of three interaction terms: $\mu_j \times s_z$, $\sigma_j \times s_z$, and $\sigma_j \times s_z^2$. As a final robustness check, I now assume that the effect of $\mu$and σ on the dependent variable is captured through the sum of two terms: $g_\mu \left(s_z, \mu_j\right) + g_\sigma \left(s_z, \sigma_j\right)$. This specification retains the additive separability of the effects of skill abundance and skill diversity on trade flows, but allows for a more general effect of these two variables than that allowed in my baseline specification.

The functions $g_\mu(\cdot)$ and $g_\sigma(\cdot)$ could be estimated non-parametrically. Such an estimation would be burdensome and the exposition of such results is difficult to convey in an easily interpretable manner. It is for this reason that I do not proceed with a fully non-parametric estimation, but rather approach the problem through an exploration of the (s,μ) and (s,σ) spaces using step functions to approximate $g_\mu(\cdot)$ and $g_\sigma(\cdot)$.[44] That is, g_μ and g_σ are approximated as

$$
\begin{aligned}
g_\mu(s,\mu) &\simeq \sum_a \sum_b \varphi_{ab} \left(I_{ja} \times d_{zb}\right) \\
g_\sigma(s,\sigma) &\simeq \sum_c \sum_b \zeta_{cb} \left(I_{jc} \times d_{zb}\right),
\end{aligned}
$$

[44] The results from this approach can be made arbitrarily close to those from non-parametric estimation since any continuous function can be arbitrarily well approximated through step functions (see Bartle [1976]). In this sense the approach here is similar in spirit to the *method of sieves,* discussed in Chen [2008], for the estimation of semi-nonparametric models.

where

$$I_{jc} = \begin{cases} 1 & \text{if exporter } j \text{ is in skill dispersion cell } c \\ 0 & \text{otherwise} \end{cases}$$
$$I_{ja} = \begin{cases} 1 & \text{if exporter } j \text{ is in skill abundance cell } a \\ 0 & \text{otherwise} \end{cases}$$
$$d_{zb} = \begin{cases} 1 & \text{if industry } z \text{ is in skill bin } b \\ 0 & \text{otherwise,} \end{cases}$$

Under this parametrization, the estimating equation becomes

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \sum_a \sum_b \varphi_{ab} \left(I_{ja} \times d_{zb}\right) + \sum_c \sum_b \zeta_{cb} \left(I_{jc} \times d_{zb}\right) + W_{jz}\delta + \varepsilon_{ijz},$$

where the vector W_{jz} controls for alternative source of comparative advantage through simple interaction terms as in the previous section.

The $\mu-$space is divided into three bins: low, middle, and high skill abundance. Exporters are roughly evenly distributed into these three categories. I divide the $\sigma-$space into three bins, with bin 2 containing the median dispersion, and the $s-$space into five bins, with bin 3 containing the median skill intensity.[45] The distribution of manufacturing industries across these bins is (10,26,26,9,5). Because the econometric model already includes a full set of exporter and industry fixed effects, the full set of interactions $I_{ja} \times d_{zb}$ or $I_{jc} \times d_{zb}$ cannot be included. In the former case, I decide to normalize against the lowest skill intensity bin and the lowest skill abundance cell, while in the latter I normalize against the middle skill dispersion countries and the intermediate skill-intensity industries.

Given the normalizations that I have chosen, the hypotheses that skill abundant countries possess a comparative advantage in skill intensive industries implies that we should expect to observe the following inequalities on coefficients:

$$\varphi_{25} > \varphi_{24} > \varphi_{23} > \varphi_{22} > 0$$
$$\varphi_{35} > \varphi_{34} > \varphi_{33} > \varphi_{32} > 0$$

On the other hand, the hypothesis that skill diverse countries should specialize in low and

[45] Here bins are constructed based solely on the subsample of manufacturing industries.

high-skill intensity sectors imply that we should expect the following inequalities on the coefficients:

$$\begin{aligned}\zeta_{11} &< \zeta_{12} < 0\\ \zeta_{15} &< \zeta_{14} < 0\\ \zeta_{31} &> \zeta_{32} > 0\\ \zeta_{35} &> \zeta_{34} > 0\end{aligned}$$

The inequalities on the $\varphi's$ state that, since I am normalizing against lowest skill abundant countries and the lowest skill intensity sectors, the effect of moving to a higher skill abundance cell is positive, and that this effect becomes stronger as we move towards higher skill intensity bins. The inequalities on the $\zeta's$ say that, since I am normalizing against the exporters with an intermediate skill diversity and the intermediate skill intensity sectors, moving to a lower skill dispersion cell should have a negative effect, with this effect becoming more pronounced as we move towards the extremes in terms of skill intensity, while moving towards a higher skill dispersion cell should have a positive effect, with the effect increasing in magnitude as we move towards the extreme skill intensity bins.

	$\mathscr{B}_2$	$\mathscr{B}_3$	$\mathscr{B}_4$	$\mathscr{B}_5$
$\mathscr{A}_2$	-0.01	0.17^{***}	0.50^{***}	0.62^{***}
$\mathscr{A}_3$	-0.212^{***}	-0.09	0.19^{**}	0.26^{***}
$\mathscr{C}_1$	-0.07	-0.12^{***}	-0.04	-0.08^{*}
$\mathscr{C}_3$	$-0.09^{\star}$	-0.24^{***}	0.04	0.17^{***}

***, **, *, and $\star$ denote significance at the 0.1, 1,5 and 10 percent levels, respectively. $\mathscr{B}_i$ correspond to skill intensity bin i, $\mathscr{A}_i$ corresponds to skill abundance cell i, and $\mathscr{C}_i$ corresponds to skill diversity cell i.

Table 18: Approximating $g(s,\mu,\sigma)$ through step functions

Table 18 reports the estimates from this specification of the estimating equation. The estimates for $\varphi_2 = (\varphi_{22}, \varphi_{23}, \varphi_{24}, \varphi_{25})'$ respect all of the expected inequalities, except the sign restriction on φ_{22}, but this estimate is not statistically significant at conventional levels. The estimates for $\varphi_3 = (\varphi_{32}, \varphi_{33}, \varphi_{34}, \varphi_{35})'$ satisfy the string of inequalities $\varphi_{35} > \varphi_{34} > \varphi_{33} > \varphi_{32}$, but not the sign restriction on either φ_{32} or φ_{33}, the latter estimate not being statistically significant at conventional levels. Regarding the estimates for the $\zeta's$, the sign and inequality restrictions on $\zeta_1 = (\zeta_{11}, \zeta_{12}, \zeta_{14}, \zeta_{15})'$ are all satisfied. However, with respect to $\zeta_3 = (\zeta_{31}, \zeta_{32}, \zeta_{34}, \zeta_{35})'$ there are several violations. The sign restrictions are satisfied for

ζ_{34} and ζ_{35}, but not for ζ_{31} or ζ_{32}. Nonetheless, all the inequality restrictions among the $\zeta's$ do hold. The estimates from this specification provide evidence favoring the hypothesis that skill abundant countries tend to specialize in skill intensive industries. There is also evidence congruent with that from section 4.2, that suggests that greater skill diversity induces specialization in skill intensive industries.